# Big-Box Store Expansion and Consumer Welfare*

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**Abstract**

Supercenters and warehouse clubs have surged in the US, offering many product categories at low prices. Complementing a literature on their competitive effects, we study how these big-box stores affect consumer welfare by impacting shopping behavior. Our event studies show consumers change product categories per trip, adjust spending across store formats, and pay lower prices after store entries. We develop a novel demand model to incorporate these choices across stores and categories, and separately quantify consumption gains and trip-cost savings. We find households benefit substantially from consuming in supercenters relative to competing retailers, highlighting the importance of the store format.

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# 1 Introduction

The US has experienced striking changes in big-box store formats over the past few decades. From 2004 to 2019, the number of supercenters grew by about 240% to more than 4000 (Figure 1a). Another type of big-box store, warehouse clubs, also stands out with a 35% growth in the number of stores during the same period (Figure 1b).[1]

What makes these big-box stores unique? These retail establishments are physically large and offer a broad range of product categories at relatively low prices. For example, supercenters combine general merchandise with groceries, providing a large assortment of consumer packaged goods (CPG). Warehouse clubs usually operate membership warehouses that offer large wholesale quantities of products at low prices, covering a wide range of categories but a relatively limited assortment per category.

Despite the unique shopping opportunities provided by big-box stores, members of local communities often organize to block proposals of big-box store entries, citing reasons such as negative effects on local businesses, competition, and employment. Many local governments have enacted store cap ordinances to constrain store sizes (Zhou 2017).[2] However, given that variety is highly correlated with store size, these regulations would limit consumers' one-stop-shopping experience that precisely differentiates big-box stores and potentially affect the prices consumers face.

How does big-box stores' ability to provide substantial variety affect consumer shopping behavior and impact consumer welfare? On the one hand, consumers with preferences for variety can directly benefit from a broad range of product categories. On the other hand, consumers can save trip costs by buying multiple categories from the same store. Quantifying the value of providing an additional product category requires an understanding of cross-category effects driven by trip costs, which in turn affects consumer store choice

[1] Major supercenters include Walmart Supercenter, Super Target, Meijer etc. Major warehouse clubs include Costco, BJ's, Sam's Club etc. Hortaçsu and Syverson (2015) also documents the growth of both supercenters and warehouse clubs since 1990 using employment data.

[2] Bertrand and Kramarz (2002) and Sadun (2014) study the effects of entry regulation in Europe.

decisions.

In this paper, we first provide new empirical evidence on the effects of big-box store expansion on consumers' store-category choice patterns. Motivated by the reduced-form results, we develop and estimate a novel multi-store multi-category demand model that allows us to decompose the welfare benefits of more categories into components driven by utility gains from consuming product categories and trip cost savings.

We estimate the impact of big-box store entries on consumer shopping behavior by utilizing an event-study approach. Combining hundreds of thousands of households' shopping trip records from the NielsenIQ Consumer Panel (henceforth HMS) with data on opening dates and locations of four major big-box chains, we present three facts on the effect of big-box store entries.

First, households substitute toward big-box stores from other stores. We find a sharp hike in average households' spending share at a big-box store after its entry, for both supercenter and warehouse club entries. Concurrently, households' spending share in other stores declines, with grocery stores being the most affected. This finding suggests a reallocation of expenditure toward big-box stores, which is consistent with Arcidiacono et al. (2020), who show revenues drop in incumbent stores after the entry of Walmart Supercenters.

Second, households change the number of product categories purchased per shopping trip. After a supercenter entry, households purchase more categories per trip from the supercenter, but fewer categories per trip from other stores. This finding implies complementarities across categories within store due to one-stop shopping. Surprisingly, we find households do more multi-stop shopping after a warehouse club enters. This change may relate to the strategy of warehouse clubs, which is to provide a limited assortment within a wide range of categories.

Third, for all categories, households pay lower prices than the national average, with food seeing the most notable drop. This effect lines up with the low-price strategy of big-box stores, which is supported by previous research (e.g. Hausman and Leibtag 2007; Ellickson et al. 2012; Ailawadi et al. 2018).

To quantify the effects of big-box store entries in a way that simultaneously incorporates substitution across stores, cross-category complementarities, and price changes that our empirical analysis reveals, we develop a multi-store multi-category demand model. We build on a category-choice model in Mehta and Ma (2012) by adding a multi-store choice that nests category-level choices. Our model allows households to visit up to two stores each week to fulfill their shopping needs.[3] For each store choice, households' utility is determined by the choice of quantity for each product category and their trip costs to the chosen stores. For the quantity choice, we use a non-homothetic indirect translog utility function that takes prices, a measure of quality for each store-category, and household budget as inputs. This utility function allows for flexible complementarity patterns across categories and income effects.

We estimate the model with a large sample of households in the HMS who shop across a wide range of retail chains. We focus on four major categories: food, non-food grocery, health and beauty care, and general merchandise. These product categories cover around 18% of all expenditure in the CPI. We obtain quality-adjusted price measures that allow us to compare prices for a given category across stores, holding quality fixed. We find that supercenters have relatively low quality-adjusted prices in all four categories. Warehouse clubs have relatively low quality-adjusted prices in food and non-food grocery, but not in the other categories.

We show cross-category complementarity patterns with a counterfactual analysis on removing different product categories in big-box stores. We find that different categories in the same store are substitutes, holding store choices fixed, but they exhibit more complementarities when households can freely choose across stores. This result is driven by households one-stop shopping for different categories in the same store. Once the probability of choosing the store becomes lower due to the exit of a category, the expected quantity purchased from other categories in the same store also declines. This cross-category effect is more pronounced in supercenters compared to warehouse clubs, suggesting that the

[3]This assumption is not very restrictive, because households rarely visit more than two stores per week in our sample.

convenience of one-stop shopping is more prevalent in supercenters.

We quantify the value of each category using the welfare loss from removing each single category, while other categories remain available. We also calculate the welfare loss of removing all categories from a store, which we denote as the value of a store. To illustrate the importance of cross-category effects, we compare the value of each category to the value of a store. Our estimates suggest each category accounts for a substantial share of the value of a supercenter. For example, general merchandise in a supercenter accounts for 29% of the total value, even though the spending share in this category is only 7.6%. The sum of all category values is greater than the value of a supercenter, suggesting a diminishing effect of removing each category when more categories are removed. The reason is that removing a category also lowers spending in other categories and the overall probability of visiting that store. If a category is the first to be removed while other categories are still available, it creates a greater loss in welfare than when that same category is the last one to be removed. For warehouse clubs, we find this amplification effect only applies to food. The sum of all category values is smaller than the value of a warehouse club, which implies an increasing effect of removing each category. In addition, we compare the effect of category provision and price increase. We find that welfare loss due to a 10% increase in the price of a category is only 1.3% of the welfare loss due to the exit of a category.

Finally, we compare the value of big-box stores with other store types, and decompose the difference into changes in the utility from consuming product categories, which we denote as consumption utility, and trip costs. First, we calculate the welfare loss when a supercenter is replaced by a competing store. Households face new availability of categories with new quality-adjusted prices and also pay different trip costs based on their new store choices. Second, we compare the welfare losses when different stores exit their current markets. Our estimates show that a supercenter generates a value about twice that of most store types, with one-third of the gain from savings in trip costs. A warehouse club mostly generates the same value as other stores. Therefore, even though both supercenters and warehouse clubs offer a wide range of product categories, supercenters generate substantially higher welfare gains for consumers through their lower quality-adjusted prices and cross-category complementarities, highlighting the importance of a one-stop-shopping experience.

Our paper contributes to several strands of literature. First, it enriches a literature on the impact of big-box stores, as summarized in Carden and Courtemanche (2016) and Ellickson (2016). These papers study the effects of supercenters, and to a lesser extent warehouse clubs, on outcomes such as prices, competition, welfare, market structure, labor markets, sociocultural effects, and health.[4] However, less is known about the mechanisms of how big-box stores affect consumer demand and shopping behavior by facilitating one-stop shopping as a multi-product retailer, which underpin the aforementioned outcomes.[5] In this paper, we provide new empirical evidence on how households change various dimensions of their shopping behavior, such as product categories per trip, in response to both supercenter and warehouse club entries. Interestingly, we find different results for these two store formats. We further develop a novel structural model that provides a microfoundation for store-category choice, which allows us to simultaneously quantify various sources of welfare gains from these store entries. This model can also explain the differential effects of supercenters and warehouse clubs.

Second, we contribute to a literature on demand models for retail markets. Consumers incur trip costs to visit multiple stores and purchase multiple categories in retail markets. Microfounded demand systems that accommodate cross-category complementarities typically do not model the store-choice process (Song and Chintagunta,

[4]For example, Jia (2008) and Holmes (2011) assess the density economies of Walmart with a focus on competition and market structure. Ailawadi et al. (2010) examine incumbent retailers reactions to a Wal-Mart entry and the impact of these reactions on the retailers sales. More recent work includes Arcidiacono et al. (2020), who estimate competitive price effects. Atkin et al. (2017) provide empirical evidence on the impact of Walmart entry in Mexico and estimate large welfare gains for households. Beresteanu et al. (2024) focus on the overall impact of Wal-Marts entry on incumbent supermarket firms in a framework of dynamic discrete game between heterogeneous firms.

[5]One exception is Hwang and Park (2016), who estimate the impact of Walmart supercenter conversions on household shopping behavior and find an increase in per-visit expenditures drives revenue gains in Walmart. They also find evidence of increases in category-level spending in nine pre-existing product groups, particularly for food categories.

2007; Bhat, 2005; Mehta and Ma, 2012; Mehta, 2015). To incorporate our empirical evidence on household shopping behavior across stores, we build on Mehta and Ma (2012) and develop a unified multi-store multi-category demand model by adding a multi-store choice that depends on trip costs and nests category-level choices. The model is discrete in store choice but continuous in quantity choice for each category, while allowing for corner solutions.[6] This model structure allows us to decompose the consumer welfare into components driven by consuming multiple categories and trip cost savings. To the best of our knowledge, the only paper that has a similar store-category-choice design is Thomassen et al. (2017).[7] They allow for a single-store choice for each category and estimate the model using UK consumer data to quantify cross-category pricing effects due to one-stop shopping, finding that internalizing them substantially reduces market power. In contrast, our model allows multi-store choice for each category and income effects.[8] Also, we focus on the effects of category exit and consumer welfare.

Third, our paper links to a broad literature on the relationship between concentration and market power summarized in Berry et al. (2019) and Syverson (2019). They highlight that the theoretical relationship between market concentration and average market power is ambiguous and call for a surge in industry-level research to characterize heterogeneity more fully both across and within markets.[9] Big-box stores are the largest retailers in the CPG industry. They are capturing a larger market share over time, leading to increased retail concentration. We complement Leung and Li (2021), who use detailed micro-data on

[6]This allows us to account for the fact that many households do not purchase all categories in the same week.

[7]Seo (2019) and Florez-Acosta and Herrera-Araujo (2020) both construct discrete store-category-choice models that include shopping costs. The former studies the welfare impact of allowing liquor sales at grocery stores and shows large gains for consumers due to one-stop shopping. The latter estimates the shopping costs of visiting supermarkets for a basket of products. We develop a discrete-continuous two-level choice model while allowing broader categories and a quantity choice of each category, and provide a general framework to study the impact of increased firm scope.

[8]Multi-store choice for each category fits better with our data because we frequently observe households purchasing in multiple stores for the same category. We also consider income effects as they directly affect welfare calculations.

[9]Many empirical studies find patterns of simultaneous concentration and productivity growth, and Syverson (2019) argues that the case for large and general increases in market power is not yet dispositive.

firms and consumers in the retail sector to decompose rising concentration, and focus on the potential welfare benefits for consumers from shopping in these stores. While we leave the overall welfare analysis of big-box store entries for future research, this paper shows multi-product shopping as one mechanism of why consumers value such stores.

The rest of the paper is organized as follows. Section 2 describes the data. Section 3 presents reduced-form analysis on the entry of big-box stores. Section 4 develops a multi-store multi-category choice model of households. Section 5 estimates the model and demonstrates the results. Section 6 provides counterfactuals and welfare analysis. Section 7 concludes.

# 2 Data

## 2.1 NielsenIQ Consumer Panel

The NielsenIQ Consumer Panel Dataset (HMS) represents a longitudinal panel of approximately 40,000 to 60,000 US households from 2004 to 2019 who continually provide information to NielsenIQ about their households and what products they buy, as well as when and where they make purchases.[10] Panelists use in-home scanners to record all their purchases, from any outlet, intended for personal, in-home use. Products include all NielsenIQ-tracked categories of food and non-food items, across all retail outlets in the US. NielsenIQ samples all states and major markets. Panelists are geographically dispersed and demographically balanced.

Panelists report the products they purchase in each shopping trip. For each product as defined by its universal product code (UPC), we know the quantity purchased and total price paid for all units. Over 5 million products are classified into about 1,100 product modules, 125 product groups, and 10 product departments, which allows us to calculate varieties at

[10] The data are available through a partnership between NielsenIQ and the James M. Kilts Center for Marketing at the University of Chicago Booth School of Business. Information on access to the the consumer panel data as well as the retail scanner data described below is available at http://research.chicagobooth.edu/nielsen/.

various levels. We further group products into five departments: food, non-food grocery, health and beauty care, general merchandise, and others.

An anonymized retail-chain identifier is specified for each trip and a channel type of each retail chain is provided. Major channel types in our analysis are discount store, warehouse club, grocery store, drug store and dollar store. We also observe where the household resides at various geographic levels from the NielsenIQ Scantrack market level (NielsenIQ classifies regions into around 50 market areas) down to the level of county and 5-digit zip code. Because the location of each shopping trip is not revealed, we assume households visit the closest store of each retail chain.

## 2.2 Store Locations

We obtain the store locations and opening dates of four big-box chains including Walmart supercenters and three warehouse club chains: Costco, Sam's Club, and BJ's. Data of Walmart supercenter openings are from Arcidiacono et al. (2020) and covers 2004-2013. Data of warehouse club openings are from Coibion et al. (2021) and covers 2004-2015. These data allow us to conduct event studies to study the impact of big-box stores.

We use the National Establishment Time Series (NETS) dataset from 1990-2019, which covers the location of the universe of stores in the US to construct distance measures for structural estimation.[11]

We also use the Nielsen TDLinx data from 2004-2019 to obtain monthly-level store counts for each retail chain at the market level.

[11]For each household-store pair, we calculate the distance between store locations and the population centroid of the 5-digit zip area where the household lives. We match retail chains in the HMS to stores in the NETS conditioning on channel type and geographical distribution.

# 3 Empirical Analysis on Big-Box Store Entry

In this section, we utilize an event-study approach to present empirical evidence on how households change various dimensions of their shopping behavior when big-box stores enter. We document three main facts. First, households substitute toward big-box stores from other stores. Second, households change the number of product categories purchased per shopping trip. Third, households pay lower prices. These facts are consistent with the assortment and pricing strategies of supercenters and warehouse clubs.

## 3.1 Empirical Strategy

We begin with a two-way fixed effects model to estimate the impact of the entry of big-box stores. Our baseline independent variable measures the number of stores for each chain within the 5-digit zip code of each household. As shown in equation (1), we regress outcomes of interest $Y_{it}$ for household $i$ in quarterly period $t$, on the number of stores $Num_{m(i)t}$ for the 5-digit zip code $m(i)$ that household $i$ resides in, and add household fixed effects to control for fixed household characteristics, as well as period fixed effects to control for national time trends:

$$Y_{it} = \beta \times Num_{m(i)t} + \alpha_i + \alpha_t + \varepsilon_{it}. \tag{1}$$

If a store enters in periods when unobservable local household characteristics correlated with the outcome change, or households anticipate these openings by changing patterns in significant ways, then this would be a threat to our identification. A priori, we believe that it is difficult for households or stores to exactly time store entry with sharp changes in unobservables. Holmes (2011) provides evidence that the roll-out of new Walmart supercenters was more about saving shipping costs and achieving economies of density in the distribution center network rather than demand or cost characteristics of local markets.

To alleviate these concerns, we first estimate the trends before and after the entry event by adding leads and lags of the independent variable $Num_{m(i)t}$. If the pre-trends are parallel, this suggests that stores are not selectively entering regions with different trends in unobservables before the entry after we control for household and time fixed effects. We also use an estimator robust to heterogeneous treatment effects from de Chaisemartin and DHaultfuille (2020) and de Chaisemartin and D'Haultfoeuille (2022) (hereafter DCDH).

However, one may argue that stores or households may have ability to anticipate the precise timing and location of the entry. To further address these concerns, we also follow Arcidiacono et al. (2020) and construct distance bands measuring the number of supercenters or warehouse club exposures around the population-weighted centroid of each household's 5-digit zip code. This allows us to compare households treated at different distances and further alleviate endogeneity concerns. If we find that the effect of entry decays quickly with distance, a violation of our identification assumption would require retailers to precisely choose locations with sharp changes in unobservables while surrounding locations experience no sharp changes.

## 3.2 Results

We document three main facts on the effects of big-box store entries. First, we find households substitute toward big-box stores from other stores. We show the effects of supercenter and warehouse club entry on spending share in Table 1 and Table 2, respectively. We find a sharp hike of about 6 percentage points (p.p.) in average households' spending share for supercenters after its entry, and about 3.5 p.p. for clubs. Concurrently, households' spending share in other stores declines, with grocery stores being the most affected, decreasing by 3.6 p.p. and 2.3 p.p. for supercenter and club entries, respectively. This finding suggests a reallocation of expenditure toward big-box stores.

In Figure 2, we show pre-trends are parallel around store entries roughly two years before the event, whereas the effects are dynamic and continue to rise for an extended period after the event. This observation is consistent with both households taking time to learn about the presence of new stores and adjusting their purchasing habits.[12] Our results are also similar when using an estimator robust to heterogeneous treatment effects from DCDH, as shown in Appendix Tables B1 and B2 and Appendix Figures C4 and C5.

We also show that these effects dissipate quickly within a few miles for supercenters and warehouse clubs in Appendix Tables B3 and B4. The fact that the effect dissipates as the distance from each household rises increases our confidence in a causal interpretation of our estimates.

Second, we find households change the number of product categories purchased per shopping trip when big-box stores enter. We show the effects of supercenter and warehouse club entry on varieties per trip, as measured by the number of product departments, by store type in Table 3 and Table 4, respectively. After a supercenter entry, households increase product departments per trip from supercenters by about 0.006. Households also purchase fewer varieties per trip from other stores. This finding suggests complementarities across categories within supercenters due to one-stop shopping. Surprisingly, we find households purchase fewer varieties per trip when warehouse clubs enter. This finding may relate to the strategy of warehouse clubs, which is to provide a limited assortment within a wide range of categories.

We also measure varieties at different levels, starting from the number of UPCs, which is the lowest level, to the number of product departments, which is the highest level. We show the effects of store entry on the number of UPCs per trip by store type in Appendix Tables B5 and B6, which show the same patterns qualitatively. We display results for each level of variety in Appendix Tables B7 and B8. Consistent with the fact that varieties per trip decrease when warehouse clubs enter, we find households do more multi-stop shopping, with the number of trips increasing significantly by about 0.023 per quarter. We also find the number of retailers visited decreases when supercenters enter, but increases when warehouse

[12] We show in Appendix Figure C1 that spending shares are increasing in both supercenters and warehouse clubs in all product departments over the sample period. We also show effects on spending share in other store types in Appendix Figures C2 and C3.

clubs enter in Appendix Table B9 and Table B10, respectively. We show that pre-trends are again parallel in Figure 3 for departments for trip, and in Appendix Figures C6, C7, and C8 for trip number and other variety measures. These results are again robust when using methods from DCDH as shown in Appendix Tables B11, B12 and Appendix Figures C9, C10, C11, and dissipate quickly with distance as shown in Appendix Tables B13 and B14.

To provide suggestive evidence of why supercenters generate a different effect from warehouse clubs, we show how supercenters and warehouse clubs differ in product variety. In Figure 4, we show the average number of UPCs and departments per household-quarter for supercenters, warehouse clubs, and other channel types over the sample period. The number of UPCs can capture variety depth of a store, whereas the number of departments can capture variety breadth. Households buy far more varieties in supercenters than any other channel type, whereas warehouse clubs sell fewer UPCs but a similar number of departments compared with grocery stores and supercenters. The number of UPCs in warehouse clubs is closer to other channel types such as discount stores and dollar stores, but higher than drug stores and other miscellaneous channel types. This would be consistent with the hypothesis that supercenters with larger variety depth and breadth allow households to engage in more one-stop shopping, whereas warehouse clubs focus mostly on variety breadth but less on depth.

Third, we find that households pay lower prices when big-box stores enter. We calculate the relative price index (RPI) of each household following Aguiar and Hurst (2007):

$$RPI_{it} = \frac{\sum_{j \in J_{it}} p_{jit} q_{jit}}{\sum_{j \in J_{it}} \bar{p}_{jt} q_{jit}}, \tag{2}$$

where $p_{jit}$ and $q_{jit}$ are the price and quantity for UPC $j$ for household $i$ at time $t$, respectively, and $\bar{p}_{jt}$ is the average national price for UPC $j$. In other words, to construct a household RPI, we calculate the ratio between total expenditure and the counterfactual expenditure of each good at its average price in the reference region.

We show the effects of supercenter and warehouse club entry on household RPIs in Table 5 and Table 6, respectively. RPIs decrease by about 0.5% when supercenters enter. This drop holds for all product categories, with health and beauty care and food seeing the most notable drop. RPIs decrease by about 0.15% when warehouse clubs enter, although this result is statistically insignificant. We show pre-trends are again parallel in Figures 5 for all products, and in Appendix Figure C12 and C13 for different product categories. These results are again robust when using methods from DCDH as shown in Appendix Tables B15 and B16 and Appendix Figures C14 and C15, and dissipate quickly with distance as shown in Appendix Tables B17 and B18.

There are several reasons for these price decreases. First, given the low-price strategy of big-box stores, which is supported by previous research (Hausman and Leibtag, 2007; Ellickson et al., 2012; Ailawadi et al., 2018), households may now be able to enjoy the lower prices of supercenters for the same products they previously consumed. Second, households may shift their consumption bundle to products with lower RPIs. Third, prices of other stores may decrease as a competitive response to supercenter entry. However, Arcidiacono et al. (2020) find supercenter entry has no causal effect on incumbent prices.

To provide suggestive evidence of why supercenters generate a different effect from warehouse clubs, we show how supercenters and warehouse clubs differ in prices. In Figure 6, we calculate the RPI of each retailer or channel type. We find supercenters consistently offer lower prices than their competitors nationally, although their price advantage has been decreasing. Although warehouse clubs generally have an RPI below one, they tend to have higher RPIs than supercenters over the sample period, with the exception of Club 2 offering lower prices in the last periods, which our entry data do not capture. These patterns are consistent with our empirical result that supercenters generate larger price decreases.

# 4 A Model of Household Demand

Motivated by the reduced-form results, we develop a novel multi-store multi-category demand model that simultaneously incorporates substitution across stores, cross-category complementarities, and price changes. This model allows us to decompose the welfare benefits of more categories into components driven by consumption utility and trip cost savings.

## 4.1 Model Overview

Consider a household's weekly shopping decision that includes a store-choice decision for each shopping trip and a quantity-choice decision for each product category. The decision process for the household is as follows:

1. For each given store choice, a household chooses the quantity for each product category such that the utility of purchasing products in the chosen stores is maximized.

2. The household weighs the utility generated from purchasing products against trip costs for each store choice, and pick the stores that achieve the highest total utility.

Let $\mathcal{S} = \{s_1, s_2, ..., s_{|\mathcal{S}|}\}$ denote the set of available stores that a household faces. We allow the household to choose up to two stores to visit per week[13]. Let $\mathcal{R}$ be the set of store choices. For each element $r \in \mathcal{R}$, it can be one store $\{s_i\}, i \in \{1, ..., |S|\}$, or a set of two stores $\{s_i, s_j\}, i \neq j, i, j \in \{1, ..., |S|\}$, or none of the stores, $\emptyset$. The possible choices for the weekly store-visit decision thus include $|\mathcal{S}|$ one-store choices, $\frac{|\mathcal{S}|(|\mathcal{S}|-1)}{2}$ two-store choices and one choice of not visiting any stores.

We consider $M$ focal categories of products that a household may have shopping needs for. Each store sells at least one product category and heterogeneity exists for the same category across different stores. Let $\mathcal{M}_r$ denote the set of store-product categories that are

[13]This a assumption is not too restrictive as only a small share of household-week observations sees more than two stores visited, with spending share less than 10% in the third store or above .

available for store-choice option $r \in \mathcal{R}$. If $r$ only includes one store, $\mathcal{M}_r$ is the categories available in that single store. If $r$ includes two stores, $\mathcal{M}_r$ includes the categories in both stores. We use $j \in \mathcal{M}_r$ to denote each store-category (e.g., "Costco-Food"). $c = c(j)$ denotes the product category of $j$ (e.g., "Food") and $s = s(j)$ denotes the store of $j$ (e.g., "Costco").

We introduce category 0 as a composite good of products outside our $M$ focal categories that households may purchase in the same week. We also introduce store 0 as an outside option to allow households to shop outside focal stores $\mathcal{S}$. We assume all the products sold in store 0 belong to category 0.

For a given store choice $r \in \mathcal{R}$, the household makes purchase decisions across store-categories $\mathcal{M}_r$ to maximize the utility with a fixed weekly budget $y$:

$$\begin{aligned} V_r = & \max_{Q_0, Q_1, \ldots, Q_{M_r}} U\left(\psi_1 Q_1, \ldots, \psi_{M_r} Q_{M_r}, Q_0\right) \\ & s.t. \sum_{j \in \mathcal{M}_r} P_j Q_j + P_0 Q_0 = y, Q_j \geq 0, j \in \mathcal{M}_r, Q_0 > 0. \end{aligned} \tag{3}$$

Store-category $j$'s price is given as $P_j$, and $Q_j$ is the quantity to be determined. $\psi_j$ indicates the quality for store-category $j \in \mathcal{M}_r$, which we further explain below.

