The Impact of the Dollar Store on Households and Local Retail Competition*

Camilla Schneier

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Abstract

Dollar stores have dramatically changed the food retail landscape of the United States. This expansion has raised concern that dollar stores negatively impact consumer welfare and cause households to substitute away from (healthier) preexisting retail formats. This paper estimates the effects of the dollar store on household shopping basket, substitution across retailers, and welfare. Leveraging the first dollar store entry into a zip code, we show that dollar store entry expands the household choice set without significantly affecting local retail competition, thus increasing household welfare. Leveraging plausibly exogenous shocks to consumer's retailer availability, we estimate consumer demand and find that welfare increases by 2% with dollar store entry. Demand estimates indicate little substitution between dollar stores and preexisting retailers, alleviating concerns that dollar stores cause unhealthy eating.

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1 Introduction

Dollar stores are an important food source for many Americans. With over 35,000 stores in the U.S. –more than Walmart, Starbucks, and McDonald's combined–, policymakers and academics have become increasingly concerned with how dollar stores enter into household consumption. Their concerns—which this paper will test—include that dollar stores charge seemingly-low prices that are only cheap due to small packaging size (rather than per-unit price); that the limited choices stocked by dollar stores lead households to purchase less healthy food; and that dollar store competition drives out store formats that are more beneficial to consumers.[1] Policymakers in over twenty cities have thus limited dollar stores entry.[2]

However, dollar stores' popularity and rapid proliferation suggests they provide value to consumers. Yet little is known on how or why dollar stores change consumer shopping patterns and welfare. Understanding the effect on consumers requires computing the direct effect of dollar stores on consumer behavior, the indirect competitive effects on preexisting retail formats, and how consumers value different aspects of the dollar store (e.g. product offerings, variety, product sizes and prices).

In this work, we quantify the value of dollar stores to consumers. We first provide descriptive evidence of product offerings at dollar stores to show how they might change the household choice set. Then, using a combination of event study analysis and a structural model, we document how the consumption bundle changes and how these changes translate to consumer welfare. We show that consumers react to dollar stores by reducing the quantity of dry goods, shifting consumption from a bundle with higher prices and more varieties to a cheaper bundle with fewer varieties, and that consumers continue shopping at preexisting retailer formats. Overall, we find that dollar stores increase welfare and estimate that the lowest-income household values the dollar store at 2% of annual grocery expenditure.

To understand how dollar stores affect consumers, we first establish how they change the household choice set. First, we find that dollar stores specialize heavily in dry goods and offer a different product assortment than grocery stores. Second, we find that dollar stores have much less within-category variety in their offerings at every level; compared to grocery stores, dollar stores have 20% fewer unique bar codes. Third, for the same product, we find that dollar stores are much cheaper than all other store types: compared to grocery stores, dollar stores consumers pay 23% less for the same product, even after controlling for the size of the good. Almost every food product category is cheaper per-unit at dollar stores than at grocery stores. Overall, we find little evidence that dollar stores' low price point is driven by small sizes, with the exception of milk, ice cream, and gum.

Turning to the consumer response, we study how dollar stores change consumer shopping

[1] Critics worry that dollar stores are cheap per good but not per unit, shift consumers away from fresh produce, and in doing so are deleterious.

[2] See, for example, restriction in Chicago and Tusla.

behavior, focusing on expenditure, quantities, and varieties. We find that households reduce expenditures by 5% or save 20$ per quarter on food once a dollar store opens in their neighborhood. The reduction in overall expenditure is driven by consumers switching from a bundle with more varieties and higher prices to a bundle with fewer varieties but lower prices. The reduction in quantities is driven by dry goods, the most commonly sold food category at dollar stores.

We then investigate how other retail formats react to dollar store entry. First, we consider prices and substitution. We find a precise null effect across both dimensions: (1) preexisting retailers do not change their prices on the goods that consumers used to buy and (2) consumers do not switch from preexisting retailers to dollar stores, holding product choices fixed. This means that when a dollar store enters a neighborhood, if consumers continue to purchase the same basket of goods as they had before, they would pay the same prices. While surprising, this null price result is consistent with previous results on retail competition in different settings: Walmart's entry does not cause preexisting grocers to change their prices (Arcidiacono et al. (2019)) and grocery store prices are more constrained by within-store category competition than cross-store competition from multi-stop shoppers (Thomassen et al. (2017)).

Next, we consider net entry and shopping frequency. Focusing on grocery stores, we find that the average number of stores remain unchanged following dollar store entry. The lack of competitive response from preexisting retailers suggests that consumers have the same choice set as before dollar store entry. If households continue to have the same choice set, a natural question is whether they continue shopping at the same stores with similar frequency. We test this and find no change in the number of trips households take to grocery stores, club stores, discount stores (including big box stores), and any other format we observe in our data. These results are consistent with the finding that consumers invariably shop at the grocery stores (Allcott et al. (2019)). Together, these three facts: (1) no change in price (2) no change in net entry/exit (3) no change in number of trips suggest consumers have access to the same retailer formats they did before the dollar store entered.

We investigate whether the results change for different populations and different retail environments. We show that dollar stores locate disproportionately in lower-income neighborhoods and sparse retail environments, such as non-metro neighborhoods and food deserts. We re-run our analysis for different income groups as well as for households in sparse retail environments. Lower-income groups and households in sparse retail environments tend to shop more on average at the dollar store, but the observed decline in average household total food expenditure and a decline in unique bar code variety largely hold across all groups.

While the event study results show how outcomes of interest shift in response to dollar store entry, they alone cannot quantify the value of different aspects of the dollar store bundle. We thus use a model to translate how these changes to the consumer basket affect consumer welfare. We estimate a demand model where consumers have preference over product groups, variety, product sizes, and prices. We estimate consumer preferences leveraging geographic variation in retailer presence and prices using a detailed panel of consumer household purchases.

We introduce a novel instrument and use preexisting standard instruments to account for endogeneity in prices and store format availability. To isolate consumer preferences, we exploit variation in the retailers available to consumers resulting from shocks to the commercial real estate available to new retailers. Specifically, throughout the 2010s, several non-food brick and mortar stores went bankrupt (e.g., Blockbuster Video), forcing these retailers to close stores across the country in a short time frame. These closures created vacancies, thereby lowering the fixed cost of entry for new entrants like dollar stores. These bankruptcies thus created variation in the retailers' consumers have access to, independent of consumer demand. We take two steps to ensure that this variation affects consumers only through supply. First, we focus on national bankruptcies where the timing is likely unrelated to local demand for food, and second, we focus on non-food retailers (e.g. Blockbuster's bankruptcy was driven by the advent of video streaming platforms, not local food demand). To illustrate the instrument for dollar stores, we show that dollar store entry is correlated with the preexisting bankrupt retailer exit only when dollar stores occupy a similar store size to the preexisting bankrupt retailer.