The household's overall utility from shopping weekly is determined by both the utility from consuming at the chosen store(s), namely $V_r$, and costs of shopping trips to the store(s), $\Gamma_r$. The household chooses the store set $r \in \mathcal{R}$ that maximizes the overall utility $\mathcal{U}$:

$$\begin{aligned} & \max_{r \in \mathcal{R}} \mathcal{U}\left(V_r, \Gamma_r\right) \\ \text{where } V_r = & \max_{Q_0, Q_1, \ldots, Q_{M_r}} U\left(\psi_1 Q_1, \ldots, \psi_{M_r} Q_{M_r}, Q_0\right) \\ & s.t. \sum_{j \in \mathcal{M}_r} P_j Q_j + P_0 Q_0 = y, Q_j \geq 0, j \in \mathcal{M}_r, Q_0 > 0. \end{aligned} \tag{4}$$

## 4.2 Category-Level Decision

We first solve for the optimal quantity of each store-category given each store choice following Mehta and Ma (2012). We define quality-adjusted prices and quantity as $P_j^* = P_j/\psi_j$, $Q_j^* = Q_j\psi_j$, for $j \in \mathcal{M}_r$ and $P_0^* = P_0$, $Q_0^* = Q_0$. The quantity decision problem within store choice $r$ hence becomes

$$V_r = \max_{Q_0^*, Q_1^*, \ldots, Q_{M_r}^*} U\left(Q_1^*, \ldots, Q_{M_r}^*, Q_0^*\right) \tag{5}$$
$$s.t. \sum_{j \in \mathcal{M}_r} P_j^* Q_j^* + P_0^* Q_0^* = y, Q_j^* \geq 0, Q_0^* > 0.$$

Note we allow zero consumption of the focal categories and assume the composite good 0 is always purchased. The household thus needs to make two decisions at the category-choice level: purchase incidence, that is which store-categories to purchase, and quantity for purchased store-categories.

As mentioned in Mehta and Ma (2012), the utility-maximization problem can be solved using two approaches. In the first approach, we can specify a strictly increasing and quasi-concave functional form for direct utility $U$ and solve for a set of Kuhn-Tucker (KT) conditions to get the optimal quantities and purchase incidence, which is employed by Thomassen et al. (2017). In the second approach, we can give a functional form for the indirect utility $V$ that corresponds to a strictly increasing and quasi-concave direct utility $U$, and derive optimal quantities and purchase incidence using methods introduced by Lee and Pitt (1986). We follow Mehta and Ma (2012) to use the latter approach and apply a nonhomothetic indirect translog utility:

$$\ln V_r = -\sum_{j=0}^{M_r} a_{c(j)} \ln \frac{P_j^*}{y} + \frac{1}{2} \sum_{j=0}^{M_r} \sum_{k=0}^{M_r} b_{c(j)c(k)} \ln \frac{P_j^*}{y} \ln \frac{P_k^*}{y}. \tag{6}$$

This indirect utility form has several advantages. First, it allows us to solve for demand functions explicitly and remains flexible enough to approximate general utility functions. Second, it accommodates flexible complementarity patterns across different product categories $c(j)$ and $c(k)$. Third, the non-homothetic design can incorporate income effects from budget changes, which can be important in welfare estimation.

Assume focal store-categories $j \in \{m+1, ..., M_r\}$ are purchased and $j \in \{1, ..., m\}$ are not purchased. For the purchased store-categories, we invoke Roy's identity to solve for the budget share $\{S_j\}$:

$$S_j(\{P_j^*\}_{j=0}^{M_r}, y) \equiv -\frac{\partial \ln V_r(\{P_j^*\}_{j=0}^{M_r}, y)/\partial \ln P_j^*}{\partial \ln V_r(\{P_j^*\}_{j=0}^{M_r}, y)/\partial \ln y}, \ \forall j \in \{m+1, ..., M_r\}. \tag{7}$$

Quantity can be calculated using $Q_j^* = y \times S_j$. For non-purchased store-categories, we use virtual price $T_j$ instead of $P_j^*$ in the indirect utility function. The virtual price $T_j$ is defined as the price such that $S_j = 0$ is an interior solution for category $j$. In other words, when $P_j^* \geq T_j$, the optimal quantity for store-category $j$ is zero. We solve for $\{T_j\}_{j=1}^m$ from the following equation:

$$S_j(\{T_j\}_{j=1}^m, \{P_j^*\}_{j=m+1}^{M_r}, P_0^*, y) = 0, \ j = 1, ..., m. \tag{8}$$

Given purchase incidence $\{I_j = 0\}_{j=1}^m, \{I_j = 1\}_{j=m+1}^{M_r}, \{I_0 = 1\}$, where $I_j = 1$ indicates purchased categories, the budget shares and quality-adjusted prices should satisfy the following conditions:

$$S_j(\{T_j(\{P_j^*\}_{j=m+1}^{M_r}, P_0^*, y)\}_{j=1}^m, \{P_j^*\}_{j=m+1}^{M_r}, P_0^*, y) > 0, \qquad j = 0, m+1, ..., M_r. \tag{9}$$

$$T_j(\{P_j^*\}_{j=m+1}^{M_r}, P_0^*, y) \leq P_j^*, \qquad j = 1, ..., m. \tag{10}$$

The first condition says the solution for purchased store-categories should be strictly greater than zero, and the second condition requires the actual quality-adjusted price to be greater than or equal to the calculated virtual price such that it is too high for households to purchase any products from the store-category.

Using the functional form of indirect utility, we are able to specify the solutions for budget shares and purchase incidence conditions of all combinations of purchase and non-purchase decisions. The household chooses the purchase incidence that gives the highest indirect utility.

Next, we specify a detailed functional form for quality-adjusted price $P^*$. Recall that $P_j^* = P_j/\psi_j$. We assume quality $\psi_j$ depends on both store-category observed and unobserved characteristics. For each store-category $j$ in category $c$ and store $s$, we define

$$\ln \psi_j = (\alpha_{s(j)} + \lambda_{c(j)} + \rho X_j + \varepsilon_j)/\mu_{c(j)}. \tag{11}$$

Store fixed effect $\alpha_{s(j)}$ accounts for store-specific characteristics including store amenities, retailer reputation, common features of products sold in the store (e.g., products in warehouse clubs in general have larger package size), etc. Category fixed effect $\lambda_{c(j)}$ captures common categorical tastes of consumers. For example, households usually have higher demand for food products than for health and beauty care products. Because $\lambda_c$ and $a_c$ cannot be separately identified for each category, we further set $a_c = 0, c = 1, ..., M$ to allow only one category fixed effect in each category. Note we normalize $\sum_{c=0}^{M} a_c = 1$ in equation (6), because the spending share of all categories including category 0 sums up to 1. Thus, we have $a_0 = 1$ for category 0. $X_j$ captures store-category characteristics. Here, we define $X_j$ as the number of UPCs per store-category, which measures the variety depth of each store-category. We expect $\rho > 0$ because households usually enjoy more varieties of products.

$\varepsilon_j$ is store-category-household-week specific and describes households' needs and tastes that are not observed by researchers. We assume $\varepsilon_j$ is i.i.d. and follows a standard extreme-value distribution. $\mu_{c(j)} > 0$ is the scale parameter that varies across categories to allow different spreads of tastes in each category.

Hence, we can write the quality-adjusted prices with full subscripts for household $i$ in week $t$ and store-category $j$ as follows:

$$\ln P^*_{ijt} = \ln P_{jt} - \frac{\alpha_{s(j)} + \lambda_{c(j)} + \rho X_j + \varepsilon_{ijt}}{\mu_{c(j)}}. \tag{12}$$

We also assume for category 0 that $\ln P^*_{i0t} = \varepsilon_{i0t}$, where $\varepsilon_{i0t}$ is i.i.d. and follows a standard normal distribution. This outside-option category 0 serves as a benchmark for other store-categories.

## 4.3 Store-Level Decision

Given indirect utility $V_{irt}$ for store choice $r \in \mathcal{R}$ from the category-level decision, household $i$ in week $t$ chooses $r$ that gives the highest total utility. We assume the functional form of $\mathcal{U}$ is a linear combination of log indirect utility $\ln V_{irt}$, trip costs $\Gamma_{irt}$ and idiosyncratic shock $\nu_{irt}$:

$$\max_{r \in \mathcal{R}} \mathcal{U}_{irt} = \gamma^v \ln V_{irt} + \Gamma_{irt} + \nu_{irt}. \tag{13}$$

For the observed trip costs $\Gamma_{irt}$, we specify the following functional form:

$$\Gamma_{irt} = \gamma_g(\gamma^1 D_{ir} + \gamma^2 I^{two}_{irt} + \gamma^3 I^{same}_{irt}). \tag{14}$$

$D_{ir}$ is the distance between stores and households. When choice $r$ has two stores, we use the sum of the distances for each store-household pair. $\gamma^1$ is expected to be less than 0 because a greater travelling distance suggests higher trip costs. $I^{two}_{irt}$ is 1 when a two-store option is chosen. Besides longer traveling distances, extra fixed costs may arise if the household chooses to visit two stores, so we expect $\gamma^2 < 0$. Households may choose a two-store option because the two stores are close or are convenient to visit together. Hence, we include a dummy $I^{same}_{irt}$ equal to 1 if any households in the same market visit the store pair on the same day. Thus, $\gamma^3$ should be greater than 0, and $\gamma^2 + \gamma^3$ is the benefit when two stores can be visited together. Different households may have different sensitivity to trip costs. We use the set $\{\gamma_g, g = 1, ..., G\}$ to account for household-group heterogeneity, where we normalize $\gamma_1 = 1$ for group 1. For the outside option store 0, we assume its trip costs to be $\gamma^0$.

We include $\nu_{irt}$ as the unobserved idiosyncratic shock for each store choice $r$ of household $i$ in week $t$. $\{\nu_r\}_{r\in\mathcal{R}}$ are i.i.d. across household-week-store choices, and follow a standard extreme-value distribution. We introduce a scale parameter $\gamma^v$ to determine the relative importance of log indirect utility $\ln V_{irt}$.[14]

# 5 Estimation and Results

In this section, we first introduce the data sample for estimation and a two-stage approach to estimate the parameters. Next, we show the estimation results and provide quality-adjusted prices that allow us to compare prices for a given category across stores, holding quality fixed.

## 5.1 Data for Estimation

We use a subset of households' purchase records in the HMS to construct the data for estimation. To overcome computational burdens, we choose the state with the most observations in our data, Texas. We analyze data from a single year, 2012, during which we assume there is no intertemporal variation in the product varieties and tastes. To restrict supply-side changes, we exclude counties with substantial changes in the number of retailers observed during the year, other than big-box store entries. For the remaining counties, we remove county-quarters during the big-box store entries as households may be adjusting their shopping patterns given the new entry. Households can have different access to big-box retailers across different quarters due to entries. Because we assume each household-week is independent of each other in our model, we randomly sample three weeks per quarter

[14] Alternatively, we can multiply $\nu_{irt}$ by a scale parameter. The relative importance of indirect utility $\ln V_{irt}$ and trip costs $\Gamma_{irt}$ remains the same.

per household. Our final sample includes 11,376 household-week observations from 1,137 households across 57 counties. Each household has at least three weeks of observations.

We have 17 focal chains in our analysis: eight grocery chains, four discount chains (including the major supercenter), two warehouse club chains, two drug store chains and dollar stores. Given the relatively small market share of dollar stores, we aggregate all dollar stores into a single chain. Total spending share in the 17 chains is greater than 80% for all counties, suggesting these chains cover the majority of households' store choice options. All the spending outside the 17 focal chains belongs to outside option store 0.

We define a choice set for each household as follows. As the data only contains retail chain identifiers, we cannot differentiate between "chain" and "store" in our analysis. Therefore, we assume households only visit the closest store within the same chain. A chain is included in the choice set of a household if any household living in the same county ever purchases in the chain during the year. For two-store combinations in the store-choice set $\mathcal{R}$, we include store combinations that have ever been visited in the same week by any household in the same county. As a result, the number of different chains ranges from 4 to 13 and the number of elements in choice set $\mathcal{R}$ is between 10 and 91.

Our analysis includes products from four categories: food, non-food grocery, health and beauty care, and general merchandise. Any spending outside the four focal categories is treated as the outside option and goes to category 0. We use a national average of biweekly prices for each store-category, which is assumed to be exogenous from household-week-store-category unobservables. Specifically, store-category prices are calculated using the average price for each UPC in the category weighted by sales. To fix the weights, we only include UPCs that are sold in all biweeks in 2012 are included. Within each store-category, price variation over time solely comes from price changes within products as products and weights are fixed. Thus, we are able use this variation to estimate price elasticities. We also count the number of UPCs per store-category for the 17 chains as a measure of variety depth per store-category. A summary table of prices and variety depth are provided in Appendix Table B19.

Table 7 summarizes household demographics and shopping behavior. Households' weekly budget for CPG is \$270.6 on average.[15] One store is visited in 42% of the household-weeks and two stores are visited in 47%. The spending share of the total budget is 88% when households visit one store and 90% when they visit two stores. If it is a two-store shopping week, the spending share in the second store is substantially smaller than the first store, accounting for only 25% of the weekly budget.[16] About 11% of the observations have no shopping trips to the focal stores. We thus assume the outside-option store 0 is chosen for these observations. We calculate the share of households in each income quartile interacted with whether they have children under age 18 in Table 7. We allow different sensitivities to trip costs for these household groups.

## 5.2 Estimation Strategy

We estimate parameters in both category- and store-level decisions. Ideally, we want to estimate all the parameters simultaneously because the random shocks at both levels affect both store-level and category-level decisions. However, due to the computational burden that mainly comes from solving for the optimal quantity and purchase incidence for each store choice in each iteration during the optimization, we instead use a two-stage estimation.[17]

In the two-stage estimation of the parameters, we first estimate parameters at the category level decision: $\Theta = \{\alpha_s, \lambda_c, \rho, B = \{b_{cd}, b^2_{cd}\}, \mu_c, s \in \mathcal{S}, c, d = 1, ..., M+1\}$. Matrix $B$ includes parameters in equation (6) that describe the complementarity across store-categories. For categories within the same store, we capture the complementarity patterns using the parameters $\{b_{cd}, c, d = 1, ..., M+1\}$, where $M+1$ stands for category 0, and assume these parameters are the same for all stores. For categories in two different

[15]Weekly budget is calculated based on the annual household income bracket reported in the HMS and the ratio of consumer goods expenditure to total expenditure from the Consumer Expenditure Survey in 2012 divided by 52 weeks.

[16]A small share of household-week observations have more than two stores visited. We only include the top two store visits in terms of spending and the spending shares in other stores are typically less than 10%.

[17]We write the likelihood function for simultaneous estimation in Appendix A.1.

stores that can be purchased in the same week, we capture the complementarity patterns using the parameters $\{b^2_{cd}, c, d = 1, ..., M\}$, and assume these parameters are the same for all two-store combinations. We provide more details on the parameters in Appendix A.2.

We use maximum likelihood estimation (MLE) to recover the estimates. At the category-level decision, the observed data for each household $i$ and week $t$ are the purchase incidence in the chosen store $r$ ($\{\{I_j = 0\}_{j=1}^{m}, \{I_j = 1\}_{j=m+1}^{M_r}\}_{it}$) and spending share for purchased categories in the chosen store $r$ ($\{\{S_j\}_{j=m+1}^{M_j}\}_{it}$). Purchase incidence and spending share are functions of the unobserved $\{\varepsilon_{ijt}\}$ for $j \in \mathcal{M}_r$. Their relationship is derived from equations (9) and (10). Using the distribution of $\{\varepsilon_{ijt}\}$ for $j \in \mathcal{M}_r$, we can write the log-likelihood function for each household $i$ and week $t$ observing purchase incidence $\{\{I_j = 0\}_{j=1}^{m}, \{I_j = 1\}_{j=m+1}^{M_r}\}_{it}$ and budget share $\{\{S_j\}_{j=m+1}^{M_j}\}_{it}$:[18]

$$l_{it}\left(\{\{I_j\}_{j=1}^{M_r}, \{S_j\}_{j=1}^{M_r}\}_{it}|\Theta\right) = \ln\left(\int_{\varepsilon_0=-\infty} L_{r(it)}\left(\{\{I_j\}_{j=1}^{M_r}, \{S_j\}_{j=1}^{M_r}\}_{it}|\Theta\right)\phi(\varepsilon_{i0t})d\varepsilon_{i0t}\right). \quad (15)$$

In the estimation, we use Gauss-Kronrod quadrature to integrate out the $\varepsilon_0$'s. The log-likelihood for the entire sample with $N_{obs}$ observations is

$$l(\Theta) = \frac{1}{N_{obs}}\sum_{i=1}^{N}\sum_{t=1}^{T} l_{it}\left(\{\{I_j\}_{j=1}^{M_r}, \{S_j\}_{j=1}^{M_r}\}_{it}|\Theta\right). \quad (16)$$

At the second stage, we estimate $\Theta^S = \{\gamma^v, \gamma^1, \gamma^2, \gamma^3, \{\gamma_g, g = 2, ..., 8\}, \gamma^0\}$ given estimates from the first stage $\hat{\Theta}$ using MLE. The indirect utility $\ln V_r$ depends on both $\hat{\Theta}$ and random shocks $\{\varepsilon_{i0t}\}$ and $\{\varepsilon_{ijt}\}$ for each store-category $j$. We use Monte Carlo methods to draw all the shocks from the distribution of $\{\varepsilon_{i0t}\}$ and the truncated distribution of $\{\varepsilon_{ijt}\}$ for each store-category $j$.[19] We then predict $\ln \hat{V}_r = \ln \hat{V}_r(\boldsymbol{\varepsilon})$ for each store choice $r \in \mathcal{R}$ for each household-week, where $\boldsymbol{\varepsilon}$ is a vector of $\{\varepsilon_{i0t}\}$ and $\{\varepsilon_{ijt}\}$ for each store-category $j$. Given the distribution of $\{\nu_{irt}\}$, the likelihood of observing store choice

[18] The details of the likelihood function at the category level are provided in Appendix A.3.

[19] The distribution is truncated because category-level data impose restrictions on these shocks, as explained in detail in Appendix A.4.

$\{I^S_r = 1, I^S_{r'} = 0, r' \neq r\}$, purchase incidence $\{I_j = 0\}^m_{j=1}, \{I_j = 1\}^{M_r}_{j=m+1}$ and budget share $\{S_j\}^{M_j}_{j=m+1}$ for each observation can be written in logistic form:[20]

$$\hat{L}_{it}\left(\{I^S_{r'}\}_{r'\in\mathcal{R}}, \{I_j\}_{j\in\mathcal{M}_r}, \{S_j\}_{j\in\mathcal{M}_r}|\hat{\Theta}, \Theta^S\right) = \frac{\exp(\gamma^v \ln \hat{V}_r(\boldsymbol{\varepsilon_{it}}) + \Gamma_r)}{\sum_{r'\in\mathcal{R}} \exp(\gamma^v \ln \hat{V}_{r'}(\boldsymbol{\varepsilon_{it}}) + \Gamma_{r'})}. \tag{17}$$

The log-likelihood for the entire sample with $N_{obs}$ observations is

$$l(\Theta^S) = \frac{1}{N_{obs}} \sum_{i=1}^{N} \sum_{t=1}^{T} \sum_{r\in\mathcal{R}} I^S_r \ln\left(\hat{L}_{it}\left(\{I^S_{r'}\}_{r'\in\mathcal{R}}, \{I_j\}_{j\in\mathcal{M}_r}, \{S_j\}_{j\in\mathcal{M}_r}|\hat{\Theta}, \Theta^S\right)\right). \tag{18}$$

## 5.3 Estimates and Analysis

For the category-level estimation, we first present parameters in the quality-adjusted price in Table 8. The coefficient $\rho$ for the variety-depth measure is positive and statistically significant. This finding suggests that households prefer categories with more product varieties.

We calculate the expected quality-adjusted price for each store-category averaging across household-weeks. This quality-adjusted price has two useful features. First, it is comparable between stores within each category. In the definition of store-category prices in Section 5.1, the magnitude of store-category prices is not comparable across store-categories, because different products are included in different store-categories for the price measure. However, after we make a quality adjustment by using store and category fixed effects, as well as variety depth, the quality of products in different stores within a category is accounted for. Second, the quality-adjusted price changes at the same rate as the store-category price, because the log store-category price enters the log quality-adjusted price linearly with coefficient 1 (equation (12)). Percentage changes are the same for those two terms, making it easier to calculate price elasticity and analyze price effects.

Figure 7 presents the relative log quality-adjusted price $\ln P^*$ across stores for each

[20] The details of the likelihood function at the store level are provided in Appendix A.4.

category when $\ln P^*$ of the supercenter is normalized to 1. Results suggest that relative costs of product categories after controlling for quality across store types align with people's general impressions of these stores. For the food category, both supercenter and warehouse clubs offer products at a relatively low quality-adjusted price. The only type that provides an even lower quality-adjusted price is grocery stores. Other types, including regular discount stores, have a higher quality-adjusted price. For health and beauty care products, the two drug stores dominate all other stores. Note that for categories other than food, supercenter and other discount stores have similar quality-adjusted prices. This similarity can be explained by the fact that a supercenter is a regular discount store plus a grocery department. The results also show that even though all four categories are sold in different types of stores, the price for households can be very different, given quality. For big-box stores, supercenters have relatively low quality-adjusted prices in all categories, whereas warehouse clubs only have a relatively low quality-adjusted price for food and non-food groceries.

Second, we show the estimated parameters that describe complementarity patterns across categories. Table 9 displays $\{b_{cd}, c, d = 1, ..., M+1\}$ for categories within the same store. Positive numbers for a category pair suggest the two categories are complements and negative numbers suggest substitutes. We further calculate average cross-category price elasticities for individual demand conditioning on store choice and purchase incidence (Table 10). The relatively small own-price elasticities suggest households are price elastic in all categories. Note that we estimate an elastic demand for food with price elasticity at -1.28, whereas past research often suggests less elastic food demand (Andreyeva et al., 2010). Two causes are possible. One is that we allow substitution across categories.[21] The other is related to the time frame of our analysis, which is weekly. Households may substitute intertemporally across weeks. For cross-category patterns, the majority are substitutes for each other, except that non-food grocery complements other categories. All the categories are substitutes for the outside option, which is consistent with the definition of the outside option, that is,

[21]Our food-category price elasticity is comparable to unconditional elasticities in Okrent and Alston (2012), in which substitution across categories is allowed.

any spending outside the four focal categories. We report complementarity patterns for categories across stores in Appendix Tables B20 and B21.

Estimates from the second stage are displayed in Table 11. Households' utility declines when distance increases and when they need to visit two stores separately. However, the estimated $\gamma^2 + \gamma^3$ is greater than 0, which suggests that if two stores can be visited on the same day, there can be savings on costs. High-income households have higher trip costs and are more sensitive to distance than low-income households. This finding may imply a higher value of time for high-income households. Trip costs and the effect of distance for households with no children do not differ significantly from those for households with children.

# 6 Consumer Welfare

In this section, we use the estimates from the previous sections to conduct several counterfactual analyses. We first show cross-category complementarity patterns by removing different product categories in big-box stores. Second, we quantify the value of each product category, taking cross-category effects into account. Finally, we compare the total value of big-box stores with other store types, and decompose the difference into changes in the total value from consumption utility and trip costs.

## 6.1 Cross-category Complementarity Patterns

We conduct a counterfactual analysis by removing each product category separately in big-box store, and examine how the demand for other categories changes. We show that different categories in the same store are mostly substitutes holding store choice fixed, but they exhibit more complementarities when households can freely choose between stores.

Table 12 exhibits the percentage change in spending share by an average household in each category after one category is removed from a supercenter. Panel A shows the change conditioning on the fact that the supercenter is chosen by households. Households are thus only allowed to adjust their quantity for each category in the supercenter. Panel B gives the change when households are further allowed to switch their consumption to other stores.[22] For a supercenter, if its general merchandise category is removed, which makes the supercenter more similar to its grocery competitors, the spending share of food by a household in the supercenter increases by 1.1% on average. This increase suggests food and general merchandise are substitutes. However, if we allow households to switch across stores, expected food demand decreases by -0.9%, which makes food and general merchandise complements. This complementarity comes from the fact that households one-stop shop for these categories in the same store. Once the probability of choosing the store becomes lower due to the exit of a category, the expected share from other categories also declines.[23] For category pairs that remain substitutes in Panel B, we also see a decline in their substitutability. Total spending share in the supercenter also drops more for the unconditional case (7.4%) than the conditional case (5.8%).

Panel C presents households' expected consumption in all the other stores under the unconditional case. For most of the cases, products from the same category across different stores are substitutes for each other. One exception is the general merchandise category. When the general merchandise category in the supercenter is removed, surprisingly, households also reduce the spending in the same category in other stores. This suggests that the general merchandise category in the supercenter and other stores are on average complements instead of substitutes. This makes sense as households can have their light bulbs and lamps purchased in different stores. Once lamps become unavailable, they do not need to purchase light bulbs. Note that it is a novel feature that our model allows for complementarities for the same category across stores. We also notice that the overall spending in all the stores declines once one category is removed. Households would rather

[22] Note that the diagonal cells are the spending share change of the exiting category, which is -1 by definition.

[23] Thomassen et al. (2017) show a similar cross-category complementarity for product groups in food due to price changes, while our results on category exit can be interpreted as a large price increase such that no one would purchase the category.

spend more on outside goods or save than switch to other focal stores to make a purchase.

The cross-category complementarity patterns are similar for a warehouse club, but we see a higher level of substitution across most categories within the store (Table 13). We also notice that the difference between the conditional case and the unconditional case for a warehouse club is smaller than that of a supercenter. For general merchandise exit in a warehouse club, the percentage change in the total spending share in the warehouse club drops by 7% conditional on store choice but the number is only slightly larger, 7.1%, when households can switch stores. This finding means the exit of general merchandise has little impact on the probability of choosing the store and the convenience of one-stop shopping, due to the provision of this category being limited.

## 6.2 Value of a Category

To quantify the value of each category in a store, we run two counterfactual analyses. First, we remove all four focal categories from a store and calculate the welfare loss, which we denote as the value of a store ($EV^s$). When all the focal categories of a store are removed, choosing this store gives the same utility from the category-level decision $\ln V$ as the outside store $s_0$, which provides the outside category only. We define the value of the outside store to be zero, and the welfare loss of transitioning a focal store to the outside option by removing focal categories as the value of the focal store.[24] Second, we remove each category separately from the store and calculate the welfare loss from each category exit ($EV^c$). Both welfare losses are calculated as the equivalent variation (EV): that is, we calculate the percentage reduction in the budget of a household that is required to achieve the same loss in utility as removing categories. We then calculate the share of the value of a category in the total value of a store ($EV\ Share = EV^c/EV^s$).

We present the value of the categories of a supercenter in the first row of Table 14. Each category accounts for a substantial share in the value of a supercenter. For example,

[24] In our model, the utility from choosing the outside store $s_0$ is not zero, because it also sells product category 0 that is valued by households. We are normalizing the outside option to have zero value.

general merchandise accounts for 29% of the total value, even though the spending share in this category is only 7.6%. Food has the highest spending share among the four categories (58%), and it is also the most valuable category of a supercenter, accounting for 86% of the total value. We also notice the contribution of each category in a supercenter sums up to greater than 1, which suggests a diminishing effect of removing each category when more categories are removed. The reason is that removing a category also lowers spending in other categories and the overall probability of visiting that store.

For warehouse clubs, we see that only the value of food takes a considerable share of the total value (73%) and exceeds its spending share (63%). The contribution of the other three categories ranges from 1.1% to 11%, whereas their spending share ranges from 7.7% to 16%. Additionally, the contribution of each category sums up to less than 1, which implies diminishing returns of adding each category. In other words, a category is more valuable when it is added as the first category than when it is added as the fourth category. This finding can be related to the substitutability of the categories. When categories are more substitutable, the importance of a single category is smaller given that the other categories are already provided.

In addition, to compare the value of providing a category with the effect of a price adjustment, we run another counterfactual that increases the price of a category by 10%. We calculate the EV for this price shock and examine its magnitude relative to the EV of the exit of the same category. Results for both supercenters and warehouse clubs are shown in Table 15. We find that welfare loss due to a 10% increase in the price of general merchandise in a supercenter is equivalent to a 0.04% reduction in households' budget. This effect is only as large as 0.11% of the welfare loss due to the exit of the category. For warehouse clubs, we see the price effect is greater for non-food grocery and general merchandise than for supercenters. This finding suggests that lowering prices will have larger effects on welfare for these categories. Overall, providing a category generates considerably higher benefits for consumers than lowering the price for the same category.

## 6.3 Store Value Comparison

We have shown that big-box stores such as supercenters offer lower quality-adjusted prices and exhibit a higher level of cross-category complementarities. How do these characteristics affect the value of stores for consumers? Connecting to our previous analysis on the value of a store, we further conduct two exercises to compare the value across stores.

In the first exercise, we calculate the welfare loss when a supercenter is replaced by a different store ($EV^L$). It simulates size restrictions that eliminate the entry of large stores such as supercenters, while allowing the entry of smaller stores. The new store inhabits the same location of the original supercenter (i.e. the same $\Gamma$ before and after replacement), but offers its own quality-adjusted prices. We compare the welfare loss to the value of a supercenter ($EV^s$) and report its share ($EV^L/EV^s$). A greater share implies a higher welfare loss and a lower value of the replacement. Figure 8 displays the results of replacing supercenters by each chain store respectively. The loss in value lies between 20% and 90%, with an average at around 50%, suggesting that half of the value is gone once a supercenter is replaced by another store.

The change in welfare is driven by two forces. First, households may face higher quality-adjusted prices and purchase fewer products after the replacement (denoted as "Consumption"). Second, households may pay higher trip costs as they switch across stores (denoted as "Trip Costs"). We calculate the change from both sources. As shown in Figure 8, the increase in trip costs accounts for 20-40% of the total welfare loss for most of the replacement stores. Two grocery stores see a higher share of loss from trip costs. This is because they offer lower quality-adjusted prices of food than the supercenter and the overall loss from the "Consumption" part is small given food accounts for around 60% of the spending in the HMS.

In the second exercise, we simulate the exits of retail chains from their current markets, and compare these impacts to the exit of a supercenter chain. This comparison takes into account the current location of the retail chains. We quantify the value of each existing chain ($EV^{s'}$) and normalize the value for a supercenter ($EV^s$) to 1. Figure 9 includes the comparison of store value for both exercises. On the horizontal axis, we plot the relative value (R), calculated as $1 - EV^L/EV^s$, from the first exercise. On the vertical axis, we plot the "Relative Value (E)", calculated as $EV^{s'}/EV^s$, from the second exercise. For most of the stores, their relative values calculated from the two exercises are close. Drug stores, dollar stores, and some grocery stores show a higher value using the second method, suggesting that these existing stores may have better locations than supercenters.

From both exercises, the value of an average store is only 50-60% of the value of a supercenter, whereas a warehouse club mostly generates the same value as other stores. Therefore, even though both supercenters and warehouse clubs offer a wide range of product categories, supercenters generate substantially higher welfare gains for consumers. Recall that a supercenter offers lower quality-adjusted prices in all the categories and exhibits a higher level of cross-category complementarities. These are the underlying sources of the larger welfare a supercenter generates for consumers. Notably, because supercenters are essentially a discount store combined with a grocery department, the greater the value that the supercenter generates, the more its grocery department will attract households. Although warehouse clubs provide all categories, their quality-adjusted price for each category is not as low, because warehouse clubs provide limited assortment per category. Lower levels of cross-category complementarities also restrict the value of an additional category in the store. This finding highlights the importance of a one-stop-shopping experience with categories of higher quality or lower prices.

## 6.4 Discussion

We discuss our major assumptions and potential future extensions of the welfare analysis. In our current analysis, we assume the absence of any supply-side response after a big-box store entry. Stores in the choice set, prices, and product varieties are taken as given. However, other stores may respond to the entry of big-box stores in various aspects, such as changing prices, adjusting quality, and exiting the market. We justify our assumption with three main reasons. First, using IRI store data, Arcidiacono et al. (2020) show that a supercenter entry has no effect on incumbent prices in the short- and medium-run. Thus, the price response of other stores may be limited when a big-box store enters. Second, Atkin et al. (2017) estimate a welfare gain of 5.5% due to the availability of a new store and a loss of only 0.7% due to the exit of other stores. Thus, the welfare impact from store exit may be smaller than the direct welfare increase from shopping in a new big-box store. Third, both exiting markets and adjusting qualities usually take time for a store. We estimate the model using a sample of observations within one year, and limit the change in the number of stores in the choice set. Thus, our analysis can be viewed as a short-run welfare analysis. Nevertheless, seeing changes in supply-side competition after big-box stores enter and how stores determine prices, product variety, and product quality in response is still interesting and potentially important. Our demand-side estimation can serve as a starting point for further supply-side analyses, and our welfare analysis can be a benchmark for a consumer welfare analysis that incorporates competitive responses.

# 7 Conclusion

In this paper, we investigate the impact of the rapid expansion of two types of big-box stores, supercenters and warehouse clubs, in the US over the past few decades. Using detailed consumer scanner data and an event-study approach, we document three main facts about households' responses to big-box store entries. First, households substitute toward big-box stores from other stores. Second, households change the number of product categories purchased per shopping trip, increasing the variety per trip when supercenters enter but decreasing the variety per trip when warehouse clubs enter. This finding is consistent with the fact that supercenters provide larger assortments across a broad range of product categories, whereas warehouse clubs tend to provide more limited assortments despite a similarly broad range of product categories. Third, households pay lower prices. This response is stronger for supercenters, consistent with the fact that supercenters offer lower prices than warehouse clubs.

To quantify the effects of big-box store entry in a way that incorporates our empirical findings, we develop a multi-store multi-category demand model. We find that both quality-adjusted prices and the degree of cross-category complementarities determines the value of each product category in stores and its contribution to consumer welfare. Supercenters have relatively low quality-adjusted prices and generate stronger cross-category complementarities. Through our counterfactual analyses, we find these factors lead households to derive more welfare from supercenters than other retail chains, with one-third of the difference from savings in trip costs. This implies regulations that constrain store sizes could substantially limit these benefits for consumers.

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# Tables

Table 1: Spending Share: Supercenter Entry

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Store type | Supercenter | Grocery | Discount Store | Warehouse Club | Drug Store | Dollar Store |
| Number of supercenters | 0.0607*** | -0.0357*** | -0.0085*** | -0.0067*** | -0.0040*** | -0.0023*** |
| | (0.0036) | (0.0036) | (0.0017) | (0.0016) | (0.0012) | (0.0006) |
| Observations | 1531361 | 1531361 | 1531361 | 1531361 | 1531361 | 1531361 |
| Adj R-squared | 0.819 | 0.769 | 0.637 | 0.775 | 0.653 | 0.694 |
| Within R-squared | 0.002 | 0.001 | 0.000 | 0.000 | 0.000 | 0.000 |
| Prob > F | 0.000 | 0.000 | 0.000 | 0.000 | 0.001 | 0.000 |
| Number of clusters | 106458 | 106458 | 106458 | 106458 | 106458 | 106458 |
| Household FE | X | X | X | X | X | X |
| Year-Quarter FE | X | X | X | X | X | X |
| Spending Share | 16.2% | 47.3% | 7.7% | 10.4% | 4.6% | 1.8% |

Notes: This table uses 2004-2013 NielsenIQ Consumer Panel Dataset (HMS) at the household-by-quarter level and opening records of the Walmart Supercenter from Arcidiacono et al. (2020). The sample only includes households who have never moved during the period. The dependent variable spending share for each store type is the percentage to the total expenditure in CPG products for each household-quarter observations in the HMS. Discount Store includes discount stores other than the supercenter. The reported independent variable is the number of supercenters in the zip code area where each household lives. All regressions control for household and year-quarter fixed effects. Observations are not weighted for national representativeness. Robust standard errors, clustered by household, are in parentheses. *, **, ***: statistically significant with 10, 5, and 1 percent confidence, respectively.

Table 2: Spending Share: Clubs Entry

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Store type | Clubs | Grocery | Discount Store | Warehouse Club | Drug Store | Dollar Store |
| Numer of clubs | 0.0353*** | -0.0232*** | -0.0157*** | 0.0005 | 0.0007 | -0.0008 |
| | (0.0028) | (0.0040) | (0.0034) | (0.0004) | (0.0013) | (0.0007) |
| Observations | 1865246 | 1865246 | 1865246 | 1865246 | 1865246 | 1865246 |
| Adj R-squared | 0.766 | 0.759 | 0.792 | 0.466 | 0.640 | 0.689 |
| Within R-squared | 0.001 | 0.000 | 0.000 | 0.000 | -0.000 | 0.000 |
| Prob > F | 0.000 | 0.000 | 0.000 | 0.118 | 0.644 | 0.291 |
| Number of clusters | 120135 | 120135 | 120135 | 120135 | 120135 | 120135 |
| Household FE | X | X | X | X | X | X |
| Year-Quarter FE | X | X | X | X | X | X |
| Spending Share | 8.9% | 47.3% | 23.9% | 1.5% | 4.6% | 1.8% |

Notes: This table uses 2004-2015 NielsenIQ Consumer Panel Dataset (HMS) at the household-by-quarter level and opening records of Costco, Sam's Club, and BJ's, from Coibion et al. (2021). The sample only includes households who have never moved during the period. The dependent variable spending share for each channel type is the percentage to the total expenditure in CPG products for each household-quarter observations in the HMS. Warehouse Club includes warehouse clubs other than the three focal clubs. The reported independent variable is the total number of warehouse clubs in the zip code area where each household lives. All regressions control for household and year-quarter fixed effects. Observations are not weighted for national representativeness. Robust standard errors, clustered by household, are in parentheses. *, **, ***: statistically significant with 10, 5, and 1 percent confidence, respectively.

Table 3: ln(Departments per Trip): Supercenter Entry

| Store type | (1)<br>All | (2)<br>Supercenter | (3)<br>Grocery | (4)<br>Discount Store | (5)<br>Warehouse Club | (6)<br>Drug Store | (7)<br>Dollar Store |
|---|---|---|---|---|---|---|---|
| Number of supercenters | 0.0063** | 0.0286*** | -0.0162*** | -0.0181*** | -0.0091 | -0.0115** | -0.0008 |
| | (0.0031) | (0.0084) | (0.0040) | (0.0065) | (0.0074) | (0.0047) | (0.0064) |
| Observations | 1531362 | 817370 | 1485107 | 900027 | 606703 | 905639 | 656488 |
| Adj R-squared | 0.780 | 0.570 | 0.712 | 0.423 | 0.537 | 0.354 | 0.375 |
| Within R-squared | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | -0.000 |
| Prob > F | 0.041 | 0.001 | 0.000 | 0.005 | 0.219 | 0.015 | 0.905 |
| Number of clusters | 106458 | 72827 | 104913 | 84332 | 55496 | 81656 | 65363 |
| Household FE | X | X | X | X | X | X | X |
| Year-Quarter FE | X | X | X | X | X | X | X |

Notes: This table uses 2004-2013 NielsenIQ Consumer Panel Dataset (HMS) at the household-by-quarter level and opening records of the Walmart Supercenter from Arcidiacono et al. (2020). The sample only includes households who have never moved during the period. Dependent variables are ln(number of departments per trip) for each store type, with 5 departments in total. Discount Store includes discount stores other than the supercenter. The reported independent variable is the number of supercenters in the zip code area where each household lives. All regressions control for household and year-quarter fixed effects. Observations are not weighted for national representativeness. Robust standard errors, clustered by household, are in parentheses. *, **, ***: statistically significant with 10, 5, and 1 percent confidence, respectively.

Table 4: ln(Departments per Trip): Club Entry

| Store type | (1)<br>All | (2)<br>Clubs | (3)<br>Grocery | (4)<br>Discount Store | (5)<br>Warehouse Club | (6)<br>Drug Store | (7)<br>Dollar Store |
|---|---|---|---|---|---|---|---|
| Number of clubs | -0.0188*** | -0.0428*** | -0.0177*** | -0.0203*** | 0.0268 | -0.000824 | 0.000644 |
| | (0.00363) | (0.0106) | (0.00492) | (0.00707) | (0.0521) | (0.00542) | (0.00785) |
| Observations | 1865248 | 719103 | 1805407 | 1560123 | 51782 | 1078176 | 807881 |
| Adj R-squared | 0.775 | 0.533 | 0.701 | 0.599 | 0.473 | 0.352 | 0.375 |
| Within R-squared | 0.000 | 0.000 | 0.000 | 0.000 | -0.000 | -0.000 | -0.000 |
| Prob > F | 0.000 | 0.000 | 0.000 | 0.004 | 0.608 | 0.879 | 0.935 |
| Number of clusters | 120135 | 60277 | 118277 | 112671 | 8048 | 90535 | 74641 |
| Household FE | X | X | X | X | X | X | X |
| Year-Quarter FE | X | X | X | X | X | X | X |

Notes: This table uses 2004-2015 NielsenIQ Consumer Panel Dataset (HMS) at the household-by-quarter level and opening records of Costco, Sam's Club, and BJ's, from Coibion et al. (2021). The sample only includes households who have never moved during the period. Dependent variables are ln(number of departments per trip) for each store type, with 5 departments in total. Warehouse Club includes warehouse clubs other than the three focal clubs. The reported independent variable is the total number of warehouse clubs in the zip code area where each household lives. All regressions control for household and year-quarter fixed effects. Observations are not weighted for national representativeness. Robust standard errors, clustered by household, are in parentheses. *, **, ***: statistically significant with 10, 5, and 1 percent confidence, respectively.

Table 5: ln(Relative Price Index): Supercenter Entry

| Departments | (1) All | (2) Health & Beauty Care | (3) Food | (4) Non-food Grocery | (5) General Merchandise |
|---|---|---|---|---|---|
| Number of supercenters | -0.0050*** | -0.0061*** | -0.0059*** | -0.0022* | -0.0026 |
| | (0.0007) | (0.0014) | (0.0008) | (0.0012) | (0.0021) |
| Observations | 793868 | 430754 | 792485 | 587517 | 290797 |
| Adj R-squared | 0.571 | 0.303 | 0.574 | 0.376 | 0.162 |
| Prob > F | 0.000 | 0.000 | 0.000 | 0.065 | 0.211 |
| Number of clusters | 79829 | 59428 | 79736 | 70592 | 49987 |
| Household FE | X | X | X | X | X |
| Year-Quarter FE | X | X | X | X | X |

Notes: This table uses 2004-2013 NielsenIQ Consumer Panel Dataset (HMS) at the household-by-quarter level and opening records of the Walmart Supercenter from Arcidiacono et al. (2020). The sample only includes households who have never moved during the period. The dependent variable relative price index (RPI) is defined in Equation 2. Column (1) reports RPI including all products. Column (2)-(5) report RPI including proudcts in each indicated departments respectively. The reported independent variable is the number of supercenters in the zip code area where each household lives. All regressions control for household and year-quarter fixed effects. Observations are not weighted for national representativeness. Robust standard errors, clustered by household, are in parentheses. *, **, ***: statistically significant with 10, 5, and 1 percent confidence, respectively.

Table 6: ln(Relative Price Index): Clubs Entry

| Departments | (1) All | (2) Health& Beauty Care | (3) Food | (4) Non-food Grocery | (5) General Merchandise |
|---|---|---|---|---|---|
| Number of clubs | -0.0015 | -0.0006 | -0.0020 | -0.0043** | 0.0048* |
| | (0.0012) | (0.00222) | (0.0013) | (0.0019) | (0.0028) |
| Observations | 1842295 | 1199219 | 1839768 | 1578261 | 920118 |
| Adj R-squared | 0.688 | 0.409 | 0.709 | 0.433 | 0.137 |
| Within R-squared | 0.000 | -0.000 | 0.000 | 0.000 | 0.000 |
| Prob > F | 0.205 | 0.778 | 0.108 | 0.023 | 0.091 |
| Number of clusters | 119428 | 101377 | 119382 | 113974 | 92877 |
| Household FE | X | X | X | X | X |
| Year-Quarter FE | X | X | X | X | X |

Notes: This table uses 2004-2015 NielsenIQ Consumer Panel Dataset (HMS) at the household-by-quarter level and opening records of Costco, Sam's Club, and BJ's, from Coibion et al. (2021). The sample only includes households who have never moved during the period.The dependent variable relative price index (RPI) is defined in Equation 2. Column (1) reports RPI including all products. Column (2)-(5) report RPI including proudcts in each indicated departments respectively. The reported independent variable is the total number of warehouse clubs in the zip code area where each household lives. All regressions control for household and year-quarter fixed effects. Observations are not weighted for national representativeness. Robust standard errors, clustered by household, are in parentheses. *, **, ***: statistically significant with 10, 5, and 1 percent confidence, respectively.

Table 7: Summary of Households

| | | | |
|---|---|---|---|
| Number of observations | 11376 | | |
| Average weekly budget | 270.6 | | |
| | One store | Two stores | Outside option |
| Obs Share | 0.42 | 0.47 | 0.11 |
| | One store | Two stores | |
| Spending share | | Store 1 | Store 2 |
| | 0.88 | 0.65 | 0.25 |
| Obs share | No kids | With kids | Row total |
| Income Q1 | 0.17 | 0.05 | 0.22 |
| Income Q2 | 0.19 | 0.04 | 0.23 |
| Income Q3 | 0.26 | 0.07 | 0.33 |
| Income Q4 | 0.17 | 0.04 | 0.21 |
| Column Total | 0.79 | 0.21 | 1 |

Notes: This table presents summary statstics of the sample for structural estimation. The sample is 1137 households across 57 counties with 11376 household-week observations in Texas in 2012 from NielsenIQ Consumer Panel Dataset (HMS). We randamly sample 3 weeks per quarter per household and each household has at least 3 weeks' observation. Weekly budget is calculated based on the annual household income bracket reported in the HMS and the ratio of consumer goods expenditure from Consumer Expenditure Survey in 2012 divided by 52 weeks. Outside option means a household does not visit any of the 17 focal stores during a week. Spending share is the ratio of expenditure to weekly budget. Household demographics are provided in the HMS. We group households to 8 groups by income quartile interacted with whether they have children under 18. Income Q4 has the highest income level.

Table 8: Estimates in $\ln P^*$ from Category Level

| Parameters | Estimates | s.e. | Parameters | Estimates | s.e. |
|---|---|---|---|---|---|
| log(likelihood) | -0.5653 | | $\rho$ | 1.1001 | 0.0206 |
| $\lambda_1$ | -7.0214 | 0.1445 | $\ln \mu_1$ | -1.7297 | 0.1172 |
| $\lambda_2$ | -7.5044 | 0.1577 | $\ln \mu_2$ | -2.0257 | 0.1069 |
| $\lambda_3$ | -6.4501 | 0.1771 | $\ln \mu_3$ | -2.1234 | 0.3343 |
| $\lambda_4$ | -7.3043 | 0.1473 | $\ln \mu_4$ | -1.2385 | 0.0964 |
| $\alpha_1$ | -1.6781 | 0.0617 | $\alpha_9$ | -0.744 | 0.0481 |
| $\alpha_2$ | 0.1993 | 0.0629 | $\alpha_{10}$ | -0.7777 | 0.0536 |
| $\alpha_3$ | 0.0099 | 0.0737 | $\alpha_{11}$ | -0.0614 | 0.048 |
| $\alpha_4$ | -2.2011 | 0.0618 | $\alpha_{12}$ | -1.3789 | 0.0605 |
| $\alpha_5$ | -1.9473 | 0.0681 | $\alpha_{13}$ | -1.0601 | 0.0886 |
| $\alpha_6$ | -1.7985 | 0.0552 | $\alpha_{14}$ | -1.4764 | 0.0512 |
| $\alpha_7$ | -1.8891 | 0.0804 | $\alpha_{15}$ | -1.2293 | 0.0555 |
| $\alpha_8$ | -0.9055 | 0.0645 | $\alpha_{16}$ | 0.4267 | 0.0428 |

Notes: This table presents Maximum Likelihood estimates from the first stage for parameters in 12. The sample is 1137 households across 57 counties with 11376 household-week observations in Texas in 2012 from NielsenIQ Consumer Panel Dataset (HMS). $\alpha' s$ are store fixed effects with $\alpha_{17}$ for a warehouse club being normalized to 0. $\lambda' s$ are category fixed effects. $\mu' s$ are scale parameters. $\rho$ is the coefficent for the number of UPCs per store-category. s.e. denotes standard errors.

Table 9: Estimates on Cross-category Complementarities within Stores

| | Health & Beauty Care | Food | Non-food Grocery | General Merchandise | Outside option |
|---|---|---|---|---|---|
| Health & Beauty Care | 0.204 | -0.0082 | 0.0046 | -0.0001 | -0.0258 |
| Food | -0.0082 | 0.3633 | 0.0021 | -0.0093 | -0.0291 |
| Non-food Grocery | 0.0046 | 0.0021 | 0.1122 | 0.0005 | -0.016 |
| General Merchandise | -0.0001 | -0.0093 | 0.0005 | 0.2753 | -0.0447 |
| Outside option | -0.0258 | -0.0291 | -0.016 | -0.0447 | 0.0153 |

Notes: This table presents Maximum Likelihood estimates from the first stage for $\{b_{cd}, c, d = 1, ..., M+1\}$, which describes compelmentaries across categories within the same store from Equation 6. The sample is 1137 households across 57 counties with 11376 household-week observations in Texas in 2012 from NielsenIQ Consumer Panel Dataset (HMS). Positive numbers for a category pair suggest the two categories are complements and negative numbers suggest substitutes. Estimates to generate this matrix that are described in Appendix A.2 are presented in Appendix Table B22

Table 10: Conditional Cross-category Price Elasticities for Individual Demand

| | Health & Beauty Care | Food | Non-food Grocery | General Merchandise |
|---|---|---|---|---|
| Health & Beauty Care | -1.2654 | 0.0101 | -0.0051 | 0.0005 |
| Food | 0.0064 | -1.2844 | -0.0012 | 0.0071 |
| Non-food Grocery | -0.0062 | -0.0029 | -1.1636 | -0.0006 |
| General Merchandise | 0.0008 | 0.0200 | -0.0008 | -1.5534 |

Notes: This table shows average cross-category price elasticities for individual demand conditioning on store choice and purchase incidence for categories within the same store. The sample is 1137 households across 57 counties with 11376 household-week observations in Texas in 2012 from NielsenIQ Consumer Panel Dataset (HMS). Each cell is elasticity of row demand with respect to column price.