Overall, we find that the value of dollar stores is primarily as advertised: low prices. While consumers value larger sizes and more variety, dollar store prices are sufficiently low that consumers are willing to forgo these varieties once a dollar store enters. Estimates suggest consumers are willing to give up 4-5% of bundle variety for a 1% reduction in price, which corroborates that the low-price low-variety components of the dollar store bundle (documented in our descriptive results) are important in driving the reduction in consumer expenditure and variety (documented in our event studies). With regard to dollar stores' product offerings, we find that dollar stores do not stock the products that provide the most utility to consumers, and according to our estimates, consumers prefer fresh produce to dry goods.

We find that welfare increases by 2% with dollar store entry. We also find very little substitution between product categories at the dollar store and grocery store. These two results contrast with policymakers' concerns that dollar stores are welfare-reducing for consumers or that dollar stores cause consumers to switch from produce at the grocery store to snacks at the dollar store.

1.1 Related literature

Our work contributes to three strands of literature. First, extensive work on big-box retailers has established the framework for how to study the effect of non-traditional retail formats on consumer welfare and local retail competition. Our results add to the literature that uses a structural approach to study the effect of non-traditional retailers on consumer welfare (Hausman and Leibtag (2007), Atkin et al. (2018), Leung and Li (2021)). Methods-wise, we add a novel cost-shifting instrument to estimate demand. Our results also add to the literature that leverages detailed panel data and event study methods to estimate the effect on preexisting retailer prices and net entry (Basker and Noel (2009), Ailawadi et al. (2010), Arcidiacono et al. (2019)).[3]

Second, a literature has emerged focused specifically on dollar stores. Our descriptive evidence adds documentation of the types of neighborhoods dollar stores enter into (for demographic characteristics, see Shannon (2021), Grigsby-Calage et al. (2024b), for retail environment, see Chenarides et al. (2021)). We add a pricing aspect to recent work on how dollar stores compete with other retailers, which has focused on net entry (Chenarides et al. (2024), Lopez et al. (2023), Caoui et al. (2024), Grigsby-Calage et al. (2024a), Caoui et al. (2025)). Predominantly, we add to the insights that have shown how dollar stores affect consumer expenditure (Feng et al. (2023)), surveyed shopping experience (Schmall et al. (2021)), and welfare (Cao (2024)). Using both event study and a structural model, we seek to fully understand the effect of dollar stores on consumer welfare. First, we characterize the types of goods dollar stores sell and contrast them with the product offerings at incumbent retailers. Then, we estimate the consumer response, incumbent retailer response, and consumer welfare effect leveraging the staggered expansion of first dollar store entry across neighborhoods and a novel instrument for demand estimation. We then use the results to shed light on the substitutability of dollar store and grocery store products, which is crucial for policymakers who care about the supply-side provision of food.

The empirical findings tie this paper to a literature which highlights the sometimes unexpected effects of supply-side retailers on consumer shopping behavior. First, one literature seeks to understand the correlation between neighborhood income, healthy food, and retail environment. Ex ante, policymakers hypothesized that dollar stores would have a deleterious effect on grocery shopping and nutritional inequality. However, our results find a limited role for dollar stores to worsen nutritional outcomes, which is in line with findings from Allcott et al. (2019).[4] Second, a few papers document how expansions of the household choice set can result in decreases in consumed product variety and a null price response (see Illanes and Moshary (2020) for this in the context of the liquor market or Natan (2020) in the context of takeout restaurants). In our context, the expanded choice set vis-a-vis dollar store entry induces consumers to reduce quantity and varieties consumed.

2 Data

We use Homescan (HMS) NielsenIQ data between 2008 and 2019 to study the effect of the dollar store on consumers. The HMS data tracks 40,000 to 60,000 US households and their

[3] To estimate consumer welfare, this paper builds on a large literature that estimates demand at grocers and other retailers (Bell et al. (1998), Smith (2004), Mehta (2007), Song and Chintagunta (2007), Smith and Øyvind Thomassen (2012), Mehta and Ma (2012), Thomassen et al. (2017), Handbury (2021)). A separate literature has used structural methods to study the effect of retailer competition on net entry (Jia (2008), Holmes (2011), Ellickson and Grieco (2013), and Arcidiacono et al. (2016)).

[4] Allcott et al. (2019) use grocery entry to study the impacts of grocery access on nutritional inequality and find a limited role for supply-side interventions to reduce nutritional inequality.

retail purchases. HMS households scan UPCs of all consumer packaged goods they purchase from any store. In addition to transaction variables, HMS also reports demographic variables such as household income, household composition, household size, number of children, race, and the age, education, employment status, and hours work for male and female household heads. NielsenIQ tracks the store type (called channel type) households shop at, allowing us to identify purchases specific to dollar stores, grocery stores, discount stores, etc. For our analysis, we follow NielsenIQ's definition of store types (dollar stores, grocery stores, club stores, convenience stores, drug stores, and discount stores).

Because many of most salient policy questions are around food tradeoffs, we study the effect of dollar stores on food purchasing behavior. Figure 1 details the food terminology in the NielsenIQ HMS household transactions dataset (figure source: Handbury (2021)). A UPC/barcode uniquely identifies a product, such as "Campbell's Beef Stew", which has a different code than "Campbell's Chicken Noodle Soup". Products with the same UPC are identical in composition, size, and brand. One level up is what NielsenIQ calls a "product module", which describes the type of good the UPC/barcode belongs to. Products in the same product module may have different sizes and brands but are very similar within the packaging. One more level up are product groups: product groups contain products that are not identical, but broadly similar (for example "Fresh Produce" and "Snacks" are both product groups). In this example, Campbell's Beef Stew would belong to the product module "Stew - Beef - Shelf Stable", which belongs to the product group "Prepared Food - Ready-to-Serve". Policy concerns of how dollar stores induces changes in shopping behavior have focused on dollar store-induced substitution across product groups. At the highest level of aggregation, NielsenIQ defines six food departments (dairy, deli, dry grocery, fresh produce, frozen foods, and packaged meats).[5]

Figure 1: NielsenIQ Definitions

UPC/Barcode		Product Module		Product Group
(ex: Campbell's Beef Stew)	$\subset$	(ex: Stew - Beef - Shelf Stable)	$\subset$	(ex: Prepared Food - Ready-to-Serve)
n = 2,152,647		n = 856		n = 62

We focus on food purchases. For each UPC/barcode bought, we compute price (per good) as the total price paid minus the coupon value, divided by the quantity of the UPC/barcode purchased. In order to compare across similar products with different package sizes, we compute the price per unit as the price per good divided by the amount (or size) of the product. [6] We define quantities as the amount or the weight in ounces of each good.[7] For

[5]For fresh produce, department and product group are the same.