Table 11: Estimates at Store Level Decision

| parameters | estimates | s.e. | parameters | estimates | s.e. |
|---|---|---|---|---|---|
| log(likelihood) | -2.9963 | 0.0008 | $\gamma^v$ | 0.0026 | 0.0001 |
| $\gamma^1$ | -0.0631 | 0.0001 | $\gamma^2$ | -2.283 | 0.0027 |
| $\gamma^3$ | 3.6063 | 0.0035 | $\gamma^0$ | 0.611 | 0.0029 |
| $\gamma_{g1}$ | 1 | | $\gamma_{g5}$ | 1.0136 | 0.002 |
| $\gamma_{g2}$ | 1.041 | 0.0013 | $\gamma_{g6}$ | 1.0346 | 0.0025 |
| $\gamma_{g3}$ | 1.1324 | 0.0016 | $\gamma_{g7}$ | 1.0422 | 0.002 |
| $\gamma_{g4}$ | 1.1682 | 0.0015 | $\gamma_{g8}$ | 1.1426 | 0.0026 |

Notes: This table presents Maximum Likelihood estimates for the second stage parameters in $\mathcal{U}_{irt} = \gamma^v \ln V_{irt} + \gamma_g(\gamma^1 D_{ir} + \gamma^2 I_i^{two} + \gamma^3 I_i^{same}) + \nu_{irt}$. The sample is 1137 households across 57 counties with 11376 household-week observations in Texas in 2012 from NielsenIQ Consumer Panel Dataset (HMS). $\gamma_1, ..., \gamma_4$ are households with no kids from Income Q1 to Income Q4 descrived in Table 7. $\gamma_5, ..., \gamma_8$ are households with kids from lowest income group to the highest. $\gamma_1$ is normalized to 1. $\gamma^0$ is the trip cost for outside option store 0. Bootstrap standard errors are reported in columns s.e.

Table 12: Cross-category Complementarities of a Supercenter

| | Exiting Categories | | | |
|---|---|---|---|---|
| | A: Conditional | | | |
| | Health & Beauty Care | Food | Non-food Grocery | General Merchandise |
| Health & Beauty Care | -1.000 | 0.558 | 0.072 | 0.039 |
| Food | -0.148 | -1.000 | 0.042 | 0.011 |
| Non-food Grocery | 1.417 | 1.924 | -1.000 | 0.040 |
| General Merchandise | 0.259 | 1.138 | 0.683 | -1.000 |
| All | -0.058 | -0.107 | -0.055 | -0.056 |
| | B: Unconditional | | | |
| | Health & Beauty Care | Food | Non-food Grocery | General Merchandise |
| Health & Beauty Care | -1.000 | 0.412 | 0.041 | 0.019 |
| Food | -0.169 | -1.000 | 0.012 | -0.009 |
| Non-food Grocery | 1.359 | 1.650 | -1.000 | 0.020 |
| General Merchandise | 0.229 | 0.938 | 0.635 | -1.000 |
| All | -0.080 | -0.190 | -0.082 | -0.074 |
| | C: Other Stores | | | |
| | Health & Beauty Care | Food | Non-food Grocery | General Merchandise |
| Health & Beauty Care | 0.119 | 0.030 | -0.015 | -0.015 |
| Food | 0.039 | 0.014 | 0.004 | 0.001 |
| Non-food Grocery | -0.399 | -0.313 | 0.049 | -0.004 |
| General Merchandise | -0.046 | -0.002 | -0.151 | -0.030 |
| All | -0.003 | -0.020 | -0.003 | -0.004 |

Notes: This table presents changes in spending share of an average household in column categories when row category is removed from a supercenter. The sample is 1137 households across 57 counties with 11376 household-week observations in Texas in 2012 from NielsenIQ Consumer Panel Dataset (HMS). Panel A reports the change conditional on the supercenter being chosen. Panel B and Panel C report the changes when households are allowed to switch across stores. Panel B displays the changes within the supercenter, while Panel C shows the changes in total in other stores. Numbers in the row "All" are the total change in the entire store given the removal of a column category.

Table 13: Cross-category Complementarities of a Warehouse Club

| | Exiting Categories | | | |
|---|---|---|---|---|
| | A: Conditional | | | |
| | Health & Beauty Care | Food | Non-food Grocery | General Merchandise |
| Health & Beauty Care | -1.000 | 0.870 | 0.223 | 0.170 |
| Food | -0.171 | -1.000 | -0.010 | -0.045 |
| Non-food Grocery | 1.237 | 1.848 | -1.000 | 0.066 |
| General Merchandise | 0.338 | 1.473 | 0.534 | -1.000 |
| All | -0.075 | -0.133 | -0.064 | -0.070 |
| | B: Unconditional | | | |
| | Health & Beauty Care | Food | Non-food Grocery | General Merchandise |
| Health & Beauty Care | -1.000 | 0.691 | 0.208 | 0.169 |
| Food | -0.178 | -1.000 | -0.022 | -0.046 |
| Non-food Grocery | 1.220 | 1.575 | -1.000 | 0.065 |
| General Merchandise | 0.327 | 1.237 | 0.515 | -1.000 |
| All | -0.082 | -0.216 | -0.075 | -0.071 |
| | C: Other Stores | | | |
| | Health & Beauty Care | Food | Non-food Grocery | General Merchandise |
| Health & Beauty Care | 0.024 | -0.002 | -0.010 | -0.010 |
| Food | 0.007 | 0.002 | -0.006 | -0.007 |
| Non-food Grocery | -0.097 | -0.075 | 0.037 | 0.018 |
| General Merchandise | -0.259 | -0.252 | -0.279 | -0.234 |
| All | -0.020 | -0.024 | -0.020 | -0.019 |

Notes: This table presents changes in spending share of an average household in column categories when row category is removed from a warehouse club. The sample is 1137 households across 57 counties with 11376 household-week observations in Texas in 2012 from NielsenIQ Consumer Panel Dataset (HMS). Panel A reports the change conditional on the warehouse club being chosen. Panel B and Panel C report the changes when households are allowed to switch across stores. Panel B displays the changes within the warehouse club, while Panel C shows the changes in total in other stores. Numbers in the row "All" are the total change in the entire store given the removal of a column category.

Table 14: Value of a Category vs. value of a Big-box Store (=1)

| | Health & Beauty Care | Food | Non-food Grocery | General Merchandise |
|---|---|---|---|---|
| | Supercenter | | | |
| EV Share | **34.6%** | **86.3%** | **40.4%** | **29.0%** |
| Spending Share | 19.7% | 58.2% | 14.5% | 7.6% |
| | Warehouse Club | | | |
| EV Share | **6.5%** | **73.1%** | **11.3%** | **1.1%** |
| Spending Share | 15.81% | 63.10% | 13.38% | 7.71% |

Notes: This table presents a comparision between the value of each category and the total value of a big-box store as defined in Section 6.2. The sample is 1137 households across 57 counties with 11376 household-week observations in Texas in 2012 from NielsenIQ Consumer Panel Dataset (HMS). EV share indicates the ratio of the value of a category to the value of a big-box store. Spending share is the percentage of average households' expenditure in the big-box storegiven households choose the big-box store. $\Delta \ln V$ share indicates the ratio of the utility change when the corresponding category is removed from the store to the utility change when all categories are removed.

Table 15: 10% Price Increase vs. Category Exit (=1)

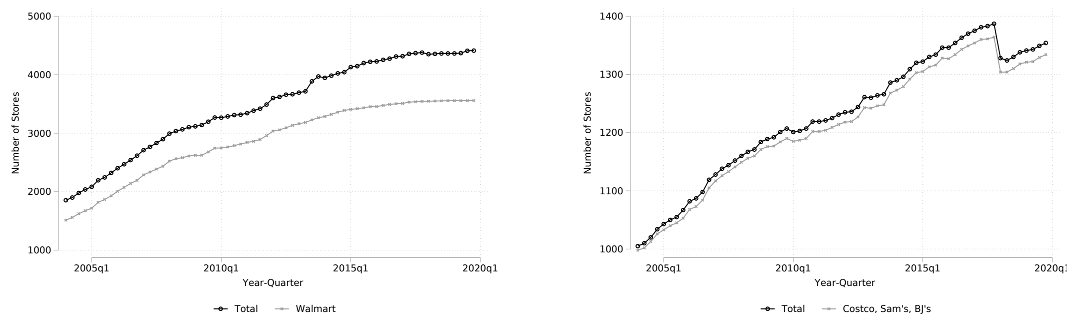
| | Health & Beauty Care | Food | Non-food Grocery | General Merchandise |
|---|---|---|---|---|
| | Supercenter | | | |
| EV | 0.28% | 1.00% | 0.25% | 0.04% |
| % of Category Exit | 0.88% | 1.27% | 0.74% | 0.11% |
| | Warehouse Club | | | |
| EV | 0.004% | 0.350% | 0.060% | 0.004% |
| % of Category Exit | 0.15% | 1.15% | 1.28% | 0.89% |

Notes: This table presents the equivalent variation for 10% increase in price for each category respectively (EV) and its comparision with the value of a category (% of Category Exit). The sample is 1137 households across 57 counties with 11376 household-week observations in Texas in 2012 from NielsenIQ Consumer Panel Dataset (HMS). The first panel shows results for a supercenter and the second panel shows results for a warehouse club.

# Figures

Figure 1: Number of Major Big-box Stores in the U.S.

(a) Supercenters (b) Warehouse Clubs

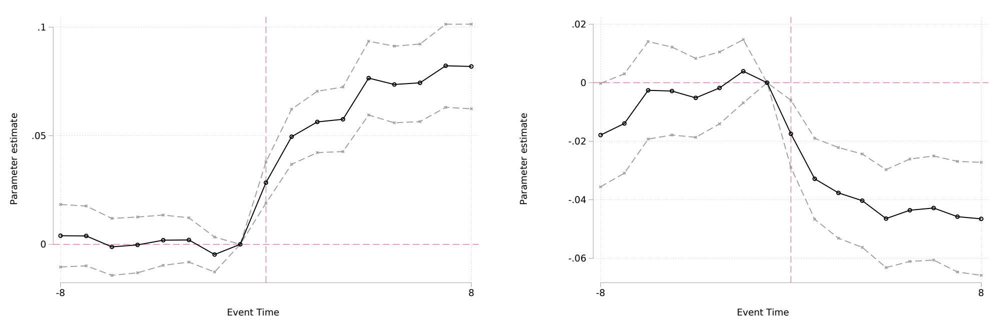



Notes: These figures present the number of major big-box stores in the US from 2004 to 2019 using TDLinx Data. Figure 1a is the number of supercenters in the U.S. and Figure 1b is the number of warehouse clubs in the U.S. The drop in the number of warehouse clubs in 2018 reflects closures of Sam's Clubs (`https://www.businessinsider.com/why-sams-club-is-closing-stores-2018-1`).

Figure 2: Event Study Graph: Big-box Store Entry on Spending Share

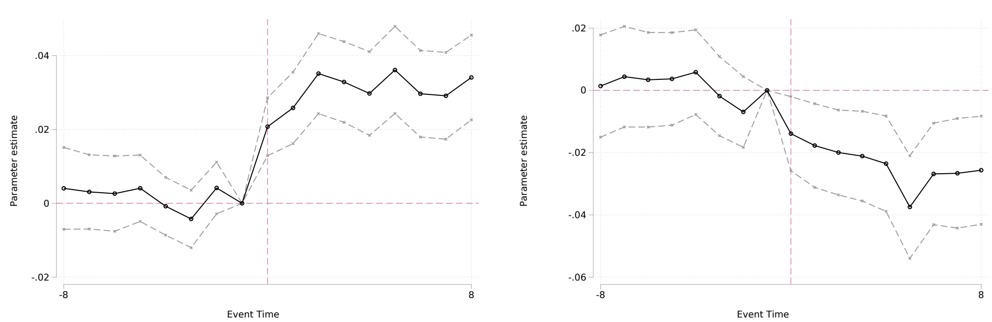
A. Supercenter Entry

(a) Supercenter (b) Grocery




B. Warehouse Club Entry

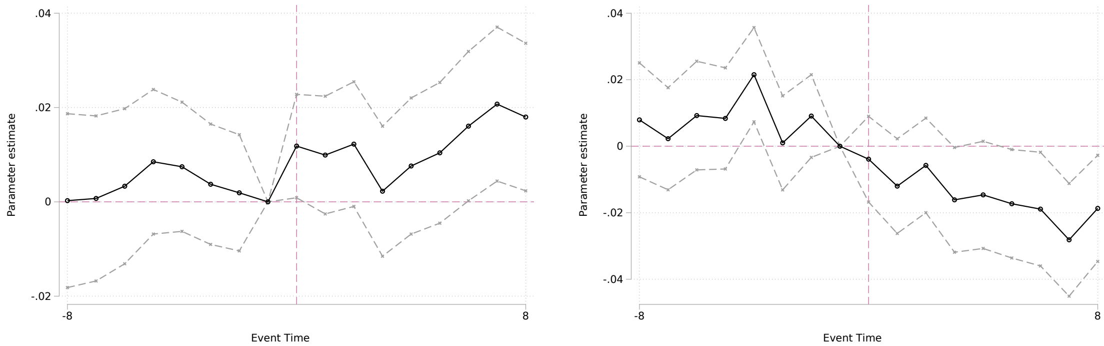
(c) Warehouse clubs (d) Grocery




Notes: These figures use 2004-2013 NielsenIQ Consumer Panel Dataset (HMS) at the household-by-quarter level and opening records of the big-box stores. The figures present coefficients for eight leading and lagging periods of big-box store entries, and 95% confidence intervals from estimates of the event study on big-box store entries. The dependent variable spending share for each store type is the percentage to the total expenditure in CPG products for each household-quarter observations in the HMS. All regressions control for year-quarter indicators and household fixed effects.

Figure 3: Event Study Graph: Big-box Store Entry on Varieties per Trip

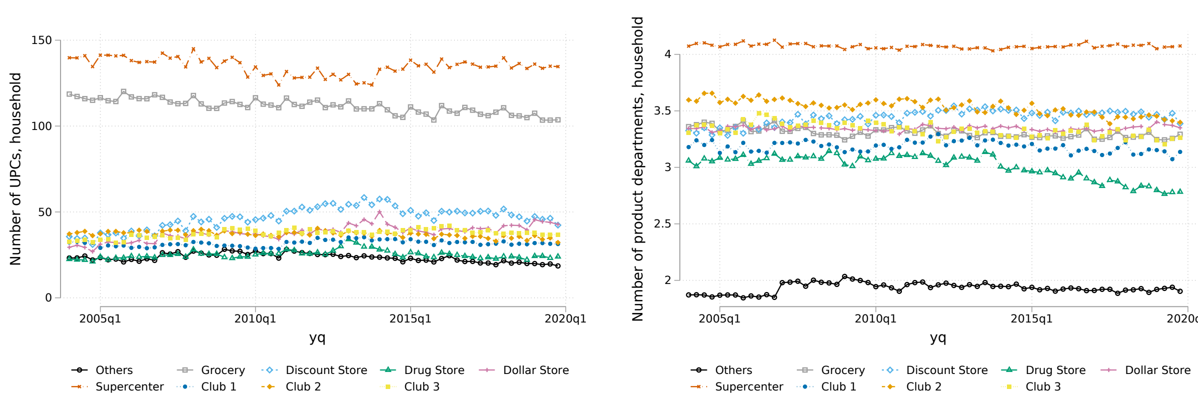
(a) Supercenter Entry (b) Warehouse Club Entry




Notes: These figures use 2004-2013 NielsenIQ Consumer Panel Dataset (HMS) at the household-by-quarter level and opening records of the big-box stores. The figures present coefficients for eight leading and lagging periods of big-box store entries, and 95% confidence intervals from estimates of the event study on big-box store entries. The dependent variable is the number of departments per trip. All regressions control for year-quarter indicators and household fixed effects.

Figure 4: Product Assortment in Different Store Types

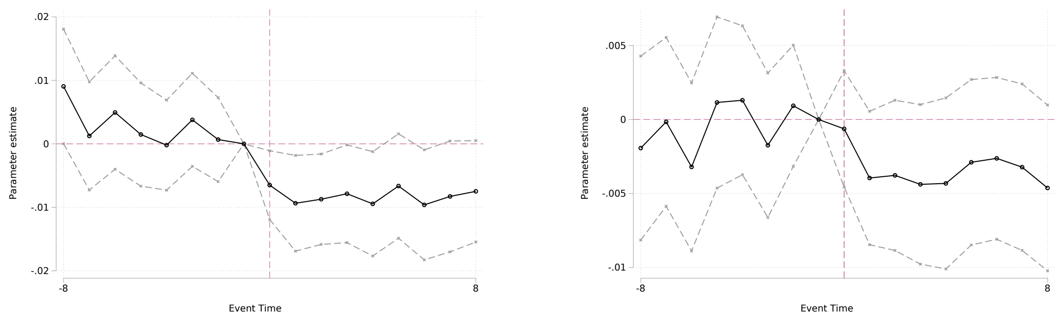
(a) UPCs (b) Departments




Notes: These figures present product varieties that households purchased from each store type using 2004-2019 NielsenIQ Consumer Panel Dataset (HMS) at the household-by-quarter level. Figure 4a shows the number of UPCs and Figure 4b shows the number of departments.

Figure 5: Event Study Graph: Big-box Store Entry on Relative Price Index

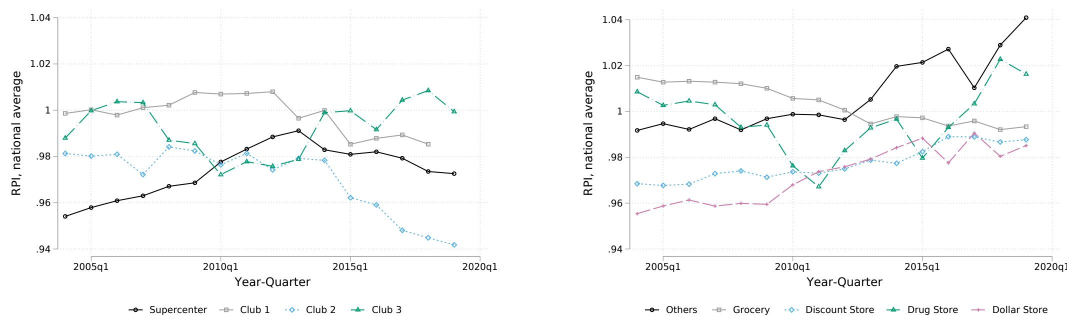
(a) Supercenter Entry (b) Warehouse Club Entry




Notes: These figures use 2004-2013 NielsenIQ Consumer Panel Dataset (HMS) at the household-by-quarter level and opening records of the big-box stores. The figures present coefficients for eight leading and lagging periods of big-box store entries, and 95% confidence intervals from estimates of the event study on big-box store entries. The dependent variables are log relative price index (RPI) for all products defined in Equation 2. All regressions control for year-quarter indicators and household fixed effects.

Figure 6: Relative Price Index in Big-box Stores and Other Channel Types

(a) Big-box Stores (b) Other Channel Types

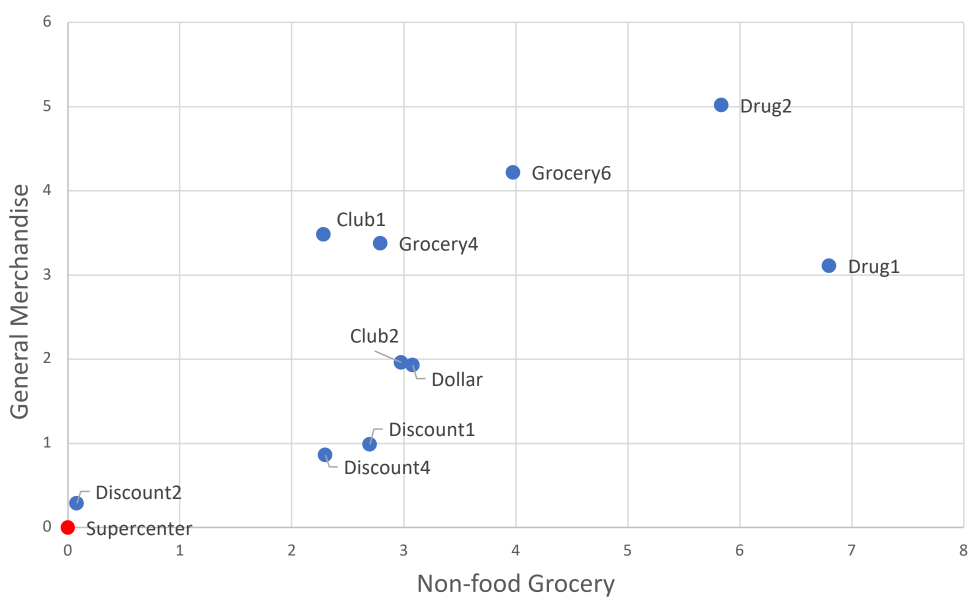



Notes: These figures present relative price index (RPI) for each store type defined as the quantity weighted averge of the ratio between total expenditure for each good and the counterfactual expenditure of each good at its national average price within a store, using 2004-2019 NielsenIQ Consumer Panel Dataset (HMS) at the household-by-quarter level. Figure 6a shows the RPI for supercenters and warehouse clubs and Figure 6b shows the RPI for other store types.

Figure 7: Relative $\ln P^*$ across Stores

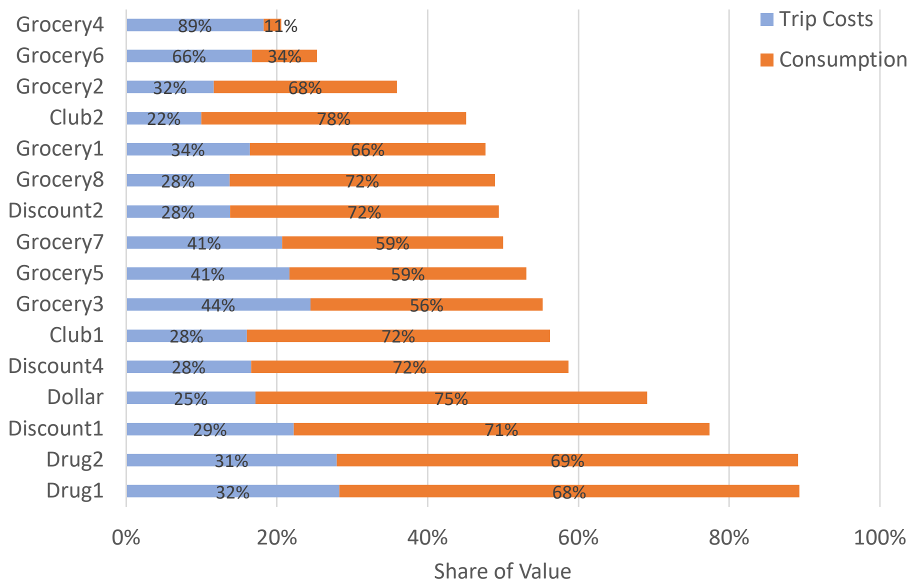
(a) Food and Health & Beauty Care


(b) Non-food Grocery and General Merchandise



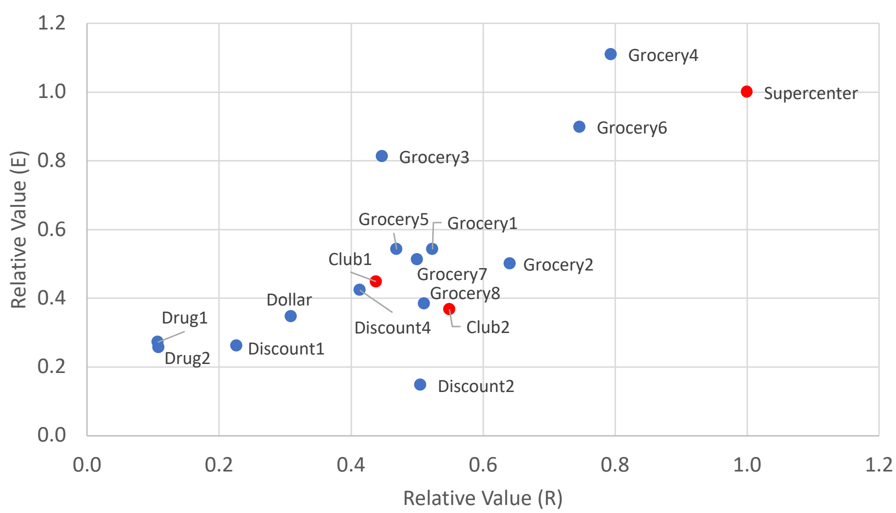

Notes: These two figures show the expected quality-adjusted price $\ln P^*$ as define in Equation 12 across all the weeks. The sample is 1137 households across 57 counties with 11376 household-week observations in Texas in 2012 from NielsenIQ Consumer Panel Dataset (HMS). $\ln P^*$ for a supercenter is normalized to 0 in each category. High $\ln P^*$ suggests higher cost for households to purchase a category given the same quality of the category across stores.

Figure 8: Welfare Loss of Replacing a Supercenter




Notes: This figure shows the welfare loss when a supercenter is replaced by a different store. The sample is 1137 households across 57 counties with 11376 household-week observations in Texas in 2012 from NielsenIQ Consumer Panel Dataset (HMS). When a supercenter is replaced, the quality-adjusted prices are replaced by that of another store. The horizontal axis shows the share of value, which is the resulting welfare loss of an average household ($EV^L$) compared to the value of a supercenter ($EV^s$). The value of a store is the welfare loss when all the categories are removed from the store. The vertical axis lists the stores that replace the supercenter. The total welfare loss of a replacement is decomposed into two parts. The"Trip Costs" part is the increase in trip costs due to switching across stores. The "Consumption" part is the loss from households purchasing less products with higher quality-adjusted prices after the replacement.