[6]Furthermore, we eliminate magnet data from the sample.

[7]NielsenIQ provides weight data in ounces (weight), pounds (weight), fluid ounces (volume), quarts (volume), and counts (dimensionless). Because they are the most popular units, we use ounces for our quantity for dry goods and fluid ounces for liquid goods, converting measurements in pounds and quarts. We impute weight measured in counts whenever possible, and eliminate data when we cannot impute a weight. The list of imputed weights is found in Table A.6.

the event study, the panel is balanced by restricting the sample to any household satisfying two criteria. First, the household is in a zip code with an eventual dollar store entry. Second, the household is observed in the same zip code in the data in the year before and after the dollar store enters.

For demand estimation, we define a market as a set of product groups in stores in a county in a year for each income rank.[8] We subset to the set of households in our event study to keep the underlying data comparable and consistent throughout the paper. That is, we require a balanced panel and only include households in zip codes that will eventually receive a dollar store. We split our households into four groups by income rank and compute separate demand parameters for each income group because income is an important dimension of heterogeneity (dollar stores disproportionately exist in low income neighborhoods) and because different income groups are expected to have different price elasticities (here we follow Atkin et al. (2018) and Allcott et al. (2019)). In addition, we drop observations whenever the price for that good is zero.

We use dollar store locations compiled from a database of Supplemental Nutrition Assistance Program (SNAP) authorized retailers. This data spans 1990-2019, and records the date and location of a store when it enters and exits the SNAP database. Since the majority of locations from the major dollar store chains had become SNAP retailers by 2008, and new stores after that period are likely to automatically enroll in SNAP, we focus on the time period between 2008 and 2019. We subset our SNAP data to the five biggest dollar store chains, roughly 85% of all dollar stores.[9]

For grocery store counts in each zip by year we use the ZIP Code Business Patterns (ZBPs) as in Allcott et al. (2019).

The retail closing instrument is constructed with data from Infogroup, which provides a historical, yearly directory information for U.S. companies, including name, address, estimated sales and number of employees. Specifically, we compute the number of retailers in each zip in each year for the most popular non-food retailers that went bankrupt throughout the 2010s. In Table A.2 we include a list of retailers and their bankruptcy year, and in Figure A.12 we plot the number of stores in each year.

[8]To estimate demand, we use a county to define a market – as opposed to a zip code, which we used in the event study analysis. In the event study analysis, we consider the effect on the households located nearest to the dollar store. However, the market for food is likely larger than a zip code, especially for grocery stores.

[9]As the SNAP dataset is not standardized, finding all true dollar stores outside of these chains would be extremely burdensome. In addition, these five chains make up roughly 85% of all dollar stores, and we are thus able to capture most of the market with these.

3 Descriptive Statistics - What is a Dollar Store?

In this section, we describe what makes a dollar store unique to other store types. Dollar stores are conceptualized by a single price point (1$). And while dollar stores do not necessarily restrict themselves to the $1 price, they are united by their ability to provide low-price merchandise at fixed price points. To document this and other key characteristics of the dollar store, we regress prices – both for the good and per unit – on store type using the consumer panel for different aggregations of goods:

$$log(y_{iksct}) = StoreType_s + \alpha_{kct} + \epsilon_{iksct} \quad (1)$$

$$log(y_{ijsct}) = StoreType_s + \gamma_{jct} + \varepsilon_{ijsct} \quad (2)$$

where i is a purchase of a good, k is the barcode (upc), j is product module, s is the store type, c is the county, and t is month-year. y_{iksct} and y_{ijsct} are our outcomes of interest. Our fixed effects specification allows us to observe differences across stores for the same product in the same location within the same month. As a result, our analysis is restricted to goods that are available across stores.

Prices across stores is the first outcome of interest, and Table 1 documents that dollar stores are able to offer significant price reductions. On average, dollar stores charge 11 percent lower prices for products with identical barcodes (as compared to grocery stores), as shown in column (1). This price reduction far outpaces discount stores, which are only 3 percent cheaper on average than grocery stores. These reductions are even bigger when we compare prices for the same product module, rather than barcode. As seen in column (2), the average product price at the module level is 47% lower at dollar stores relative to other retailers.

This price reduction is halved to 24% when the outcome is price per unit (i.e. an ounce of beef soup), as shown in column (3)[10]. That is, dollar stores offer smaller package sizes within the same product module, a finding confirmed by the same regression with log size of the good as the outcome. As shown in Table A.1, dollar store goods are 24% smaller for identical product module units compared to other store types in the same county during the same month.

Beyond the sheer size of the price and size reductions, dollar stores also stand apart in how heterogeneous these effects are. Figures A.8 and A.9 show dollar stores' price per unit and size effects for each product group. While discount stores are quite uniform in their price and size effects, dollar stores vary greatly from product to product. Notably, almost all dollar store products are on average cheaper than those same goods at grocery stores. With the exception of milk, ice cream, and gum, dollar store shoppers receive discounts on every other product, even on a per unit basis.

Next, we turn to product variety across store types. First we collapse the data down to count the number of unique barcodes in a county and run the following regression:

$$log(N_{sct}) = \beta StoreType_s + \alpha_{ct} + \varepsilon_{sct} \quad (3)$$

[10] There are no differences in size within the same barcode.

Table 1: Price Effects of Dollar Stores

Dependent Variables:	log(Price)		log(Price per Unit)
Model:	same bar code	same product	same product
Variables			
Dollar Store	-0.1106	-0.4655	-0.2384
	(0.0156)	(0.0096)	(0.0089)
Discount	-0.0311	0.0410	-0.0067
	(0.0017)	(0.0024)	(0.0022)
Club	0.4359	0.9212	0.1984
	(0.0197)	(0.0095)	(0.0060)
Convenience	-0.00006	-0.1500	0.0825
	(0.0091)	(0.0073)	(0.0089)
Drug	-0.0733	-0.1980	-0.0655
	(0.0032)	(0.0054)	(0.0034)
Fixed-effects			
county_upc_month	Yes		
county_product_month		Yes	Yes
Fit statistics			
Observations	479,718,710	479,718,710	479,718,710
R^2	0.92327	0.54447	0.77713
Within R^2	0.01631	0.11964	0.00636

Clustered (county name) standard-errors in parentheses

Notes: Table reports coefficient from regressing log price per good and price per unit of good on a store type variable. We only use sales from dollar stores, discount stores, club stores, and drug/convenience stores. Grocery stores are used as the reference group. Data is based on consumer panel microdata for years 2008-2018. Column (1) reports coefficients with county by barcode by month-year fixed effects. Column (2) and (3) report coefficients with county by product module by month-year fixed effects. Standard errors are clustered at the county level.

where N_{sct} is the number of unique barcodes in county c at month-year t at store type s. We control for county by month-year fixed effects. We also examine number of product modules and number of product groups as the outcome variable.

Grocery stores by far have the most variety in every product aggregation level, as shown in Table 2 below. Grocery stores are the reference store type in the regression; compared to dollar stores, groceries have 20 times more barcodes, 10 times more product modules, and 5 times more product groups available. Dollar stores variety offerings are on par with that of Club stores, much less than discount stores, but far more than convenience and drug stores.

Dollar stores are not only offering less variety, but product offerings also differ. Figure 2

Table 2: Variety Effects of Dollar Store

Dependent Variables:	log(No. of UPCs)	log(No. of Modules)	log(No. of Product Groups)
Model:	(1)	(2)	(3)
Variables			
Dollar Store	-2.871	-2.341	-1.643
	(0.0807)	(0.0590)	(0.0478)
Discount	-0.6223	-0.4018	-0.2050
	(0.0717)	(0.0483)	(0.0285)
Club	-2.649	-1.990	-1.308
	(0.0702)	(0.0564)	(0.0452)
Convenience	-4.696	-3.926	-2.910
	(0.0990)	(0.0715)	(0.0578)
Drug	-3.515	-3.059	-2.248
	(0.0427)	(0.0404)	(0.0489)
Fixed-effects			
county_name-state_name-month_year	Yes	Yes	Yes
Fit statistics			
Observations	1,528,436	1,528,436	1,528,436
R^2	0.83265	0.81585	0.76054
Within R^2	0.77464	0.76376	0.70110

Clustered (state_name) standard-errors in parentheses

Notes: Table reports coefficient from regressing log variety in a county-month-year on a store type variable. We only use sales from dollar stores, discount stores, club stores, and drug/convenience stores. Grocery stores are used as the reference group. Data is based on consumer panel microdata for years 2008-2018. Standard errors are clustered at the county level.

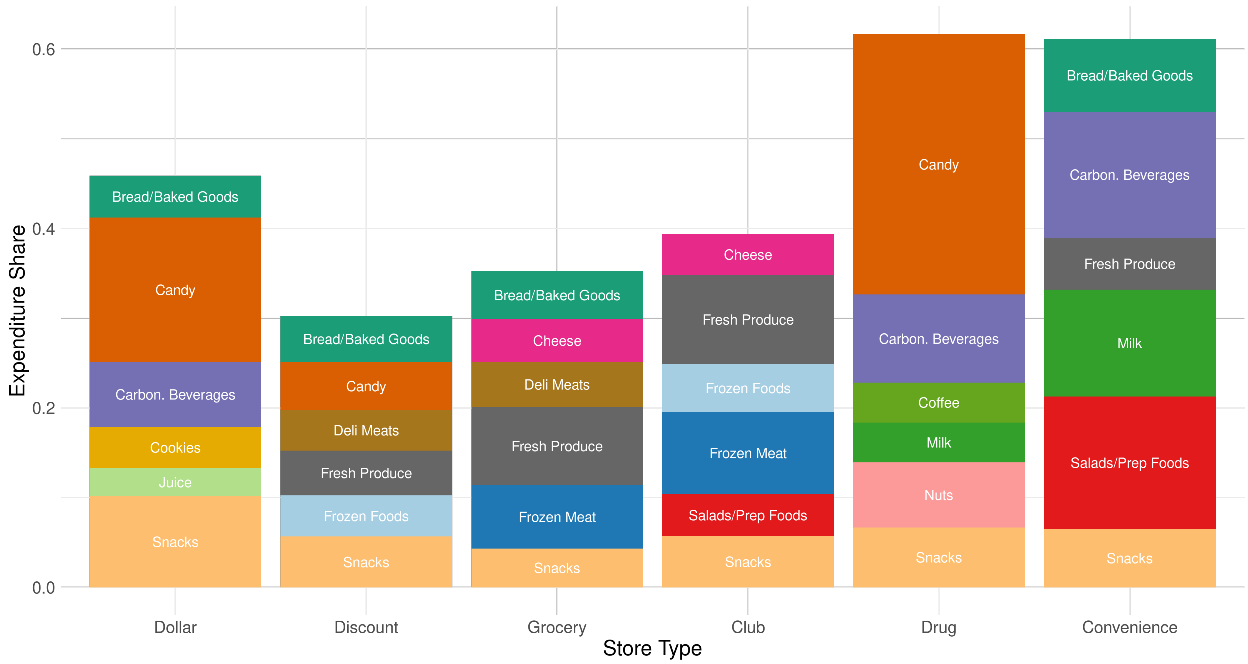
shows the top six product groups, as ranked by consumer expenditure share at each store. Grocery store consumers purchase large amounts of cheese, deli meats, and fresh produce, offerings typically not found at a dollar store. In fact, dollar stores look much more similar to discount stores.

Taken altogether, a picture emerges of an average dollar store, which offers a limited selection of products, a limited variety of brands within those products, likely at smaller sizes than available at other retailers, but all in all at a much lower price than anywhere else.

4 Empirical Analysis of the Impact of Dollar Store Entry

Our goal is to understand the effect of dollar stores on consumers and preexisting retailers. In theory, the dollar store can indirectly impact the consumer by putting competitive pressures on local rivals to change prices or exit the market.