Figure 9: Store Value Comparison




Notes: This figure compares the value across stores from two exercises. The sample is 1137 households across 57 counties with 11376 household-week observations in Texas in 2012 from NielsenIQ Consumer Panel Dataset (HMS). value is the welfare loss when all the categories are removed from a store. The horizontal axis shows the relative value of a store that replaces a supercenter. Relative value (R) is calculated as $1 - EV^L/EV^s$, where $EV^L$ is the welfare loss when a supercenter is replaced by the store and $EV^s$ is the value of a supercenter. The vertical axis displays the relative value of a store compared to a supercenter. Relative value (E) is defined as $EV^{s'}/EV^s$, where $EV^{s'}$ is the welfare loss when all the categories are removed in a store $s'$ that exists in the current choice set.

# Appendix

## A Structural Model

### A.1 Likelihood Function for Simultaneous Estimation

Given category-level parameters $\Theta$ and store-level parameters $\Theta^S$, the likelihood of observing store choice $\{I_r^S = 1, I_{r'}^S = 0, r' \neq r\}$, purchase incidence $\{I_j = 0\}_{j=1}^m, \{I_j = 1\}_{j=m+1}^{M_r}$, and budget share $\{S_j\}_{j=m+1}^{M_r}$ for household $i$ week $t$ is

$$
\begin{aligned}
& L_{it}\left(\{I_{r'}^S\}_{r'\in\mathcal{R}}, \{I_j\}_{j\in\mathcal{M}_r}, \{S_j\}_{j\in\mathcal{M}_r} | \Theta, \Theta^S\right) \\
&= \int_{\varepsilon_0=-\infty}^{\infty} \prod_{r'\in\mathcal{R}} \left[\int_{\boldsymbol{\varepsilon}_{r'\neq r}=-\infty}^{\infty} \int_{-\infty}^{-\mathbf{H}_{r,np}(\varepsilon_0)} \frac{\exp(\gamma^v \ln V_r(\boldsymbol{\varepsilon}) + \Gamma_r)}{\sum_{r'\in\mathcal{R}} \exp(\gamma^v \ln V_{r'}(\boldsymbol{\varepsilon}) + \Gamma_{r'})}\right. \\
& \left.\times \boldsymbol{\phi}(-\mathbf{H}_{r,p}(\varepsilon_0)) \boldsymbol{\phi}(\boldsymbol{\varepsilon}_{r,np}) \boldsymbol{\phi}(\boldsymbol{\varepsilon}_{r'\neq r}) \mathbf{J} d\boldsymbol{\varepsilon}_{r,np} d\boldsymbol{\varepsilon}_{r'\neq r}\right]^{I_{r'}^S} \phi_N(\varepsilon_0) d\varepsilon_0, \qquad (19)
\end{aligned}
$$

$$
H_j = \alpha_{s(j)} + \lambda_{c(j)} + \rho X_j + \mu_{c(j)}\kappa_j \ln y + \mu_{c(j)}(\kappa_j - 1)\varepsilon_0 - \mu_{c(j)} \left(\sum_{k=1}^{M_r} \delta_{jk} S_k\right) \left(1 - \sum_{j=1}^{M_r} \kappa_j S_j\right)^{-1}
$$

- $\Theta = \{\alpha_s, \lambda_c, \rho, B = \{b_{cd}, b_{cd}^2\}, \mu_c, s \in \mathcal{S}, c, d = 1, ..., M+1\}$.
- $\Theta^S = \{\gamma^v, \gamma^1, \gamma^2, \gamma^3, \{\gamma_g\}, \gamma^0\}$.
- $\phi(\cdot)$ is the pdf of joint T1EV distribution and $\phi_N(\cdot)$ is the pdf of standard normal distribution.
- $\mathbf{J} = D_{r'} \times \left(1 - \sum_{j\in\mathcal{M}_r'} \kappa_j S_j\right)^{-1-\sum_{j\in\mathcal{M}_r'} I_j} \prod_{j\in\mathcal{M}_r'} (\mu_{c(j)})^{I_j}$.
- $\boldsymbol{\varepsilon}_{r,np}$ is the shocks of non-purchased store-categories in the chosen store set.
- $\boldsymbol{\varepsilon}_{r'\neq r}$ is the shocks of store-categories in the non-chosen stores.
- $\{\delta_j\}_{j=1}^{M_r}$ and $\{\kappa_j\}_{j=1}^{M_r}$ are the reformulated parameters of the original parameters $B$, which is explained in Appendix A.2:
  - $B_f$ is a submatrix of $B$, consisting of first $M_r$ rows and $M_r$ columns of $B$.
  - $C = [C_1, ...C_{M_r}]$, $C_j = \sum_{k=1}^{M_r+1} b_{jk}$.
  - $\{\delta_j\}_{j=1}^{M_r}$ are the elements of the $M_r \times M_r$ matrix $\Delta_f = (B_f)^{-1}$.
  - $\{\kappa_j\}_{j=1}^{M_r}$ are the elements in the $M_r\times$ 1 vector $K$, where $K = (B_f)^{-1}C$.
- $D_r = 1$ if none of the focal categories are purchased. If at least one is purchased, $D_r$ takes the value of the determinant of the submatrix of the matrix $\Delta_f$ after removing none purchased store-categories.

The log-likelihood function for the entire sample is:

$$l(\Theta, \Theta^S) = \sum_{i=1}^{N} \sum_{t=1}^{T} \sum_{r \in \mathcal{R}} I_r^S \ln \left( L_{it} \left( \{I_{r'}^S\}_{r' \in \mathcal{R}}, \{I_j\}_{j \in \mathcal{M}_r}, \{S_j\}_{j \in \mathcal{M}_r} | \Theta, \Theta^S \right) . \right) . \tag{20}$$

### A.2 Category-Level Parameters

$$\Theta = \{\alpha_s, \lambda_c, \rho, B = \{b_{cd}, b^2_{cd}\}, \mu_c, s \in \mathcal{S}, c, d = 1, ..., M+1\}$$

.

- $\{\alpha_s, s = 1, ..., 16\}$: store fixed effects, $\alpha_{17}$ for chain 17 is normalized to 0.
- $\{\lambda_c, c = 1, .., 4\}$: category fixed effects.
- $\rho$: coefficient for variety depth, that is, the number of UPCs per store-category.
- $B = \{b_{cd}, b^2_{cd}, c, d = 1, ..., M+1\}$: complementarity across store-categories.
  - $B1 = \{b_{cd}, c, d = 1, ..., M+1\}$: complementarity across categories within stores.
  - $B2 = \{b^2_{cd}, c, d = 1, ..., M\}$: complementarity across categories from two different stores.
  - Let $Bf = \{b_{cd}, c, d = 1, ..., M\}$ and $B1_{M+1} = [b_{1,M+1}, ..., b_{4,M+1}]$. For two-store options with $M \times 2$ categories, we have

$$B = \begin{array}{c} \\ \\ \\ \\ \end{array}\begin{array}{cc} & \begin{array}{ccc} \text{Store 1} & \text{Store 2} & \text{Category 0} \end{array} \\ & \begin{pmatrix} Bf & B2 & B1^T_{M+1} \\ B2 & Bf & B1^T_{M+1} \\ B1_{M+1} & B1_{M+1} & b_{M+1,M+1} \end{pmatrix} \begin{array}{l} \text{Store 1} \\ \text{Store 2} \\ \text{Category 0.} \end{array} \end{array}$$

  - Matrices $B$, $B1$, $B2$ are all symmetric. Matrices $B$ and $B1$ are positive semi-definite with Bf being positive definite. Give the structure and properties of B, we generate it in the following two steps:
    * We generate the $B1$ matrix as $B1 = Ch \times Ch^T$, where $Ch$ is a lower triangular $(M+1) \times (M+1)$ Cholesky with elements $\{Ch_{cd}\}$. The last diagonal element $Ch_{M+1,M+1}$ is normalized to 0 because we do not have information on category 0. There are 14 parameters to be estimated in $Ch$.
    * We generate $B2$ by estimating the upper triangle of an $M \times M$ matrix $Cho$. Other elements in the low triangular part of $Cho$ are functions of the elements in the upper triangle such that the structure of $B$ is as defined. $B2 = Cho \times Ch^T$. There are 10 parameters to be estimated in $Cho$.
- $\mu_c > 0, c = 1, ..., M$: scale parameters for each category:
  - We estimate $\ln \mu_c$ to ensure $\mu_c > 0$ for $c = 1, ..., M$.

### A.3 Likelihood Function for Category Level

Given store choice $r$ for household $i$ week $t$, the likelihood of observing purchase incidence $\{I_j = 0\}_{j=1}^{m}, \{I_j = 1\}_{j=m+1}^{M_r}$ and budget share $\{S_j\}_{j=m+1}^{M_j}$ given parameter $\Theta$ and random shock $\varepsilon_0$ is

$$\begin{aligned} & L_r\left(\{I_j\}_{j=1}^{M_r}, \{S_j\}_{j=1}^{M_r} | \Theta, \varepsilon_0\right) \\ =& D_r \times \left(1 - \sum_{j=1}^{M_r} \kappa_j S_j\right)^{-1-\sum_{j=1}^{M_r} I_j} \times \prod_{j=1}^{M_r} (\mu_{c(j)})^{I_j} \exp(-\exp(H_j))(\exp(H_j))^{I_j} \end{aligned} \tag{21}$$

$$H_j = \alpha_{s(j)} + \lambda_{c(j)} + \rho X_j + \mu_{c(j)} \kappa_j \ln y + \mu_{c(j)}(\kappa_j - 1)\varepsilon_0 - \mu_{c(j)} \left(\sum_{k=1}^{M_r} \delta_{jk} S_k\right) \left(1 - \sum_{j=1}^{M_r} \kappa_j S_j\right)^{-1}.$$

Notations are the same as in Appendix A.1. Derivation of the likelihood function refers to online appendix of Mehta and Ma (2012).

### A.4 Likelihood Function for Store Level

Given estimates from stage one $\hat{\Theta}$, the likelihood of observing purchase incidence $\{I_j = 0\}_{j=1}^{m}, \{I_j = 1\}_{j=m+1}^{M_r}$ and budget share $\{S_j\}_{j=m+1}^{M_j}$ given parameter $\Theta^S$ is

$$
\begin{aligned}
&L_{it}\left(\{I_{r'}^S\}_{r'\in\mathcal{R}}, \{I_j\}_{j\in\mathcal{M}_r}, \{S_j\}_{j\in\mathcal{M}_r}|\hat{\Theta}, \Theta^S\right) \\
&= \int_{\varepsilon_0=-\infty}^{\infty} \prod_{r'\in\mathcal{R}} \Bigg[\int_{\boldsymbol{\varepsilon}_{r'\neq r}=-\infty}^{\infty} \int_{-\infty}^{-\hat{\mathbf{H}}_{r,np}(\varepsilon_0)} \frac{\exp(\gamma^v \ln \hat{V}_r(\boldsymbol{\varepsilon}) + \Gamma_r)}{\sum_{r'\in\mathcal{R}} \exp(\gamma^v \ln \hat{V}_{r'}(\boldsymbol{\varepsilon}) + \Gamma_{r'})} \\
&\quad \times \boldsymbol{\phi}(-\hat{\mathbf{H}}_{r,p}(\varepsilon_0))\boldsymbol{\phi}(\boldsymbol{\varepsilon}_{r,np})\boldsymbol{\phi}(\boldsymbol{\varepsilon}_{r'\neq r})\hat{\mathbf{J}}d\boldsymbol{\varepsilon}_{r,np}d\boldsymbol{\varepsilon}_{r'\neq r}\Bigg]^{I_{r'}^S} \phi_N(\varepsilon_0)d\varepsilon_0, \qquad (22)
\end{aligned}
$$

$$
\hat{H}_j = \hat{\alpha}_{s(j)} + \hat{\lambda}_{c(j)} + \hat{\rho}X_j + \hat{\mu}_{c(j)}\hat{\kappa}_j \ln y + \hat{\mu}_{c(j)}(\hat{\kappa}_j - 1)\varepsilon_0 - \hat{\mu}_{c(j)}\left(\sum_{k=1}^{M_r} \hat{\delta}_{jk}S_k\right)\left(1 - \sum_{j=1}^{M_r} \hat{\kappa}_j S_j\right)^{-1}.
$$

Notations are the same as in Appendix A.1. We draw $\{\varepsilon_{0,it}\}$ and $\{\boldsymbol{\varepsilon}_{it}\}$ from their distribution given category level decision. The steps of drawing one set of random errors for each household-week are as follows:

1. Draw $\varepsilon_0$ from standard normal distribution $\mathcal{N}(0, 1)$.
2. For store choice $r$ that are not chosen, draw $\{\varepsilon_j, j \in \mathcal{M}_r\}$ from standard extreme value distribution.
3. For the chosen store choice $r$, we set $\{\varepsilon_j, j \in \mathcal{M}_r\}$ based on purchase incidence and spending share:
   - If $j$ is purchased, $\varepsilon_j$ is the value such that the spending share of $j$ is the observed $S_j$. After some derivation, $\varepsilon_j = -\hat{H}_j(\varepsilon_0)$.
   - If $j$ is not purchased, $\varepsilon_j$ needs to satisfy the condition such that virtual price for $j$ is smaller than observed quality-adjusted price $P_j^*$. After some derivation, $\varepsilon_j$ is drawn from standard extreme value distribution with upper bound $-\hat{H}_j(\varepsilon_0)$.

For each set of $\{\varepsilon_{0,it}\}$ and $\{\boldsymbol{\varepsilon}_{it}\}$, the likelihood thus becomes:

$$
\hat{L}_{it}\left(\{I_{r'}^S\}_{r'\in\mathcal{R}}, \{I_j\}_{j\in\mathcal{M}_r}, \{S_j\}_{j\in\mathcal{M}_r}|\hat{\Theta}, \Theta^S\right) = \frac{\exp(\gamma^v \ln \hat{V}_r(\boldsymbol{\varepsilon_{it}}) + \Gamma_r)}{\sum_{r'\in\mathcal{R}} \exp(\gamma^v \ln \hat{V}_{r'}(\boldsymbol{\varepsilon_{it}}) + \Gamma_{r'})}. \qquad (23)
$$

## B Tables

Table B1: Spending Share: Supercenter Entry, DCDH

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Spending Share | | | | | |
| Variables | Supercenter | Grocery | Discount Store | Warehouse Club | Drug Store | Dollar Store |
| NumSup | 0.0636*** | -0.0417*** | -0.00657*** | -0.00520*** | -0.00380*** | -0.00229*** |
| | (0.00303) | (0.00327) | (0.00166) | (0.00160) | (0.00111) | (0.000651) |
| Observations | 1390263 | 1390263 | 1390263 | 1390263 | 1390263 | 1390263 |

Notes: This table uses 2004-2013 NielsenIQ Consumer Panel Dataset (HMS) at the household-by-quarter level and opening records of the Walmart Supercenter from Arcidiacono et al. (2020). The sample only includes households who have never moved during the period. The dependent variable spending share for each store type is the percentage to the total expenditure in CPG products for each household-quarter observations in the HMS. Discount Store includes discount stores other than the supercenter. The reported independent variable is the number of supercenters in the zip code area where each household lives. All regressions control for household and year-quarter fixed effects. Observations are not weighted for national representativeness. Robust standard errors, clustered by household, are in parentheses. *, **, ***: statistically significant with 10, 5, and 1 percent confidence, respectively.

Table B2: Spending Share: Clubs Entry, DCDH

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Spending Share | | | | | |
| Variables | Clubs | Grocery | Discount Store | Warehouse Club | Drug Store | Dollar Store |
| NumClubs | 0.0308*** | -0.0169*** | -0.0149*** | 0.000975*** | -0.000461 | -0.000442 |
| | (0.00271) | (0.00364) | (0.00307) | (0.000335) | (0.00136) | (0.000641) |
| Observations | 1704830 | 1704830 | 1704830 | 1704830 | 1704830 | 1704830 |

Notes: This table uses 2004-2015 NielsenIQ Consumer Panel Dataset (HMS) at the household-by-quarter level and opening records of Costco, Sam's Club, and BJ's, from Coibion et al. (2021). The sample only includes households who have never moved during the period. The dependent variable spending share for each channel type is the percentage to the total expenditure in CPG products for each household-quarter observations in the HMS. Warehouse Club includes warehouse clubs other than the three focal clubs. The reported independent variable is the total number of warehouse clubs in the zip code area where each household lives. All regressions control for household and year-quarter fixed effects. Observations are not weighted for national representativeness. Robust standard errors, clustered by household, are in parentheses. *, **, ***: statistically significant with 10, 5, and 1 percent confidence, respectively.

Table B3: Spending Share: Supercenter Entry

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Spending Share | | | | | |
| Variables | Supercenter | Grocery | Discount Store | Warehouse Club | Drug Store | Dollar Store |
| Num < 1 mile | 0.0589*** | -0.0354*** | -0.00838*** | -0.00604*** | -0.00383*** | -0.00228*** |
| | (0.00363) | (0.00348) | (0.00164) | (0.00162) | (0.00112) | (0.000589) |
| 1 mile ≤ Num < 3 miles | 0.0218*** | -0.0125*** | 0.000167 | -0.00148 | -0.00482*** | -0.00121* |
| | (0.00257) | (0.00315) | (0.00173) | (0.00197) | (0.00134) | (0.000622) |
| 3 miles ≤ Num < 5 miles | 0.00553*** | 0.000921 | 0.000928 | -0.00314*** | -0.00248*** | -0.00120*** |
| | (0.00156) | (0.00187) | (0.00106) | (0.00105) | (0.000775) | (0.000389) |
| 5 miles ≤ Num < 7 miles | 0.00403*** | -0.00221 | 0.00127 | -0.000686 | -0.00172*** | -0.000981*** |
| | (0.00147) | (0.00171) | (0.000931) | (0.000957) | (0.000639) | (0.000332) |
| 7 miles ≤ Num < 9 miles | -0.00102 | 0.000577 | 0.00357*** | -0.0000528 | -0.000917 | -0.000949*** |
| | (0.00121) | (0.00151) | (0.000813) | (0.000930) | (0.000616) | (0.000330) |
| 9 miles ≤ Num < 11 miles | -0.000653 | -0.00131 | 0.00296*** | 0.00123 | -0.00134** | -0.000612** |
| | (0.00114) | (0.00144) | (0.000778) | (0.000821) | (0.000636) | (0.000302) |
| Observations | 1528447 | 1528447 | 1528447 | 1528447 | 1528447 | 1528447 |

Notes: This table uses 2004-2013 NielsenIQ Consumer Panel Dataset (HMS) at the household-by-quarter level and opening records of the Walmart Supercenter from Arcidiacono et al. (2020). The sample only includes households who have never moved during the period. The dependent variable spending share for each store type is the percentage to the total expenditure in CPG products for each household-quarter observations in the HMS. Discount Store includes discount stores other than the supercenter. The reported independent variable is the number of supercenters in the zip code area where each household lives. All regressions control for household and year-quarter fixed effects. Observations are not weighted for national representativeness. Robust standard errors, clustered by household, are in parentheses. *, **, ***: statistically significant with 10, 5, and 1 percent confidence, respectively.

Table B4: Spending Share: Clubs Entry

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Spending Share | | | | | |
| Variables | Clubs | Grocery | Discount Store | Warehouse Club | Drug Store | Dollar Store |
| Num < 1 mile | 0.0349*** | -0.0221*** | -0.0151*** | 0.000143 | 0.000311 | -0.000442 |
| | (0.00264) | (0.00370) | (0.00309) | (0.000512) | (0.00136) | (0.000689) |
| 1 mile ≤ Num < 3 miles | 0.0130*** | -0.0166*** | -0.0000220 | 0.000592 | -0.00235 | 0.000434 |
| | (0.00253) | (0.00348) | (0.00244) | (0.000403) | (0.00155) | (0.000770) |
| 3 miles ≤ Num < 5 miles | 0.00799*** | -0.00276 | -0.00471*** | -0.000169 | -0.0000907 | -0.000748* |
| | (0.00132) | (0.00209) | (0.00154) | (0.000272) | (0.000957) | (0.000421) |
| 5 miles ≤ Num < 7 miles | 0.00419*** | -0.00612*** | -0.000527 | 0.0000277 | 0.000978 | -0.000858* |
| | (0.00125) | (0.00192) | (0.00136) | (0.000226) | (0.000877) | (0.000454) |
| 7 miles ≤ Num < 9 miles | 0.00205* | -0.00710*** | 0.00515*** | 0.00000260 | -0.000800 | -0.000719* |
| | (0.00111) | (0.00169) | (0.00127) | (0.000243) | (0.000766) | (0.000385) |
| 9 miles ≤ Num < 11 miles | -0.00000621 | -0.00350** | 0.00398*** | -0.000198 | 0.000739 | -0.000780** |
| | (0.00103) | (0.00160) | (0.00118) | (0.000270) | (0.000715) | (0.000339) |
| Observations | 1861872 | 1861872 | 1861872 | 1861872 | 1861872 | 1861872 |

Notes: This table uses 2004-2015 NielsenIQ Consumer Panel Dataset (HMS) at the household-by-quarter level and opening records of Costco, Sam's Club, and BJ's, from Coibion et al. (2021). The sample only includes households who have never moved during the period. The dependent variable spending share for each channel type is the percentage to the total expenditure in CPG products for each household-quarter observations in the HMS. Warehouse Club includes warehouse clubs other than the three focal clubs. The reported independent variable is the total number of warehouse clubs in the zip code area where each household lives. All regressions control for household and year-quarter fixed effects. Observations are not weighted for national representativeness. Robust standard errors, clustered by household, are in parentheses. *, **, ***: statistically significant with 10, 5, and 1 percent confidence, respectively.

## Table B5: ln(UPCs per Trip): Supercenter Entry

| Store type | (1) All | (2) Supercenter | (3) Grocery | (4) Discount Store | (5) Warehouse Club | (6) Drug Store | (7) Dollar Store |
|---|---|---|---|---|---|---|---|
| Number of supercenters | 0.0008 | 0.0249* | -0.0289*** | -0.0430*** | -0.0150 | -0.0268*** | -0.0217** |
| | (0.0057) | (0.0141) | (0.0073) | (0.0114) | (0.0104) | (0.0079) | (0.0106) |
| Observations | 1531362 | 817494 | 1485110 | 900542 | 606764 | 905899 | 656557 |
| Adj R-squared | 0.823 | 0.636 | 0.763 | 0.492 | 0.616 | 0.418 | 0.473 |
| Within R-squared | -0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Prob > F | 0.890 | 0.078 | 0.000 | 0.000 | 0.150 | 0.001 | 0.041 |
| Number of clusters | 106458 | 72837 | 104913 | 84354 | 55502 | 81671 | 65365 |
| Household FE | X | X | X | X | X | X | X |
| Year-Quarter FE | X | X | X | X | X | X | X |

Notes: This table uses 2004-2013 NielsenIQ Consumer Panel Dataset (HMS) at the household-by-quarter level and opening records of the Walmart Supercenter from Arcidiacono et al. (2020). The sample only includes households who have never moved during the period. Dependent variables are ln(number of UPCs per trip) for each store type. Discount Store includes discount stores other than the supercenter. The reported independent variable is the number of supercenters in the zip code area where each household lives. All regressions control for household and year-quarter fixed effects. Observations are not weighted for national representativeness. Robust standard errors, clustered by household, are in parentheses. *, **, ***: statistically significant with 10, 5, and 1 percent confidence, respectively.

## Table B6: ln(UPCs per Trip): Club Entry

| Store type | (1) All | (2) Clubs | (3) Grocery | (4) Discount Store | (5) Warehouse Club | (6) Drug Store | (7) Dollar Store |
|---|---|---|---|---|---|---|---|
| Number of clubs | -0.0449*** | -0.0931*** | -0.0310*** | -0.0293** | 0.00528 | -0.00828 | -0.0115 |
| | (0.00637) | (0.0156) | (0.00865) | (0.0123) | (0.0885) | (0.00921) | (0.0135) |
| Observations | 1865248 | 719160 | 1805410 | 1560387 | 51785 | 1078435 | 807950 |
| Adj R-squared | 0.816 | 0.614 | 0.752 | 0.651 | 0.545 | 0.415 | 0.471 |
| Within R-squared | 0.000 | 0.000 | 0.000 | 0.000 | -0.000 | 0.000 | 0.000 |
| Prob > F | 0.000 | 0.000 | 0.000 | 0.017 | 0.952 | 0.369 | 0.394 |
| Number of clusters | 120135 | 60281 | 118277 | 112681 | 8048 | 90549 | 74643 |
| Household FE | X | X | X | X | X | X | X |
| Year-Quarter FE | X | X | X | X | X | X | X |

Notes: This table uses 2004-2015 NielsenIQ Consumer Panel Dataset (HMS) at the household-by-quarter level and opening records of Costco, Sam's Club, and BJ's, from Coibion et al. (2021). The sample only includes households who have never moved during the period. Dependent variables are ln(number of UPCs per trip) for each store type. Warehouse Club includes warehouse clubs other than the three focal clubs. The reported independent variable is the total number of warehouse clubs in the zip code area where each household lives. All regressions control for household and year-quarter fixed effects. Observations are not weighted for national representativeness. Robust standard errors, clustered by household, are in parentheses. *, **, ***: statistically significant with 10, 5, and 1 percent confidence, respectively.