Figure 2: Expenditure Share of 6 Most Popular Products by Store Type



Notes: Figure reports consumer expenditure shares of the top 6 product groups for each store type. Data is based on consumer panel microdata for years 2008-2018.

We leverage an event study design to examine supply-side changes in response to the first dollar store entry in a zipcode. To investigate the grocery count in a zipcode, we run the following regression:

$$Y_{zt} = \Sigma_{k=-T_1}^{-2} \beta_k \times D_{zk} + \Sigma_{k=0}^{T_2} \beta_k \times D_{zk} + \gamma \boldsymbol{X}_{zt} + \nu_z + \phi_t + \varepsilon_{zt} \tag{4}$$

Let Y_{zt} denote grocery count in zipcode z in year t, D_{zk} is the years before or after entry of the first dollar store in a zipcode, $\boldsymbol{X}_{zt}$ are lagged zipcode level demographic controls, ν_z are zipcode fixed effects, and ϕ_t are year fixed effects.[11] Our parameter of interest is β_k, the amount by which the average zipcode experiences a change in number of grocery stores upon entry of the first dollar store into their zip code. Standard errors are robust and clustered by zip code.

We run an analogous household-level regression at the quarterly level, q, to investigate visits to other retailers and changes in prices:

$$Y_{iqt} = \Sigma_{k=-T_1}^{-2} \delta_k \times D_{ik} + \Sigma_{k=0}^{T_2} \delta_k \times D_{ik} + \sigma_i + \tau_{qt} + \epsilon_{iqt} \tag{5}$$

Here, conditioning on σ_i allows us to look at variation within households, rather than variation across households, and replaces demographic controls. Standard errors are robust and clustered by zip code.

[11] Controls include average household income, proportion of households married, average household size, average age, proportion white, proportion black, and average working hours.

The panel is balanced by restricting the sample to any household satisfying two criteria. First, the household is in a zip code with an eventual dollar store entry. The control group here is thus the not-yet-treated group. For estimation, we use heterogeneity-robust estimators developed by Callaway and Sant'Anna (2021). This method alleviates concerns over bad control groups, as discussed by the recent literature on staggered roll-out and two-way fixed effect (TWFE) designs (Baker et al., 2022). Second, the household is observed in the same zip code in the data in the year before and after the dollar store enters.

To ensure the cleanest identification, the event is defined as the first dollar store entry in the zip code. That is, the control group comprises the not-yet treated, which is identical for each event. Had the event been defined as higher dollar store entry (e.g. 2nd or 3rd dollar store entry), household substitution between dollar stores within the same zip would likely have contaminated the resulting dollar store effect. Although the first dollar store entry is not without contamination – household could have shopped at a dollar store outside of their zipcode in the pre-period – the first entry provides the cleanest identification possible given the data available.[12]

The study also benefits from using variation from the first dollar store entry. Figure A.4 shows that zero and one dollar store entry are the modal entry for all households and households with at least one dollar store, respectively. The first entry is the relevant future margin for the 45% of the population that does not yet have a dollar store in their zip code. 36% of households with at least one dollar store in their zip code have just one dollar store in their zip code. For the remaining 64% of the population with at least one dollar store (22% have two, 15% have three, 7% have four, etc...), the analysis captures the effect of further dollar entry for four years after the initial entry event, but the timing is determined by the first entry. Results show changes in outcomes for the first year after the first dollar store entry, and then the outcome tends to remain stable afterwards.

The assumptions required for the event study design are no anticipation and common trends. While dollar store entry maybe be announced a quarter or so in advance, it is likely that households would not adjust their consumption until the dollar store actually enters. Furthermore, anticipation would likely induce a change in outcomes before entry, but pre-trends are flat. Our identifying assumption is that households in different zip codes that receive dollar stores in different times but will eventually receive a dollar store would have followed the same pattern absent dollar store entry.

A common concern with the event study strategy is dollar store entry is related to other features of the local retail environment that would affect household consumption patterns. However, if dollar stores respond to changes in local demand conditions, household consumption patterns would likely change even before the dollar store enters. To test for changing patterns before dollar store entry, we estimate the treatment effect in the eight quarters leading up to the entry of a dollar store. We find a precisely estimated flat pre-trend before

[12]Policymakers who have banned dollar store entry tend to operate in areas with at least fifty dollar stores. We do not claim to speak to the normative implications of this many dollar stores in an area.

dollar store entry for all outcomes, and a significant trend break at the time of the entry.[13]

4.1 Results - No evidence of grocery store exit

Does the first dollar entry crowd out the grocery store? This question stems from media concern that dollar stores induce households to substitute away from healthy products at the grocery store (e.g. grocery store produce) to unhealthy food at the dollar store (e.g. dollar store snacks).[14] One concern is dollar stores crowd out grocery stores, limiting household access to healthy food. A second concern is that dollar store products and grocery store products are close enough substitutes that dollar store entry induces consumers to switch from healthy groceries to unhealthy dollar store products.[15] These concerns are tested in three ways: an event study design to understand the effect of dollar store entry on grocery store exit, an event study design to understand the effect of dollar store entry on grocery shopping trips, and demand estimation to understand the elasticity of substitution between products at the dollar store and products at the grocery store.

To understand whether dollar store entry directly causes grocery store exit, we use our event study analysis from Equation 4 to look at the effect of crowd out for the first dollar store. As shown in Figure 3, there is no change in the number of grocery stores after the first dollar entry[16]. This pattern holds across neighborhoods with different socioeconomic characteristics, as shown by the second and third panels. Thus, on average, there is no grocery exit after the first dollar entry. While some of the prior literature has found a small but significant decline in independent grocers, in our setting we find no change in the number of grocers, indicating that independent grocers are replaced by chain grocers. This result alleviates the concern that consumers no longer have the option to shop at for produce at the grocery store following the first dollar store entry.