Table B7: Number of Trips and Varieties per Trip: Supercenter Entry

| Variables | (1) Trip | (2) UPC | (3) Brand | (4) Product Group | (5) Department |
|---|---|---|---|---|---|
| Number of supercenters | -0.0039 | 0.0008 | 0.0027 | 0.0023 | 0.0063** |
| | (0.0064) | (0.0057) | (0.0054) | (0.0049) | (0.0031) |
| Observations | 1531362 | 1531362 | 1531362 | 1531362 | 1531362 |
| Adj R-squared | 0.759 | 0.823 | 0.825 | 0.819 | 0.780 |
| Within R-squared | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Prob > F | 0.542 | 0.890 | 0.621 | 0.633 | 0.041 |
| Number of clusters | 106458 | 106458 | 106458 | 106458 | 106458 |
| Household FE | X | X | X | X | X |
| Year-Quarter FE | X | X | X | X | X |

Notes: This table uses 2004-2013 NielsenIQ Consumer Panel Dataset (HMS) at the household-by-quarter level and opening records of the Walmart Supercenter from Arcidiacono et al. (2020). The sample only includes households who have never moved during the period. Dependent variables from Column (1)-(5) are log number of total shopping trips, log number of UPCs per trip, log number of brands per trip, log number of product groups per trip, and log number of departments per trip. The reported independent variable is the number of supercenters in the zip code area where each household lives. All regressions control for household and year-quarter fixed effects. Observations are not weighted for national representativeness. Robust standard errors, clustered by household, are in parentheses. *, **, ***: statistically significant with 10, 5, and 1 percent confidence, respectively.

Table B8: Number of Trips and Varieties per Trip: Clubs Entry

| Variables | (1) Trip | (2) UPC | (3) Brand | (4) Product Group | (5) Department |
|---|---|---|---|---|---|
| Number of clubs | 0.0233*** | -0.0449*** | -0.0386*** | -0.0367*** | -0.0188*** |
| | (0.0078) | (0.0064) | (0.0059) | (0.0057) | (0.0036) |
| Observations | 1865248 | 1865248 | 1865248 | 1865248 | 1865248 |
| Adj R-squared | 0.748 | 0.816 | 0.817 | 0.813 | 0.775 |
| Within R-squared | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Prob > F | 0.003 | 0.000 | 0.000 | 0.000 | 0.000 |
| Number of clusters | 120135 | 120135 | 120135 | 120135 | 120135 |
| Household FE | X | X | X | X | X |
| Year-Quarter FE | X | X | X | X | X |

Notes: This table uses 2004-2015 NielsenIQ Consumer Panel Dataset (HMS) at the household-by-quarter level and opening records of Costco, Sam's Club, and BJ's, from Coibion et al. (2021). The sample only includes households who have never moved during the period. Dependent variables from Column (1)-(5) are log number of total shopping trips, log number of UPCs per trip, log number of brands per trip, log number of product groups per trip, and log number of departments per trip. The reported independent variable is the total number of warehouse clubs in the zip code area where each household lives. All regressions control for household and year-quarter fixed effects. Observations are not weighted for national representativeness. Robust standard errors, clustered by household, are in parentheses. *, **, ***: statistically significant with 10, 5, and 1 percent confidence, respectively.

Table B9: ln(Number of Retailers Visited): Supercenter Entry

| Store type | (1)<br>All | (2)<br>Grocery | (3)<br>Discount Store | (4)<br>Warehouse Club | (5)<br>Drug Store | (6)<br>Dollar Store |
|---|---|---|---|---|---|---|
| Number of supercenters | -0.0356*** | -0.0361*** | -0.0609*** | -0.0176*** | -0.0326*** | -0.0108** |
| | (0.0050) | (0.0048) | (0.0056) | (0.0040) | (0.0052) | (0.0046) |
| Observations | 1531362 | 1531362 | 1531362 | 1531362 | 1531362 | 1531362 |
| Adj R-squared | 0.710 | 0.659 | 0.534 | 0.680 | 0.552 | 0.609 |
| Within R-squared | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Prob > F | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.020 |
| Number of clusters | 106458 | 106458 | 106458 | 106458 | 106458 | 106458 |
| Household FE | X | X | X | X | X | X |
| Year-Quarter FE | X | X | X | X | X | X |

Notes: This table uses 2004-2013 NielsenIQ Consumer Panel Dataset (HMS) at the household-by-quarter level and opening records of the Walmart Supercenter from Arcidiacono et al. (2020). The sample only includes households who have never moved during the period. Dependent variables are ln(number of retailers visited) for each store type. Discount Store includes discount stores other than the supercenter. The reported independent variable is the number of supercenters in the zip code area where each household lives. All regressions control for household and year-quarter fixed effects. Observations are not weighted for national representativeness. Robust standard errors, clustered by household, are in parentheses. *, **, ***: statistically significant with 10, 5, and 1 percent confidence, respectively.

Table B10: ln(Number of Retailers Visited): Warehouse Club Entry

| Store types | (1)<br>All | (2)<br>Grocery | (3)<br>Discount Store | (4)<br>Warehouse Club | (5)<br>Drug Store | (6)<br>Dollar Store |
|---|---|---|---|---|---|---|
| Number of clubs | 0.0267*** | 0.0090 | -0.0037 | 0.0035* | -0.00302 | 0.0089 |
| | (0.0059) | (0.0059) | (0.0055) | (0.0019) | (0.0062) | (0.0056) |
| Observations | 1865248 | 1865248 | 1865248 | 1865248 | 1865248 | 1865248 |
| Adj R-squared | 0.706 | 0.649 | 0.544 | 0.410 | 0.548 | 0.604 |
| Within R-squared | 0.000 | 0.000 | 0.000 | 0.000 | -0.000 | 0.000 |
| Prob > F | 0.000 | 0.129 | 0.509 | 0.069 | 0.627 | 0.108 |
| Number of clusters | 120135 | 120135 | 120135 | 120135 | 120135 | 120135 |
| Household FE | X | X | X | X | X | X |
| Year-Quarter FE | X | X | X | X | X | X |

Notes: This table uses 2004-2015 NielsenIQ Consumer Panel Dataset (HMS) at the household-by-quarter level and opening records of Costco, Sam's Club, and BJ's, from Coibion et al. (2021). The sample only includes households who have never moved during the period. Dependent variables are ln(number of retailers visited) for each store type. Warehouse Club includes warehouse clubs other than the three focal clubs. The reported independent variable is the total number of warehouse clubs in the zip code area where each household lives. All regressions control for household and year-quarter fixed effects. Observations are not weighted for national representativeness. Robust standard errors, clustered by household, are in parentheses. *, **, ***: statistically significant with 10, 5, and 1 percent confidence, respectively.

Table B11: ln(Departments per Trip): Supercenter Entry, DCDH

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | log(department number per trip) | | | | | | |
| Variables | All | Supercenter | Grocery | Discount Store | Warehouse Club | Drug Store | Dollar Store |
| NumSup | 0.00668** | 0.0298*** | -0.0168*** | -0.0121 | -0.0114 | -0.000870 | 0.00104 |
| | (0.00300) | (0.0113) | (0.00421) | (0.00950) | (0.0105) | (0.00824) | (0.0106) |
| Observations | 1390264 | 707088 | 1345953 | 786879 | 529398 | 790557 | 560721 |

Notes: This table uses 2004-2013 NielsenIQ Consumer Panel Dataset (HMS) at the household-by-quarter level and opening records of the Walmart Supercenter from Arcidiacono et al. (2020). The sample only includes households who have never moved during the period. Dependent variables are ln(number of departments per trip) for each store type, with 5 departments in total. Discount Store includes discount stores other than the supercenter. The reported independent variable is the number of supercenters in the zip code area where each household lives. All regressions control for household and year-quarter fixed effects. Observations are not weighted for national representativeness. Robust standard errors, clustered by household, are in parentheses. *, **, ***: statistically significant with 10, 5, and 1 percent confidence, respectively.

Table B12: ln(Departments per Trip): Club Entry, DCDH

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | log(department number per trip) | | | | | | |
| Variables | All | Clubs | Grocery | Discount Store | Warehouse Club | Drug Store | Dollar Store |
| NumClubs | -0.00881** | -0.0571*** | -0.00726 | -0.0114 | 0.137* | 0.00864 | 0.000478 |
| | (0.00376) | (0.0156) | (0.00545) | (0.00842) | (0.0723) | (0.0106) | (0.0146) |
| Observations | 1704832 | 624561 | 1647400 | 1409276 | 23468 | 953771 | 697431 |

Notes: This table uses 2004-2015 NielsenIQ Consumer Panel Dataset (HMS) at the household-by-quarter level and opening records of Costco, Sam's Club, and BJ's, from Coibion et al. (2021). The sample only includes households who have never moved during the period. Dependent variables are ln(number of departments per trip) for each store type, with 5 departments in total. Warehouse Club includes warehouse clubs other than the three focal clubs. The reported independent variable is the total number of warehouse clubs in the zip code area where each household lives. All regressions control for household and year-quarter fixed effects. Observations are not weighted for national representativeness. Robust standard errors, clustered by household, are in parentheses. *, **, ***: statistically significant with 10, 5, and 1 percent confidence, respectively.

## Table B13: ln(Departments per Trip): Supercenter Entry

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | log(department number per trip) | | | | | | |
| Variables | All | Supercenter | Grocery | Discount Store | Warehouse Club | Drug Store | Dollar Store |
| Num $<$ 1 mile | 0.00689** | 0.0292*** | -0.0162*** | -0.0174*** | -0.00575 | -0.0111** | -0.00125 |
| | (0.00300) | (0.00805) | (0.00390) | (0.00647) | (0.00724) | (0.00469) | (0.00634) |
| 1 mile $\leq$ Num $<$ 3 miles | 0.00338 | 0.0375*** | -0.00217 | 0.00389 | -0.0172** | -0.0106** | 0.00381 |
| | (0.00298) | (0.00978) | (0.00395) | (0.00620) | (0.00753) | (0.00433) | (0.00724) |
| 3 miles $\leq$ Num $<$ 5 miles | 0.00142 | 0.00586 | -0.000973 | 0.00708* | -0.00352 | -0.00638** | 0.00286 |
| | (0.00192) | (0.00538) | (0.00249) | (0.00384) | (0.00478) | (0.00284) | (0.00436) |
| 5 miles $\leq$ Num $<$ 7 miles | -0.000371 | 0.00226 | -0.000953 | 0.00284 | -0.00392 | -0.0122*** | -0.00394 |
| | (0.00163) | (0.00477) | (0.00210) | (0.00354) | (0.00384) | (0.00254) | (0.00384) |
| 7 miles $\leq$ Num $<$ 9 miles | -0.00384*** | -0.00571 | -0.00196 | -0.000381 | -0.00381 | -0.00681*** | 0.000751 |
| | (0.00147) | (0.00401) | (0.00187) | (0.00305) | (0.00369) | (0.00224) | (0.00343) |
| 9 miles $\leq$ Num $<$ 11 miles | -0.00155 | -0.00736* | -0.00322* | 0.00434 | 0.00151 | -0.00423** | -0.00215 |
| | (0.00144) | (0.00393) | (0.00183) | (0.00296) | (0.00370) | (0.00210) | (0.00320) |
| Observations | 1528448 | 815386 | 1482315 | 898604 | 605809 | 904182 | 655171 |

Notes: This table uses 2004-2013 NielsenIQ Consumer Panel Dataset (HMS) at the household-by-quarter level and opening records of the Walmart Supercenter from Arcidiacono et al. (2020). The sample only includes households who have never moved during the period. Dependent variables are ln(number of departments per trip) for each store type, with 5 departments in total. Discount Store includes discount stores other than the supercenter. The reported independent variable is the number of supercenters in the zip code area where each household lives. All regressions control for household and year-quarter fixed effects. Observations are not weighted for national representativeness. Robust standard errors, clustered by household, are in parentheses. *, **, ***: statistically significant with 10, 5, and 1 percent confidence, respectively.

## Table B14: ln(Departments per Trip): Club Entry

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | log(department number per trip) | | | | | | |
| Variables | All | Clubs | Grocery | Discount Store | Warehouse Club | Drug Store | Dollar Store |
| Num $<$ 1 mile | -0.0188*** | -0.0432*** | -0.0163*** | -0.0216*** | 0.0191 | -0.000912 | 0.00508 |
| | (0.00344) | (0.00996) | (0.00459) | (0.00658) | (0.0449) | (0.00504) | (0.00768) |
| 1 mile $\leq$ Num $<$ 3 miles | -0.0121*** | -0.0377*** | -0.0152*** | -0.000851 | 0.00142 | -0.00103 | -0.00227 |
| | (0.00337) | (0.00975) | (0.00423) | (0.00653) | (0.0331) | (0.00418) | (0.00784) |
| 3 miles $\leq$ Num $<$ 5 miles | -0.00352* | -0.0122** | -0.00651** | -0.00257 | 0.0111 | 0.00528* | 0.000839 |
| | (0.00207) | (0.00501) | (0.00256) | (0.00380) | (0.0214) | (0.00278) | (0.00480) |
| 5 miles $\leq$ Num $<$ 7 miles | -0.00571*** | -0.00665 | -0.00555** | 0.000368 | 0.0115 | -0.00106 | 0.00348 |
| | (0.00187) | (0.00453) | (0.00237) | (0.00362) | (0.0180) | (0.00254) | (0.00432) |
| 7 miles $\leq$ Num $<$ 9 miles | -0.00404** | -0.0103** | -0.00738*** | 0.00352 | -0.0216 | -0.00143 | -0.00740** |
| | (0.00161) | (0.00419) | (0.00208) | (0.00316) | (0.0144) | (0.00228) | (0.00373) |
| 9 miles $\leq$ Num $<$ 11 miles | 0.000559 | -0.000602 | -0.00232 | 0.0113*** | -0.0153 | 0.000179 | 0.00571 |
| | (0.00161) | (0.00383) | (0.00207) | (0.00314) | (0.0157) | (0.00215) | (0.00382) |
| Observations | 1861874 | 718144 | 1802189 | 1557203 | 51734 | 1076531 | 806315 |

Notes: This table uses 2004-2015 NielsenIQ Consumer Panel Dataset (HMS) at the household-by-quarter level and opening records of Costco, Sam's Club, and BJ's, from Coibion et al. (2021). The sample only includes households who have never moved during the period. Dependent variables are ln(number of departments per trip) for each store type, with 5 departments in total. Warehouse Club includes warehouse clubs other than the three focal clubs. The reported independent variable is the total number of warehouse clubs in the zip code area where each household lives. All regressions control for household and year-quarter fixed effects. Observations are not weighted for national representativeness. Robust standard errors, clustered by household, are in parentheses. *, **, ***: statistically significant with 10, 5, and 1 percent confidence, respectively.

Table B15: ln(Relative Price Index): Supercenter Entry, DCDH

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | log(Relative Price Index) | | | | |
| Variables | All | Health& Beauty Care | Food | Non-food Grocery | General Merchandise |
| NumSup | -0.00401*** | -0.00412 | -0.00472*** | -0.000717 | -0.000298 |
| | (0.00113) | (0.00327) | (0.00107) | (0.00209) | (0.00581) |
| Observations | 1371800 | 868697 | 1369730 | 1174380 | 647783 |

Notes: This table uses 2004-2013 NielsenIQ Consumer Panel Dataset (HMS) at the household-by-quarter level and opening records of the Walmart Supercenter from Arcidiacono et al. (2020). The sample only includes households who have never moved during the period. The dependent variable relative price index (RPI) is defined in Equation 2. Column (1) reports RPI including all products. Column (2)-(5) report RPI including proudcts in each indicated departments respectively. The reported independent variable is the number of supercenters in the zip code area where each household lives. All regressions control for household and year-quarter fixed effects. Observations are not weighted for national representativeness. Robust standard errors, clustered by household, are in parentheses. *, **, ***: statistically significant with 10, 5, and 1 percent confidence, respectively.

Table B16: ln(Relative Price Index): Clubs Entry, DCDH

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | log(Relative Price Index) | | | | |
| Variables | All | Health& Beauty Care | Food | Non-food Grocery | General Merchandise |
| NumClubs | -0.000738 | -0.00135 | -0.000284 | -0.00113 | -0.000657 |
| | (0.00122) | (0.00369) | (0.00134) | (0.00253) | (0.00491) |
| Observations | 1682498 | 1057353 | 1680034 | 1423742 | 788415 |

Notes: This table uses 2004-2015 NielsenIQ Consumer Panel Dataset (HMS) at the household-by-quarter level and opening records of Costco, Sam's Club, and BJ's, from Coibion et al. (2021). The sample only includes households who have never moved during the period.The dependent variable relative price index (RPI) is defined in Equation 2. Column (1) reports RPI including all products. Column (2)-(5) report RPI including proudcts in each indicated departments respectively. The reported independent variable is the total number of warehouse clubs in the zip code area where each household lives. All regressions control for household and year-quarter fixed effects. Observations are not weighted for national representativeness. Robust standard errors, clustered by household, are in parentheses. *, **, ***: statistically significant with 10, 5, and 1 percent confidence, respectively.

Table B17: ln(Relative Price Index): Supercenter Entry

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | | | log(Relative Price Index) | | |
| Variables | All | Health& Beauty Care | Food | Non-food Grocery | General Merchandise |
| Num < 1 mile | -0.00634*** | -0.00720*** | -0.00640*** | -0.00455*** | -0.00282 |
| | (0.000876) | (0.00182) | (0.000964) | (0.00129) | (0.00213) |
| 1 mile ≤ Num < 3 miles | -0.00325*** | -0.00383* | -0.00325*** | -0.00115 | -0.00387* |
| | (0.00101) | (0.00207) | (0.00110) | (0.00149) | (0.00234) |
| 3 miles ≤ Num < 5 miles | -0.00130** | -0.00107 | -0.000935 | -0.00179* | -0.000896 |
| | (0.000642) | (0.00109) | (0.000712) | (0.00107) | (0.00139) |
| 5 miles ≤ Num < 7 miles | -0.00180*** | -0.00161* | -0.00216*** | -0.00126 | 0.000808 |
| | (0.000505) | (0.000945) | (0.000563) | (0.000822) | (0.00112) |
| 7 miles ≤ Num < 9 miles | -0.00205*** | -0.000594 | -0.00244*** | -0.000702 | 0.000795 |
| | (0.000498) | (0.000935) | (0.000536) | (0.000815) | (0.00105) |
| 9 miles ≤ Num < 11 miles | -0.00155*** | 0.000999 | -0.00188*** | -0.000532 | -0.000738 |
| | (0.000470) | (0.000891) | (0.000523) | (0.000771) | (0.00104) |
| Observations | 1509538 | 997518 | 1507438 | 1309344 | 775567 |

Notes: This table uses 2004-2013 NielsenIQ Consumer Panel Dataset (HMS) at the household-by-quarter level and opening records of the Walmart Supercenter from Arcidiacono et al. (2020). The sample only includes households who have never moved during the period. The dependent variable relative price index (RPI) is defined in Equation 2. Column (1) reports RPI including all products. Column (2)-(5) report RPI including proudcts in each indicated departments respectively. The reported independent variable is the number of supercenters in the zip code area where each household lives. All regressions control for household and year-quarter fixed effects. Observations are not weighted for national representativeness. Robust standard errors, clustered by household, are in parentheses. *, **, ***: statistically significant with 10, 5, and 1 percent confidence, respectively.

Table B18: ln(Relative Price Index): Clubs Entry

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | | | log(Relative Price Index) | | |
| Variables | All | Health& Beauty Care | Food | Non-food Grocery | General Merchandise |
| Num < 1 mile | 0.000406 | 0.000629 | 0.000308 | -0.00232 | 0.00499* |
| | (0.00117) | (0.00214) | (0.00133) | (0.00190) | (0.00271) |
| 1 mile ≤ Num < 3 miles | 0.000841 | 0.00604*** | 0.000878 | 0.000111 | -0.000434 |
| | (0.00125) | (0.00231) | (0.00136) | (0.00209) | (0.00336) |
| 3 miles ≤ Num < 5 miles | 0.000691 | 0.00123 | -0.0000135 | 0.000748 | 0.0000442 |
| | (0.000709) | (0.00128) | (0.000762) | (0.00110) | (0.00164) |
| 5 miles ≤ Num < 7 miles | 0.000705 | 0.00147 | 0.000670 | 0.000400 | 0.00328** |
| | (0.000661) | (0.00114) | (0.000707) | (0.00112) | (0.00143) |
| 7 miles ≤ Num < 9 miles | 0.000262 | 0.00236** | 0.000179 | 0.000437 | 0.000511 |
| | (0.000630) | (0.00101) | (0.000692) | (0.000975) | (0.00135) |
| 9 miles ≤ Num < 11 miles | -0.000143 | 0.000734 | -0.000548 | 0.000617 | -0.00191 |
| | (0.000597) | (0.00102) | (0.000649) | (0.000929) | (0.00128) |
| Observations | 1839045 | 1197747 | 1836526 | 1575827 | 918938 |

Notes: This table uses 2004-2015 NielsenIQ Consumer Panel Dataset (HMS) at the household-by-quarter level and opening records of Costco, Sam's Club, and BJ's, from Coibion et al. (2021). The sample only includes households who have never moved during the period. The dependent variable relative price index (RPI) is defined in Equation 2. Column (1) reports RPI including all products. Column (2)-(5) report RPI including proudcts in each indicated departments respectively. The reported independent variable is the total number of warehouse clubs in the zip code area where each household lives. All regressions control for household and year-quarter fixed effects. Observations are not weighted for national representativeness. Robust standard errors, clustered by household, are in parentheses. *, **, ***: statistically significant with 10, 5, and 1 percent confidence, respectively.

Table B19: Summary of Prices and Variety Depth by Store Types and Categories

| Type | Health & Beauty Care | Food | Non-food Grocery | General Merchandise |
|---|---|---|---|---|
| | | Average Price | | |
| Grocery | 2.49 | 2.09 | 2.75 | 2.55 |
| Discount | 2.91 | 2.14 | 3.53 | 3.67 |
| Club | 13.91 | 7.40 | 12.75 | 14.91 |
| Drug | 6.57 | 1.75 | 3.70 | 4.46 |
| Dollar | 1.42 | 1.28 | 2.10 | 1.16 |
| | | log(Average Number of UPCs) | | |
| Grocery | 6.19 | 8.49 | 6.14 | 5.14 |
| Discount | 6.67 | 7.83 | 6.40 | 6.23 |
| Club | 5.15 | 6.77 | 5.02 | 4.71 |
| Drug | 6.75 | 6.46 | 5.35 | 4.85 |
| Dollar | 4.78 | 6.51 | 5.01 | 4.42 |

Notes: This table shows summary statistics for prices and variety depth for each store-category. The sample is 1137 households across 57 counties with 11376 household-week observations in Texas in 2012 from NielsenIQ Consumer Panel Dataset (HMS). For both price and variety depth measure, we use the average value across all the stores in the US within each chain and further aggregate to store type level for the summary. Category price is calculated using the average price for each UPC in the category weighted by sales and only UPCs that are sold in all biweeks in 2012 are included. Thus, a high category price result from two reasons: 1. same product is sold at a higher price in the store, 2. the store sells more high-priced items, (for example, clubs sell items with larger size and thus have higher category prices).

Table B20: Estimates on Cross-category Complementarity within Stores

| | Health & Beauty Care | Food | Non-food Grocery | General Merchandise |
|---|---|---|---|---|
| Health & Beauty Care | 0.0045 | 0.0033 | 0.0005 | 0.0078 |
| Food | 0.0033 | 0.025 | -0.0005 | 0.0164 |
| Non-food Grocery | 0.0005 | -0.0005 | 0.0036 | 0.0047 |
| General Merchandise | 0.0078 | 0.0161 | 0.0047 | 0.0218 |

Notes: This table displays $\{b^2_{cd}, c, d = 1, ..., M\}$ for categories from two different stores from Equation 6. The sample is 1137 households across 57 counties with 11376 household-week observations in Texas in 2012 from NielsenIQ Consumer Panel Dataset (HMS). Positive numbers for a category pair suggest the two categories are complements and negative numbers suggest substitutes. Estimates to generat this matrix described in Appendix A.2 are presented in Appendix Table B22

Table B21: Conditional Cross-category Price Elasticities for Individual Demand

| | | Store 2 | | | |
|---|---|---|---|---|---|
| | | Health & Beauty Care | Food | Non-food Grocery | General Merchandise |
| Store 1 | Health & Beauty Care | -0.0039 | -0.0038 | -0.0003 | -0.0064 |
| | Food | -0.0032 | -0.0221 | 0.0004 | -0.0111 |
| | Non-food Grocery | -0.0005 | 0.0007 | -0.0042 | -0.0056 |
| | General Merchandise | -0.0103 | -0.0311 | -0.0063 | -0.0231 |

Notes: This table shows average cross-category price elasticities for individual demand conditioning on store choice and purchase incidence for categories from two different stores. The sample is 1137 households across 57 counties with 11376 household-week observations in Texas in 2012 from NielsenIQ Consumer Panel Dataset (HMS). The complementarity may result from some co-movement in price change of the same category across different stores

Table B22: Estimates of Elements in Cholesky Matrix

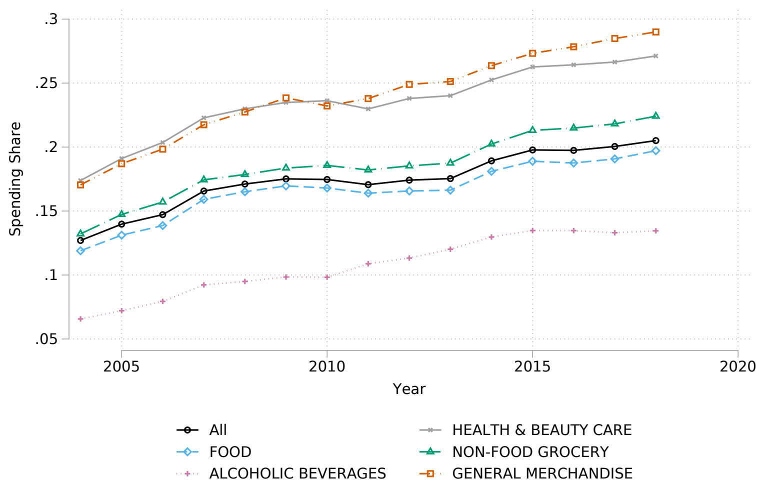
| Parameters | Estimates | s.e. | Parameters | Estimates | s.e. |
|---|---|---|---|---|---|
| $Ch_{11}$ | 0.4517 | 0.0268 | $Cho_{11}$ | 0.01 | 0.0066 |
| $Ch_{21}$ | -0.0181 | 0.0031 | $Cho_{12}$ | 0.0059 | 0.0029 |
| $Ch_{22}$ | 0.6025 | 0.0325 | $Cho_{13}$ | 0.0011 | 0.0047 |
| $Ch_{31}$ | 0.0101 | 0.0028 | $Cho_{14}$ | 0.015 | 0.0051 |
| $Ch_{32}$ | 0.0038 | 0.0017 | $Cho_{22}$ | 0.0417 | 0.005 |
| $Ch_{33}$ | 0.3347 | 0.0558 | $Cho_{23}$ | -0.0023 | 0.004 |
| $Ch_{41}$ | -0.0002 | 0.0046 | $Cho_{24}$ | 0.0326 | 0.0047 |
| $Ch_{42}$ | -0.0155 | 0.0026 | $Cho_{33}$ | 0.0109 | 0.0047 |
| $Ch_{43}$ | 0.0018 | 0.0042 | $Cho_{34}$ | 0.0088 | 0.0035 |
| $Ch_{44}$ | 0.5245 | 0.0259 | $Cho_{44}$ | 0.0424 | 0.0105 |
| $Ch_{51}$ | -0.0572 | 0.0038 | | | |
| $Ch_{52}$ | -0.05 | 0.0029 | | | |
| $Ch_{53}$ | -0.0456 | 0.0072 | | | |
| $Ch_{54}$ | -0.0866 | 0.0048 | | | |

Notes: This table presents the estimates of parameters that generate $B$ matrix. The definition of the parameters are described in Appendix A.2. The sample is 1137 households across 57 counties with 11376 household-week observations in Texas in 2012 from NielsenIQ Consumer Panel Dataset (HMS).