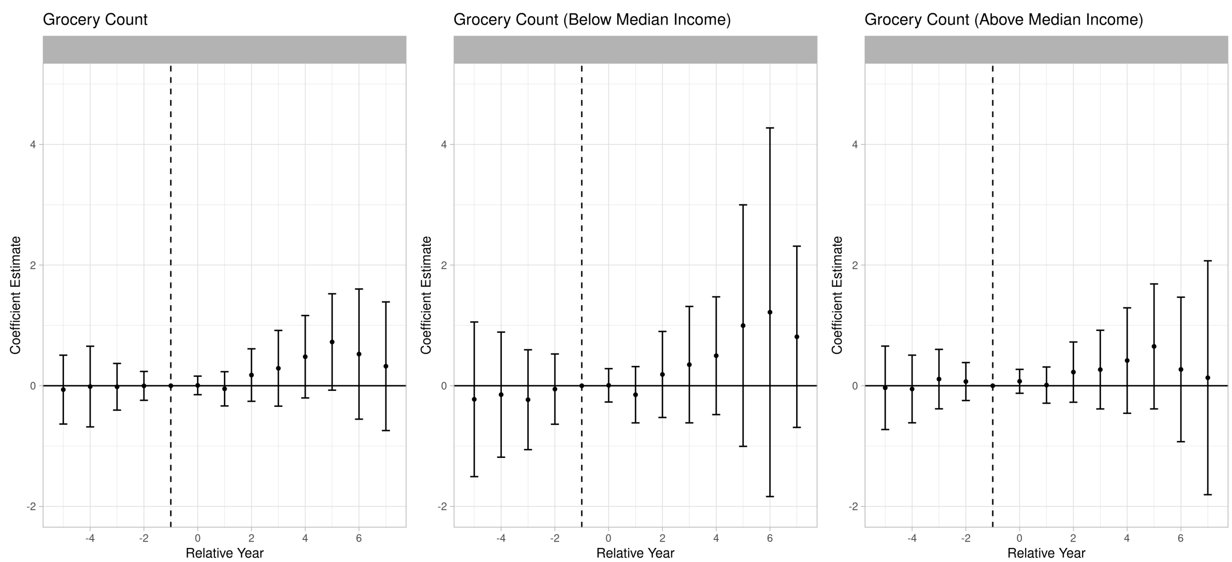
[13] Additionally, we show the event study results with 5-year average zipcode income (using American Community Survey data) as the dependent variable, shown in Figure A.11. We do see some general decline in average income in a zipcode around the time when dollar stores enter. However, note that our event study includes household fixed effects, which would control for this effect.

[14] For example, this CBS News Article details this possible concern and other common concerns regarding dollar stores.

[15] Specifically, one concern is that if dollar stores do not stock highly nutritious fresh foods, then dollar stores crowd out of grocery stores could limit the number of retailers and limit access to healthy food. A second concern is that if healthy food at the grocery store and unhealthy food at the dollar store are close enough substitutes and dollar stores makes unhealthy food relatively cheaper, then a dollar store opening can induce consumers to switch from healthy groceries to unhealthy dollar store products.

[16] As robustness, we run the same event study without demographic controls in Figure A.20, and there is still no grocery store exit.

Figure 3: Effect of First Dollar Store Entry on Grocery Count



Notes: This figure reports event study estimates with 95% confidence intervals from Equation 4, using 2008-2018 SNAP and ZBP data. The analysis uses a heterogeneity-robust estimator proposed by Callaway and Sant'Anna (2021). The figure reports the grocery count as the outcome variable. Errors are clustered at the zip code level.

4.2 Results - No evidence of local price competition

Price competition is a potentially important aspect of the consumer and local retailer response to the dollar store. Intuitively, the price of the consumer bundle may change due to competition with preexisting retailers or because household choice set expands to include new and cheaper goods. On the demand side, exposure to cheaper goods might induce households to switch to the cheaper dollar store option (within UPC/barcodes) or might induce to switch to a cheaper variety (across UPC/barcodes). On the supply side, prices may change as a result of increased competitive pressure from an additional store or competition with the dollar store's lower prices (as shown in Table 1 and Figure A.8, dollar store prices are lower on almost every product group).

To understand the effect of the first dollar store on price competition with preexisting retailers, we therefore construct a relative price index (RPI) for each household, following Aguiar and Hurst (2007) and Leung and Li (2021). Intuitively, the relative price index is the household's expenditure relative to the household's counterfactual expenditure wherein the household purchases the same goods but at an average state price:

$$RPI_{ist} = \frac{\sum_{j \in J_{it}} p_{jist} q_{jist}}{\sum_{j \in J_{it}} \bar{p}_{jst} q_{jist}} \tag{6}$$

p_{jit} and q_{jit} are the price and quantity for product module j for household i at quarter-year

t in state s. The numerator in this expression is thus the total expenditures for household i in quarter-year t. The denominator in this expression is the total expenditure if prices paid are replaced by the state average price in that product. We chose the state average price because a dollar store is quite small, and using the state average price ensures that the reference price we use is not reacting to the entry event. We will refer to the denominator as the "counterfactual expenditure", which is constructed by calculating a reference price, $\bar{p}_{jt}$ for each region s the household is located in.

$$\bar{p}_{jst} = \sum_{i \in I, d \in t} p_{jist} \left(\frac{q_{jist}}{\bar{q}_{jst}} \right) \tag{7}$$

where $\bar{q}_{jst} = \sum_{i \in I, d \in t} q_{jist}$ is used for weighting the price by the quantity purchased of the product.

The RPI essentially compares a household's true expenditure to a "fixed" counterfactual expenditure. A decrease in RPI after a dollar store enters would imply that entry induces a lower priced bundle for households, as compared to the same bundle of goods in other parts of the state. This could be either due to dollar stores offering cheaper prices, and/or a competitive response from other stores as a result of dollar store entry.