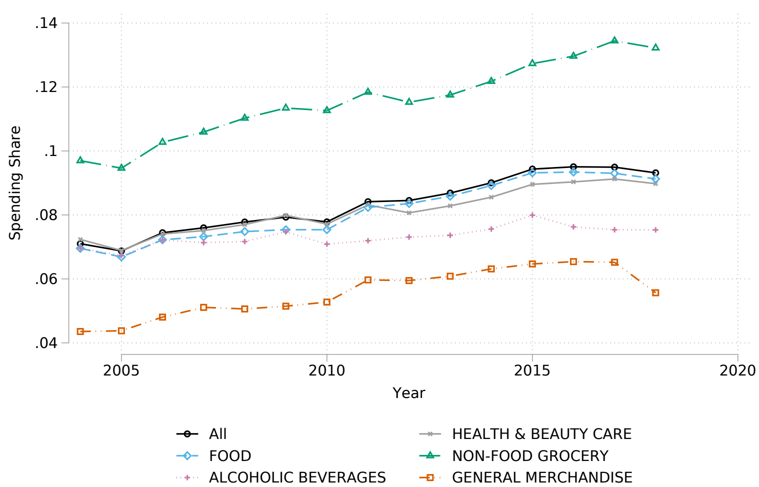
# C Figures

Figure C1: Spending Share in Supercenters and Warehouse Clubs

(a) Supercenters

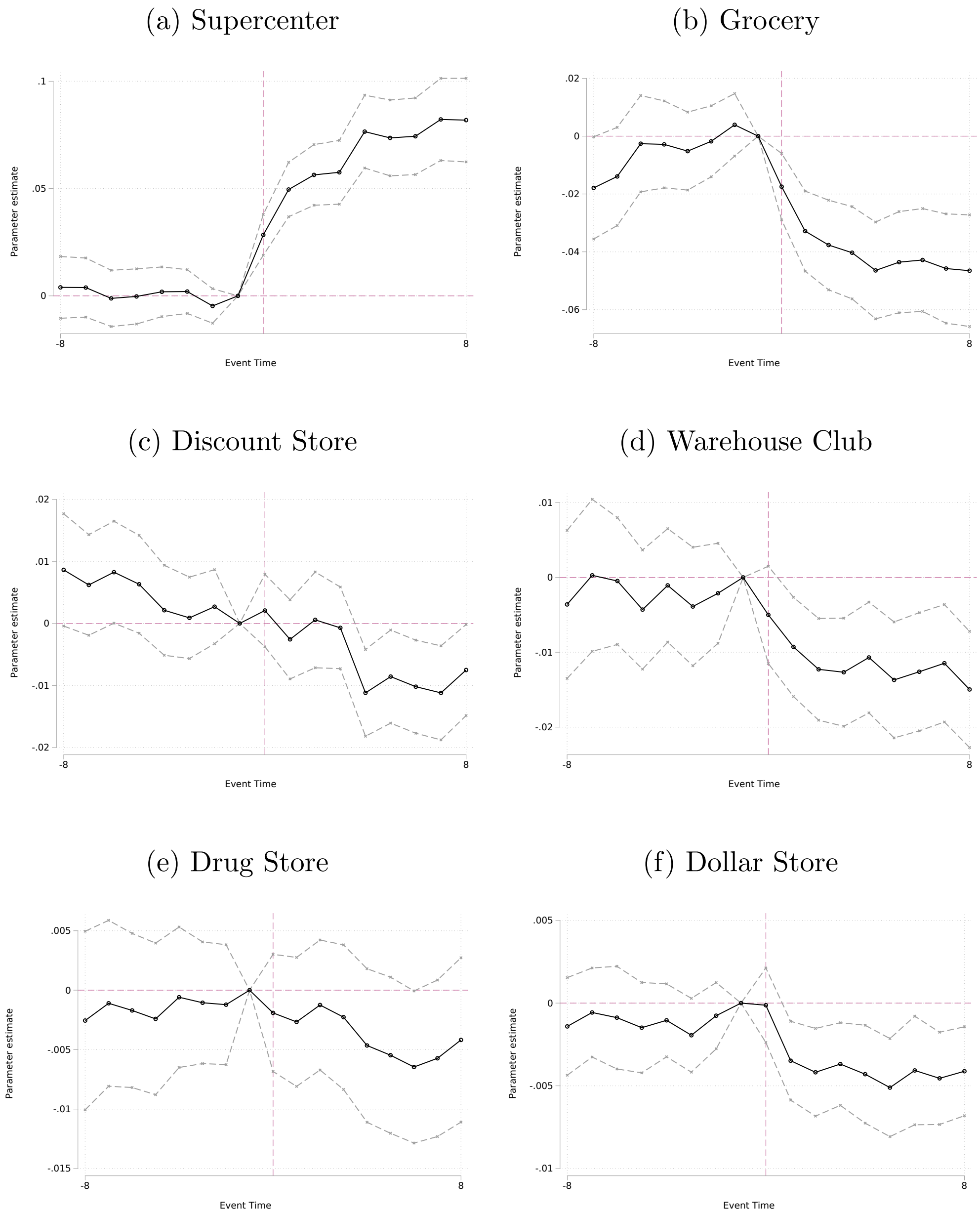



(b) Warehouse Clubs




Notes: These figures present average household spending shares in supercenters and warehouse clubs across product departments, using 2004-2018 NielsenIQ Consumer Panel Dataset (HMS) at the household-by-year level.

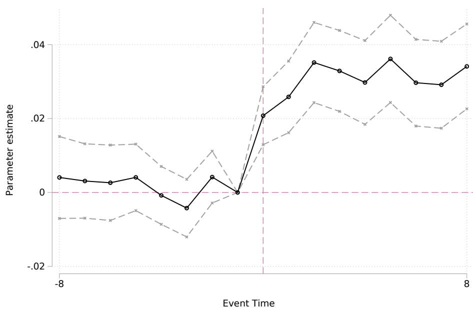
Figure C2: Event Study Graph: Supercenter Entry on Spending Share



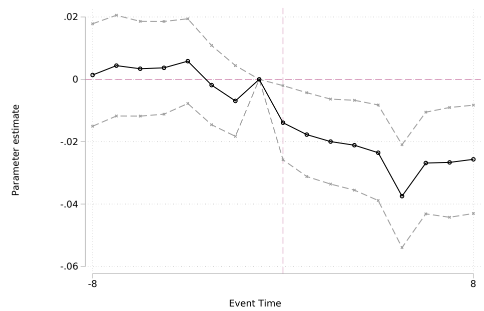

Notes: These figures use 2004-2013 NielsenIQ Consumer Panel Dataset (HMS) at the household-by-quarter level and opening records of the Walmart Supercenter from Arcidiacono et al. (2020). The figures present coefficients for eight leading and lagging periods of supercenter entries, and 95% confidence intervals from estimates of the event study on supercenter entries. The dependent variable spending share for each store type is the percentage to the total expenditure in CPG products for each household-quarter observations in the HMS. Discount Store includes discount stores other than the supercenter. All regressions control for year-quarter indicators and household fixed effects.

Figure C3: Event Study Graph: Clubs Entry on Spending Share

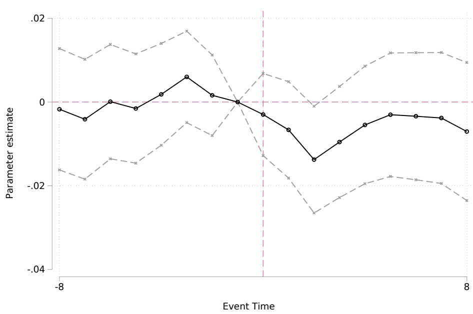
(a) Entering Warehouse clubs



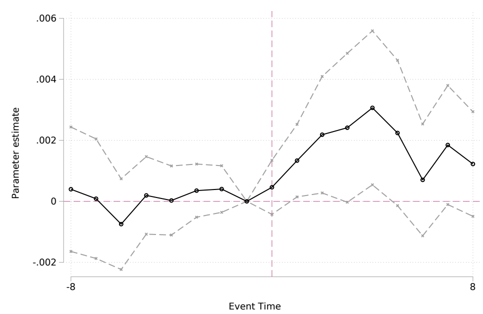

(b) Grocery



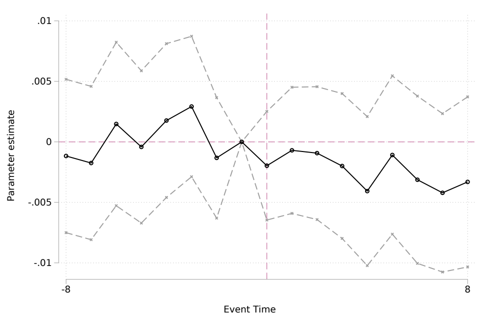

(c) Discount Store



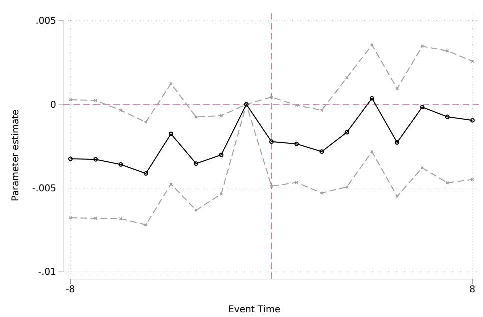

(d) Other Warehouse Clubs




(e) Drug Store



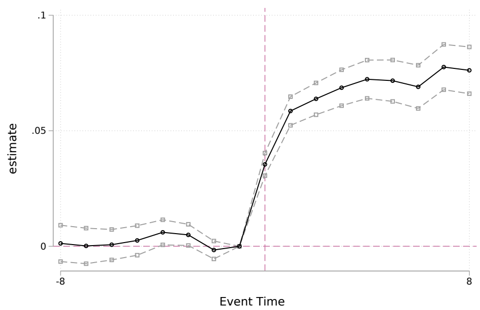

(f) Dollar Store



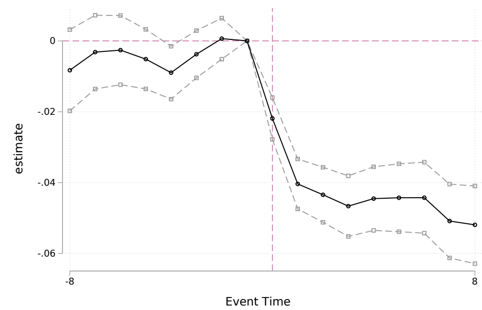

Notes: These figures use 2004-2015 NielsenIQ Consumer Panel Dataset (HMS) at the household-by-quarter level and opening records of Costco, Sam's Club, and BJ's, from Coibion et al. (2021). The figures present coefficients for eight leading and lagging periods of warehouse club entries, and 95% confidence intervals from estimates of the event study on warehouse club entries. The dependent variable spending share for each channel type is the percentage to the total expenditure in CPG products for each household-quarter observations in the HMS. Warehouse Club includes warehouse clubs other than the three focal clubs. All regressions control for year-quarter indicators and household fixed effects.

Figure C4: Event Study Graph: Supercenter Entry on Spending Share, DCDH

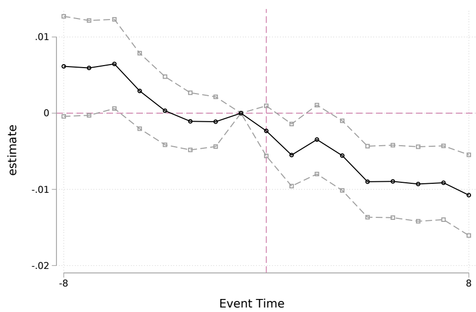
(a) Supercenter



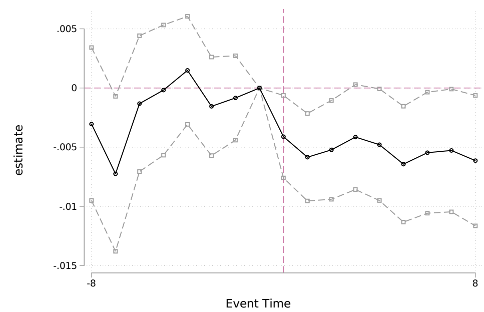

(b) Grocery



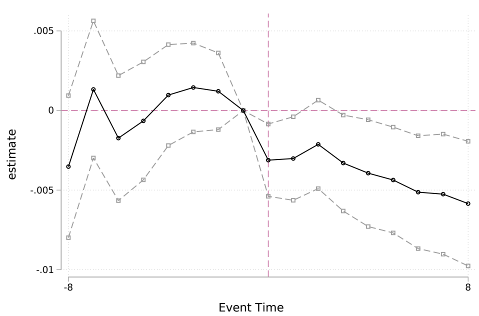

(c) Discount Store



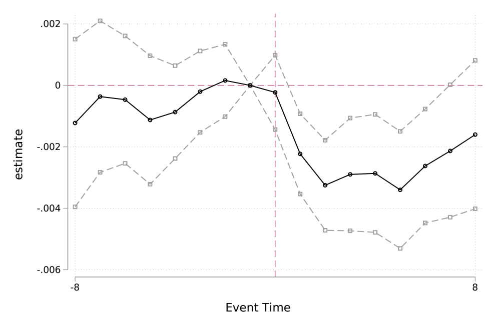

(d) Warehouse Club




(e) Drug Store



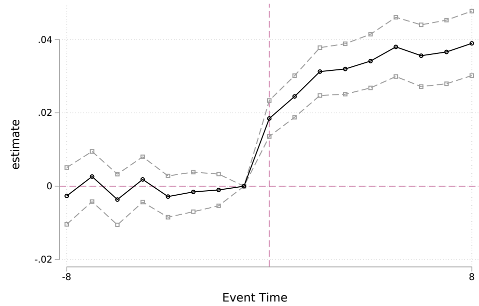

(f) Dollar Store



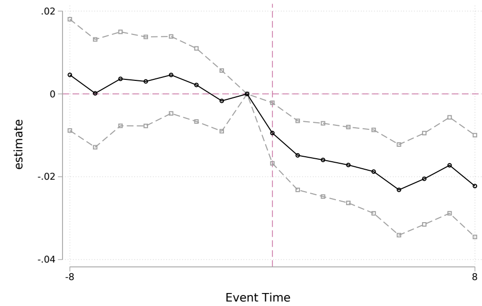

Notes: These figures use 2004-2013 NielsenIQ Consumer Panel Dataset (HMS) at the household-by-quarter level and opening records of the Walmart Supercenter from Arcidiacono et al. (2020). The figures present coefficients for eight leading and lagging periods of supercenter entries, and 95% confidence intervals from estimates of the event study on supercenter entries. The dependent variable spending share for each store type is the percentage to the total expenditure in CPG products for each household-quarter observations in the HMS. Discount Store includes discount stores other than the supercenter. All regressions control for year-quarter indicators and household fixed effects.

Figure C5: Event Study Graph: Clubs Entry on Spending Share, DCDH

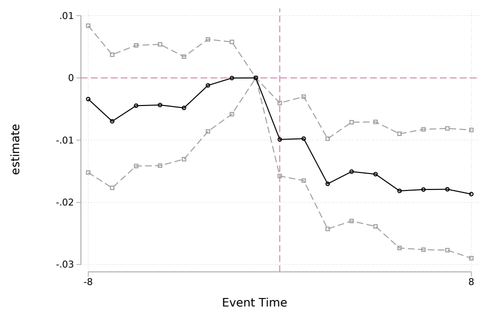
(a) Warehouse Clubs



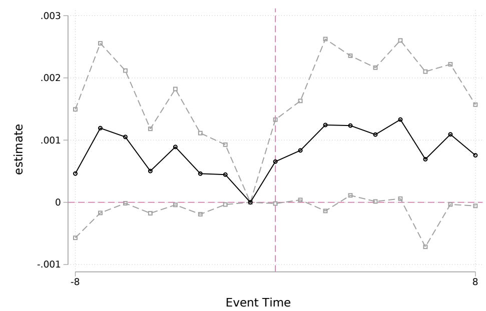

(b) Grocery



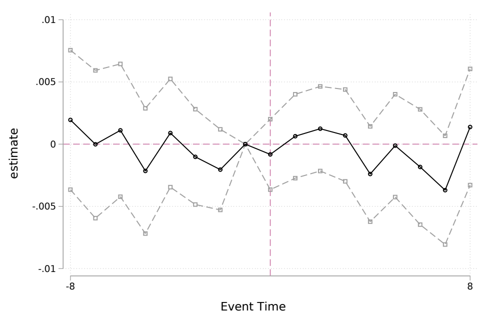

(c) Discount Store



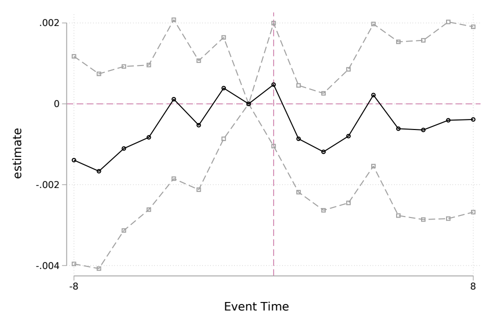

(d) Warehouse Club




(e) Drug Store



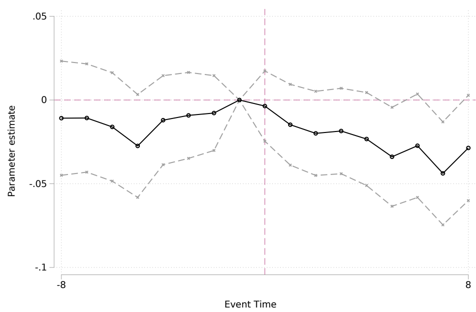

(f) Dollar Store



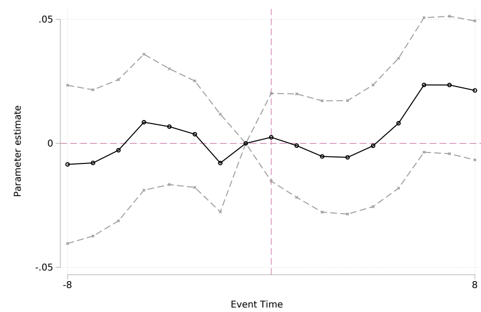

Notes: These figures use 2004-2015 NielsenIQ Consumer Panel Dataset (HMS) at the household-by-quarter level and opening records of Costco, Sam's Club, and BJ's, from Coibion et al. (2021). The figures present coefficients for eight leading and lagging periods of warehouse club entries, and 95% confidence intervals from estimates of the event study on warehouse club entries. The dependent variable spending share for each channel type is the percentage to the total expenditure in CPG products for each household-quarter observations in the HMS. Warehouse Club includes warehouse clubs other than the three focal clubs. All regressions control for year-quarter indicators and household fixed effects.

Figure C6: Event Study Graph: Supercenter Entry on Trips and Varieties per Trip

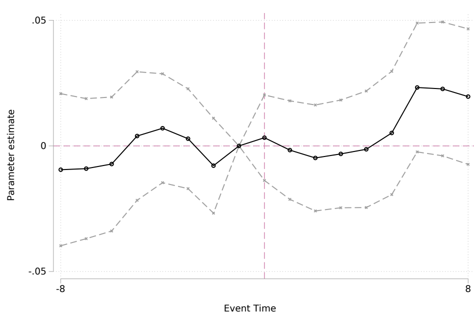
(a) Trip number



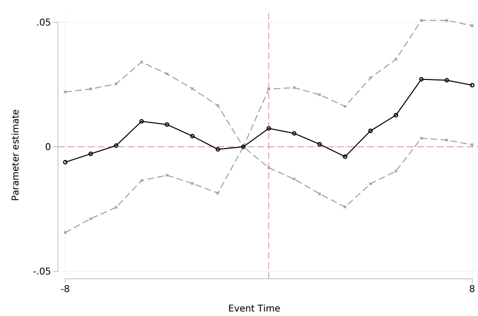

(b) UPCs




(c) Brands



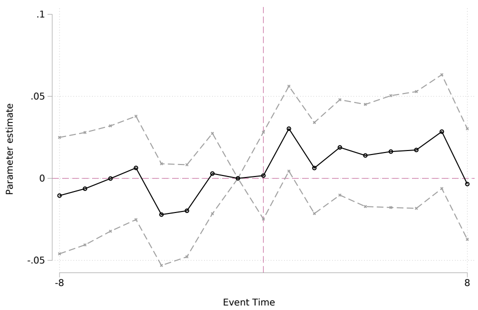

(d) Product group



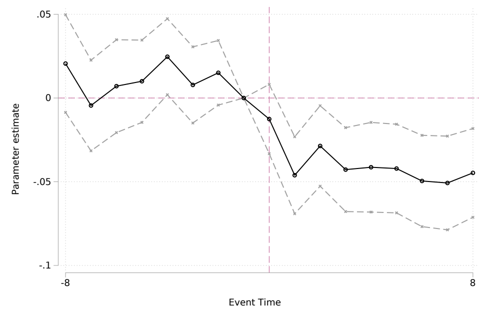

Notes: These figures use 2004-2013 NielsenIQ Consumer Panel Dataset (HMS) at the household-by-quarter level and opening records of the Walmart Supercenter from Arcidiacono et al. (2020). The figures present coefficients for eight leading and lagging periods of supercenter entries, and 95% confidence intervals from estimates of the event study on supercenter entries. The dependent variable from (a)-(d) are total number of shopping trips, number of UPCs per trip, number of brands per trip, and number of product groups per trip. Discount Store includes discount stores other than the supercenter. All regressions control for year-quarter indicators and household fixed effects.

Figure C7: Event Study Graph: Clubs Entry on Trips and Varieties per Trip

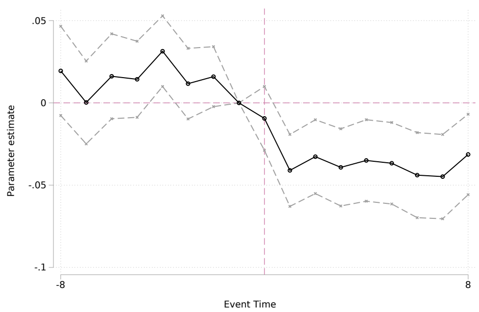
(a) Trip number



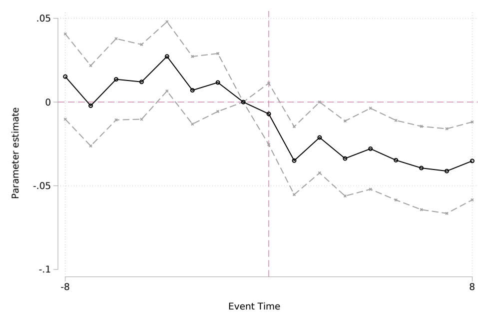

(b) UPCs




(c) Brands



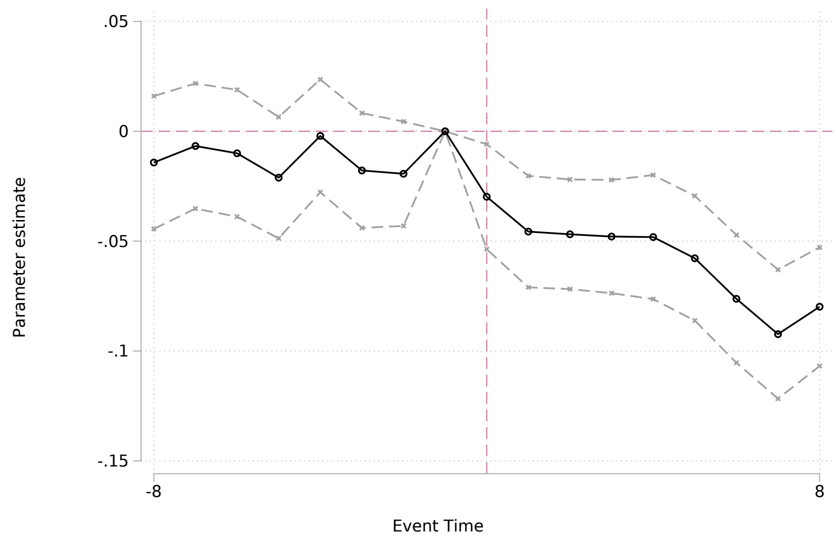

(d) Product group



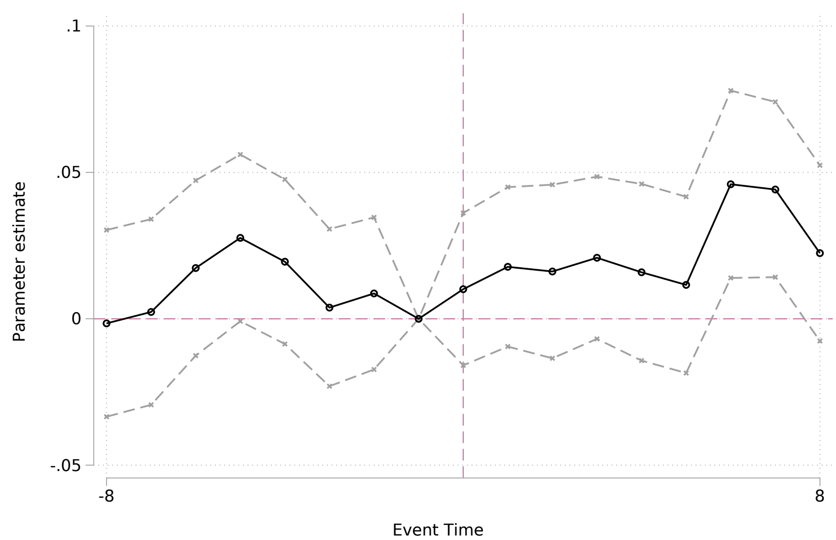

Notes: These figures use 2004-2015 NielsenIQ Consumer Panel Dataset (HMS) at the household-by-quarter level and opening records of Costco, Sam's Club, and BJ's, from Coibion et al. (2021). The figures present coefficients for eight leading and lagging periods of warehouse club entries, and 95% confidence intervals from estimates of the event study on warehouse club entries. The dependent variable from (a)-(d) are total number of shopping trips, number of UPCs per trip, number of brands per trip, and number of product groups per trip. Warehouse Club includes warehouse clubs other than the three focal clubs. All regressions control for year-quarter indicators and household fixed effects.

Figure C8: Event Study Graph: Number of Retailers Visited

(a) Supercenter Entry



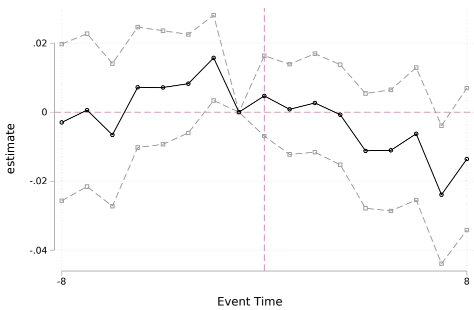

(b) Warehouse club Entry



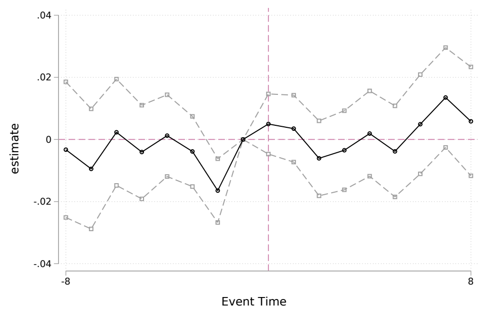

Notes: Figure C8a uses 2004-2013 NielsenIQ Consumer Panel Dataset (HMS) at the household-by-quarter level and opening records of the Walmart Supercenter from Arcidiacono et al. (2020). Figure C8b uses 2004-2015 NielsenIQ Consumer Panel Dataset (HMS) at the household-by-quarter level and opening records of Costco, Sam's Club, and BJ's, from Coibion et al. (2021). The figures present coefficients for eight leading and lagging periods of supercenter/warehouse club entries, and 95% confidence intervals from estimates of the event study. The dependent variable is the total number visited by households. All regressions control for year-quarter indicators and household fixed effects.

Figure C9: Event Study Graph: Supercenter Entry on Trips and Varieties per Trip, DCDH

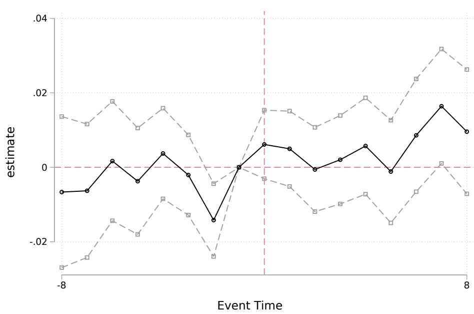
(a) Trip number



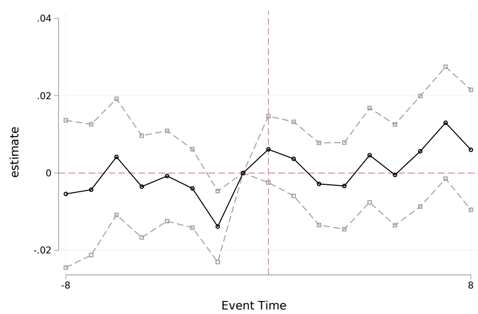

(b) UPCs



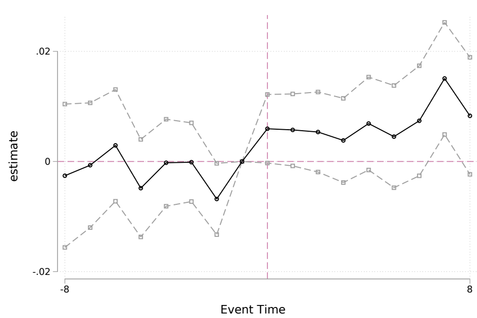

(c) Brands




(d) Product group



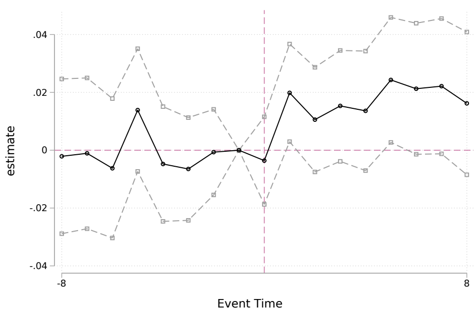

(e) Department



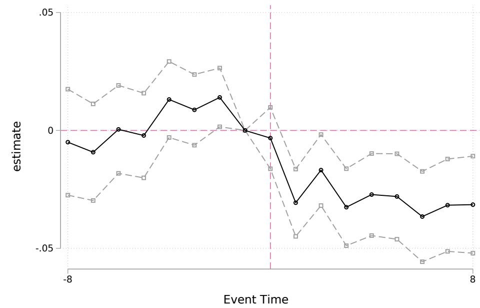

Notes: These figures use 2004-2013 NielsenIQ Consumer Panel Dataset (HMS) at the household-by-quarter level and opening records of the Walmart Supercenter from Arcidiacono et al. (2020). The figures present coefficients for eight leading and lagging periods of supercenter entries, and 95% confidence intervals from estimates of the event study on supercenter entries. The dependent variable from (a)-(e) are total number of shopping trips, number of UPCs per trip, number of brands per trip, number of product groups per trip, and number of departments per trip. Discount Store includes discount stores other than the supercenter. All regressions control for year-quarter indicators and household fixed effects.

Figure C10: Event Study Graph: Clubs Entry on Trips and Varieties per Trip, DCDH

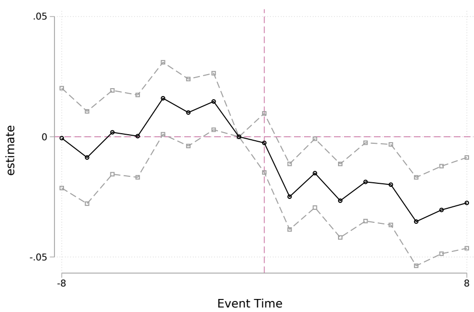
(a) Trip number



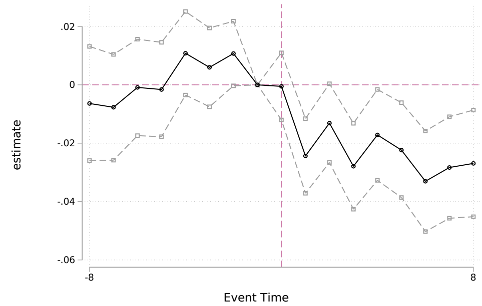

(b) UPCs



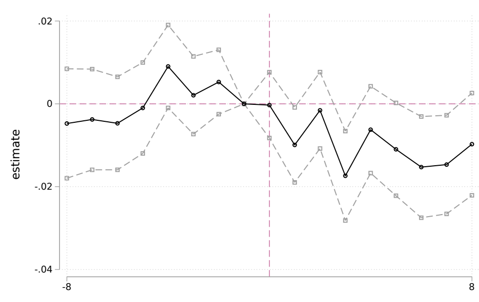

(c) Brands




(d) Product group



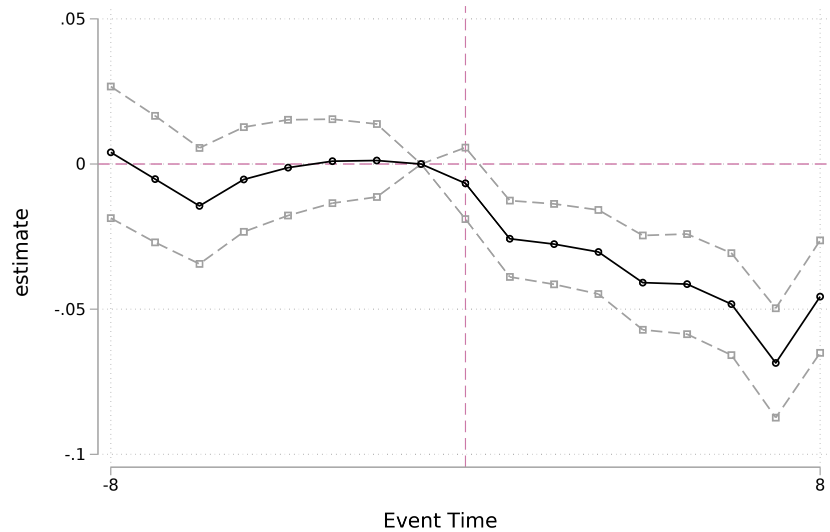

(e) Department



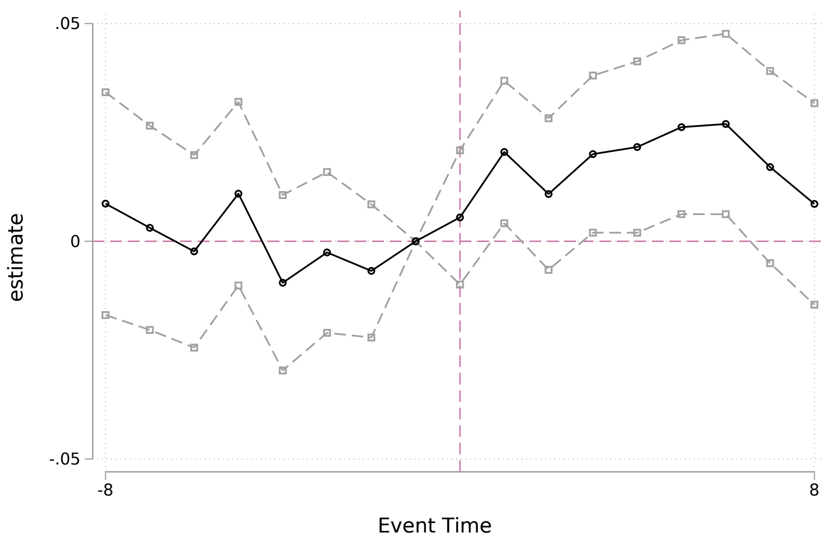

Notes: These figures use 2004-2015 NielsenIQ Consumer Panel Dataset (HMS) at the household-by-quarter level and opening records of Costco, Sam's Club, and BJ's, from Coibion et al. (2021). The figures present coefficients for eight leading and lagging periods of warehouse club entries, and 95% confidence intervals from estimates of the event study on warehouse club entries. The dependent variable from (a)-(e) are total number of shopping trips, number of UPCs per trip, number of brands per trip, number of product groups per trip, and number of departments per trip. Warehouse Club includes warehouse clubs other than the three focal clubs. All regressions control for year-quarter indicators and household fixed effects.

Figure C11: Event Study Graph: Number of Retailers Visited, DCDH

(a) Supercenter Entry



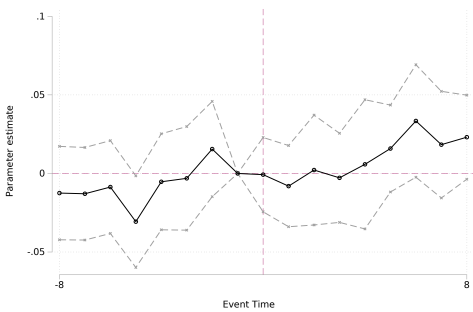

(b) Warehouse Club Entry



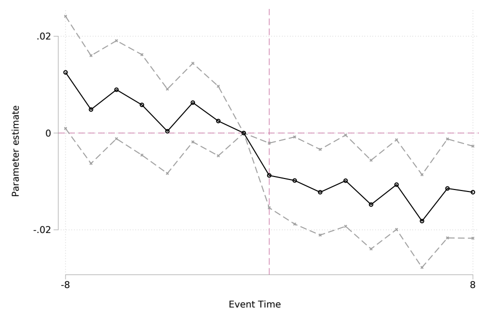

Notes: Figure C11a uses 2004-2013 NielsenIQ Consumer Panel Dataset (HMS) at the household-by-quarter level and opening records of the Walmart Supercenter from Arcidiacono et al. (2020). Figure C11b uses 2004-2015 NielsenIQ Consumer Panel Dataset (HMS) at the household-by-quarter level and opening records of Costco, Sam's Club, and BJ's, from Coibion et al. (2021). The figures present coefficients for eight leading and lagging periods of supercenter/warehouse club entries, and 95% confidence intervals from estimates of the event study. The dependent variable is the total number visited by households. All regressions control for year-quarter indicators and household fixed effects.

Figure C12: Event Study Graph: Supercenter Entry on Relative Price Index

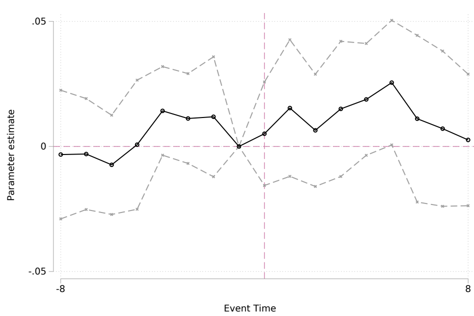
(a) Health & Beauty



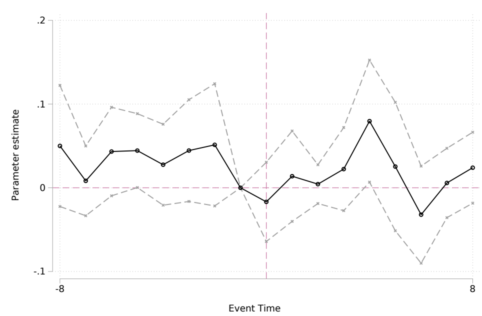

(b) Food




(c) Non-food



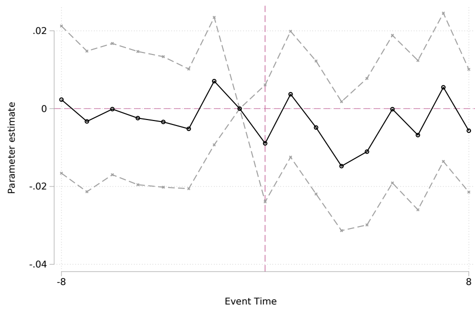

(d) General Merchandise



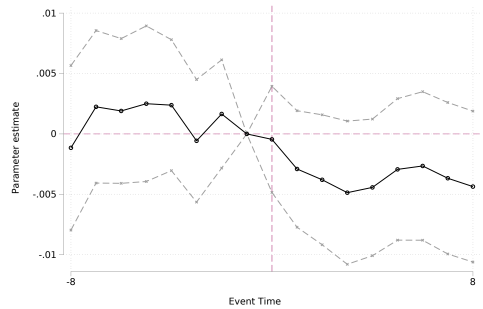

Notes: These figures use 2004-2013 NielsenIQ Consumer Panel Dataset (HMS) at the household-by-quarter level and opening records of the Walmart Supercenter from Arcidiacono et al. (2020). The figures present coefficients for eight leading and lagging periods of supercenter entries, and 95% confidence intervales from estimates of the event study on supeercenter entries. The dependent variables are log relative price index (RPI) for all products 5a and for each department C12a-C12d are defined in Equation 2. All regressions control for year-quarter indicators and household fixed effects.

Figure C13: Event Study Graph: Club Entry on Relative Price Index

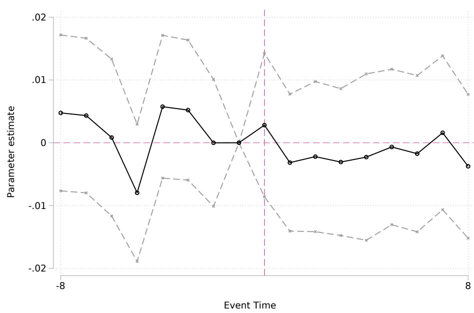
(a) Health & Beauty



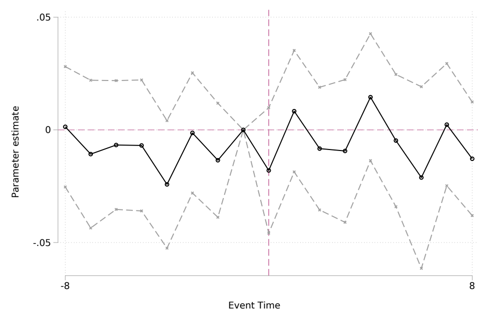

(b) Food




(c) Non-food



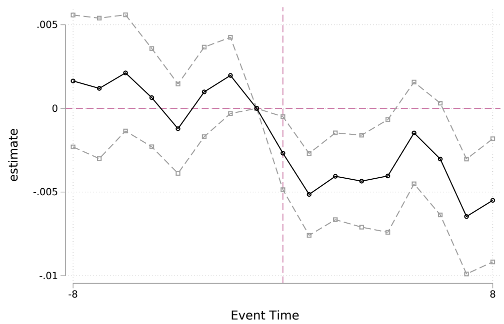

(d) GM



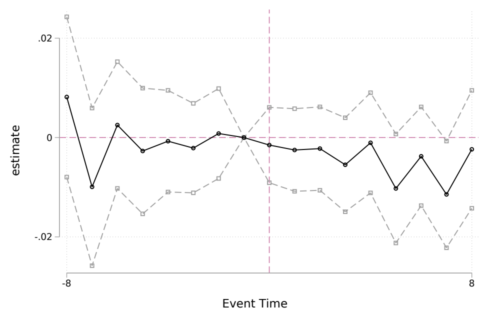

Notes: These figures use 2004-2015 NielsenIQ Consumer Panel Dataset (HMS) at the household-by-quarter level and opening records of Costco, Sam's Club, and BJ's, from Coibion et al. (2021). The figures present coefficients for eight leading and lagging periods of warehouse club entries, and 95% confidence intervals from estimates of the event study on warehouse club entries. The dependent variables are log relative price index (RPI) for all products 5a and for each department C12a-C12d are defined in Equation 2. All regressions control for year-quarter indicators and household fixed effects.

Figure C14: Event Study Graph: Supercenter Entry on Relative Price Index, DCDH

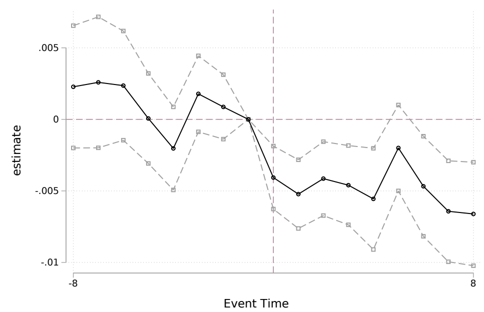
(a) All



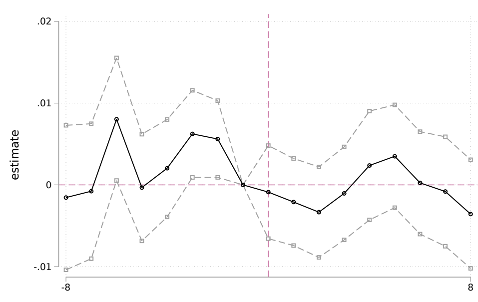

(b) Health & Beauty



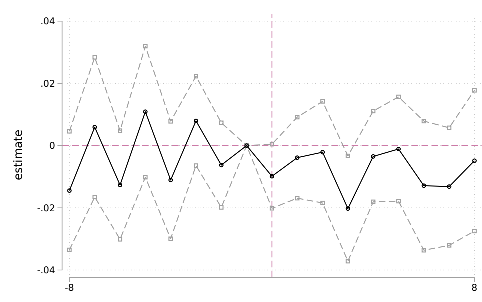

(c) Food




(d) Non-food



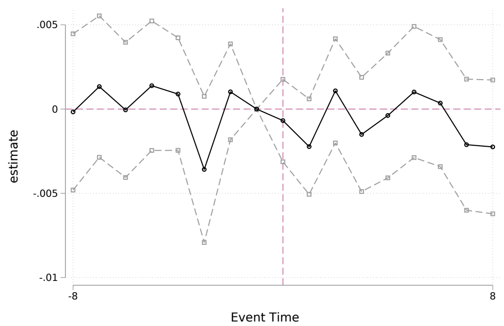

(e) General Merchandise



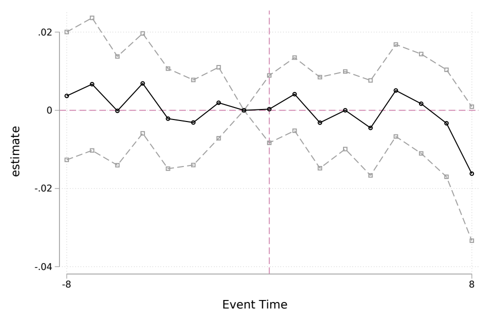

Notes: These figures use 2004-2013 NielsenIQ Consumer Panel Dataset (HMS) at the household-by-quarter level and opening records of the Walmart Supercenter from Arcidiacono et al. (2020). The figures present coefficients for eight leading and lagging periods of supercenter entries, and 95% confidence intervales from estimates of the event study on supeercenter entries. The dependent variables are log relative price index (RPI) for all products C14a and for each department C14b-C14e are defined in Equation 2. All regressions control for year-quarter indicators and household fixed effects.

Figure C15: Event Study Graph: Club Entry on Relative Price Index, DCDH

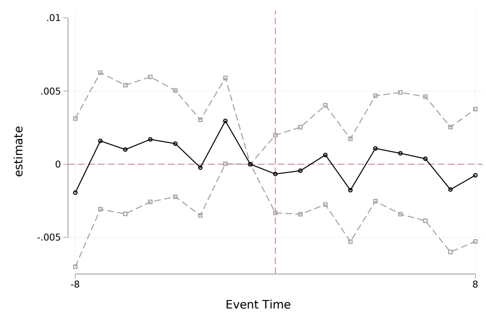
(a) All



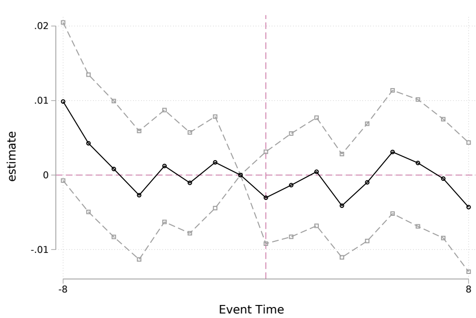

(b) Health & Beauty



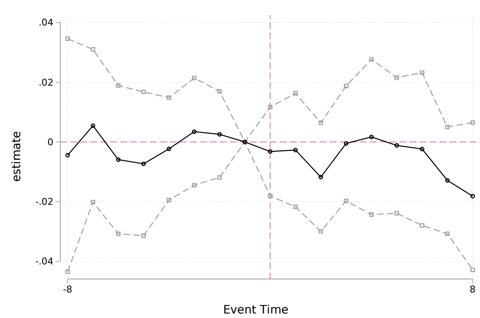

(c) Food




(d) Non-food




(e) GM




Notes: These figures use 2004-2015 NielsenIQ Consumer Panel Dataset (HMS) at the household-by-quarter level and opening records of Costco, Sam's Club, and BJ's, from Coibion et al. (2021). The figures present coefficients for eight leading and lagging periods of warehouse club entries, and 95% confidence intervals from estimates of the event study on warehouse club entries. The dependent variables are log relative price index (RPI) for all products C14a and for each department C14b-C14e are defined in Equation 2. All regressions control for year-quarter indicators and household fixed effects.