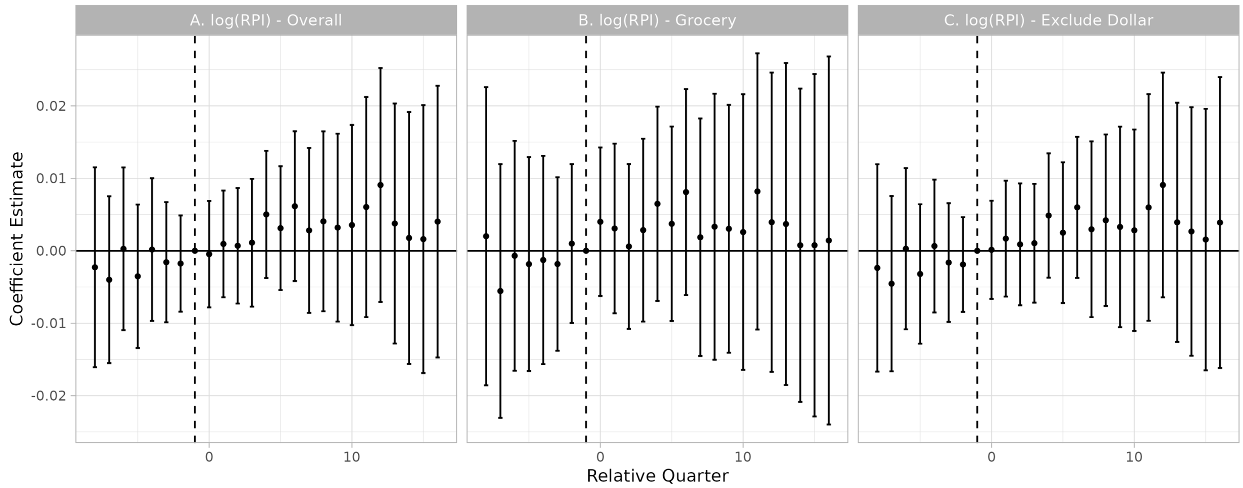
In Figure 4, we find a surprising and precise null result of dollar store entry on the RPI. That is, following dollar store entry, households pay the same amount for a representative good as households in the same state, and the confidence interval range between ± .02 percentage points. This result is surprising since even for the exact same product dollar store products are cheaper, and since consumers reduce expenditures following dollar store entry. Given these two results, one would expect that the dollar store would cause consumers to cut low expenditures due to their low relative prices.

This is not the case: the null relative price index implies that incumbent retailers are not changing prices on existing goods and consumers are not getting a price cut on existing purchases by switching to the dollar store. We discuss the demand-side further in Section 5.1.

Incumbent retailers are not changing prices on existing goods in response to the first dollar store entry. This lack of price reaction is consistent with Arcidiacono et al. (2019), who also finds a null incumbent response from Supercenter entry. Arcidiacono et al. (2019) argue that the explanation for this is stores routinely employs cost-plus pricing, or markup pricing, where a fixed percentage is added on top of the unit cost of a product. The lack of price reaction is also consistent with uniform pricing from chain retailers which price nationally (DellaVigna and Gentzkow (2019) and Hitsch et al. (2019)).

We further test whether there is a competitive price response by restricting the sample of expenditures a household makes to only grocery purchases (Figure 4 Panel B) and non-dollar store purchases (Figure 4 Panel C). Both these sets of analyses show a null RPI response. The null result in grocery prices shows us that on average, the household pays the same prices relative to the state price purchases at the grocery store before and after dollar store entry. Generalizing this to all non-dollar stores, the relative prices paid by consumers do not change, on average, after entry.

Figure 4: Effect of First Dollar Store Entry on Prices - State Average Reference Price



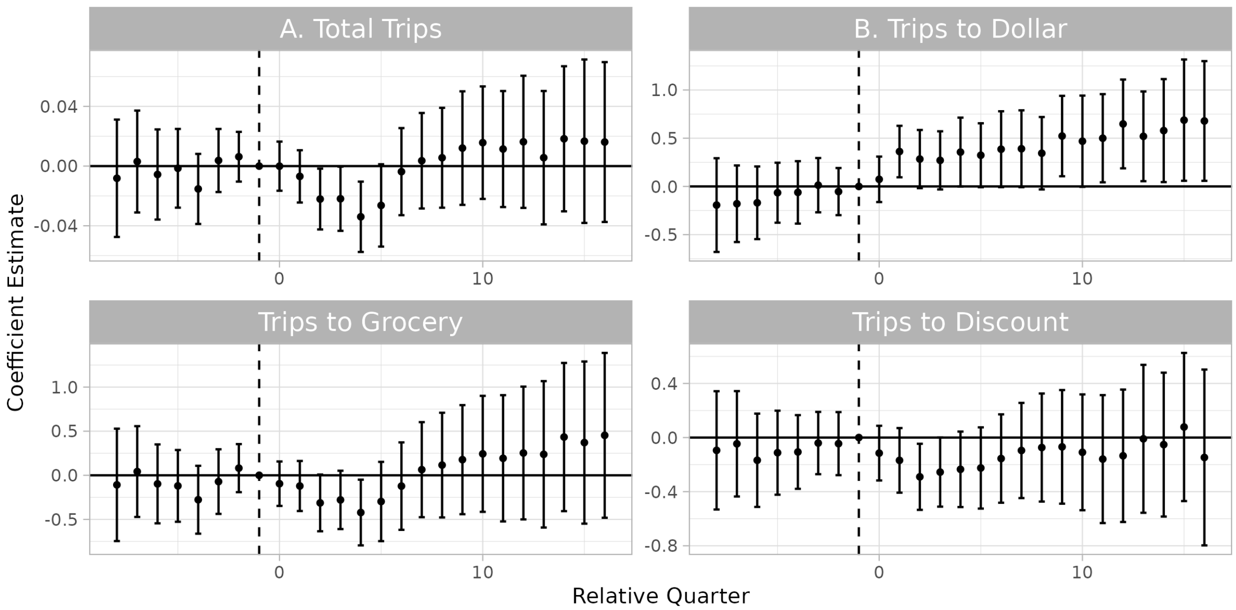
Notes: Figure reports event study estimates with 95% confidence intervals from Equation 5, using 2008-2019 Homescan data. The analysis uses a heterogeneity-robust estimator proposed by Callaway and Sant'Anna (2021). The dependent variable, the Relative Price Index (RPI), is shown in Panel A and is defined in Equation 6. Panel B and C repeat the analysis, with data restricted to purchases at the grocery store and non-dollar store, respectively. Observations are not weighted for national representativeness. Errors are clustered at the zipcode level.

4.3 Results - No change in trips to other store types

We might expect that dollar store entry could change household choice sets, or induce reactions by incumbent retailers, if households replaced some trips to other store formats with dollar store trips. To test this, we estimate the effect of dollar store entry on the number of trips to each store type using the specification in Equation 5. Here, the analysis focuses on the effect of entry on grocery stores and discount stores for two reasons. First, from the policy perspective, substituting away from stores that consistently carry healthy food options (i.e. grocery and discount stores) is a major policy concern. Second, as we will see in Section 5, dollar store entry accompanies a drop in expenditures at grocery and discount stores, but not other store types.

As shown in Figure 5, on average, households take more trips to the dollar store without significantly changing the number of trips to grocery stores and discount stores. Specifically, dollar store trips increase by 5 percentage points each quarter on average, and the effect is significant and persists at least four years after the first dollar store entry. Meanwhile, other trips (overall, to the grocery store, to the discount store), decrease slightly in the third and fourth quarter following dollar store entry but revert back afterwards. The total number of trips do not change after dollar store entry, and the effect is a precise null (the bounds on our estimates are between ± .04 percentage points each quarter). As a result, trips to other store types decrease, but this decrease is distributed over several store types in such a way that the number of trips to each store types does not change significantly. That is, the lack of significant change in number of trips to other store types provides evidence that on average, households have the opportunity to purchase the same products after the first dollar store entry. Along with a lack of grocery exit, the lack of trade-off in shopping trips between stores types implies that the household choice set is (weakly) increasing following the first dollar store entry.

Figure 5: Effect of First Dollar Store Entry on Households' Log Number of Trips



Notes: Figure reports event study estimates with 95% confidence intervals from Equation 5, using 2008-2019 Homescan data. The analysis uses a heterogeneity-robust estimator proposed by Callaway and Sant'Anna (2021). Observations are not weighted for national representativeness. Errors are clustered at the zipcode level.

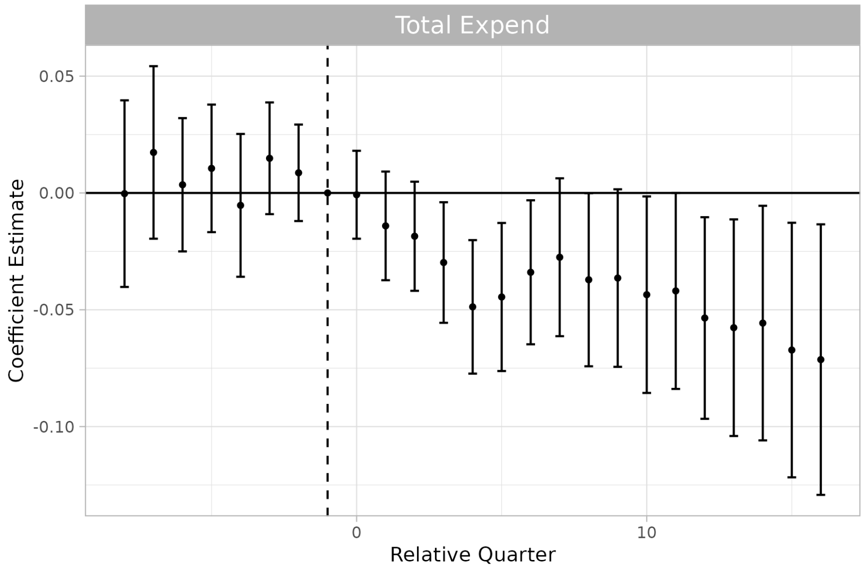
Combining the lack of price movement with the lack of grocery store exit and lack of trade-off in shopping trips between store types, we conclude that in response to the first dollar store, the supply-side of the retail market remains relatively fixed, except for the added choices the dollar store provides.

5 Effect of Dollar Store Entry on Households

We examine how the dollar store affects household consumption. Since the first dollar store does not induce a significant supply-side response, the first dollar store entry captures the direct effect of the dollar store format on consumers.

First, we document that the dollar store leads to a decrease in total food expenditures. As shown in Figure 6, total food expenditures are flat in the lead-up to the dollar store entry event, start falling as soon as the entry occurs, and stabilize at a negative and significant 5 percentage points. This drop continues even after 16 quarters, demonstrating a persistent effect.

Figure 6: Effect of First Dollar Store Entry on Households' Total Log Food Expenditure



Notes: Figure reports event study estimates with 95% confidence intervals from Equation 5, using 2008-2019 Homescan data. The analysis uses a heterogeneity-robust estimator proposed by Callaway and Sant'Anna (2021). The figure reports log of total expenditures of food. Observations are not weighted for national representativeness. Errors are clustered at the zip code level.

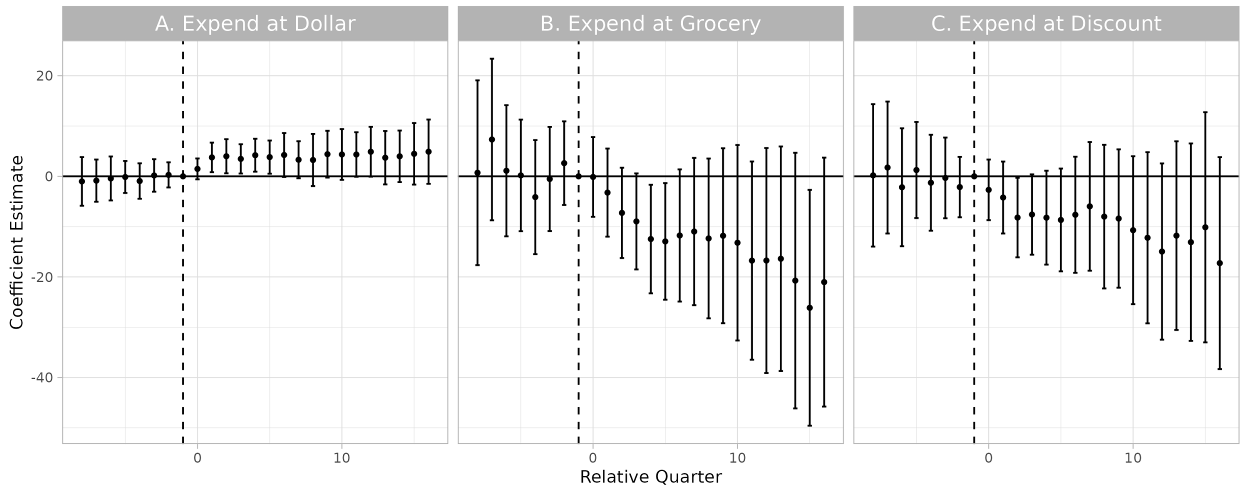
This overall decline stems from substitution from grocery stores and discount stores to dollar stores, as seen in Figure 7. The decline in total expenditures is driven by decreased expenditures at grocery and discount stores, which outweighs the increased expenditures at dollar stores. Figure A.13 shows the expenditure response from all six store types of interest. Superstore/Club, convenience, and drugstores do not exhibit a response from entry, and we thus focus our discussion on grocery and discount stores.

We turn our focus to understanding the features of the dollar store format that could explain this drop in expenditure. For household i, total expenditure at any given time is:

$$E^i = \sum_{j \in J} p_{ij} q_{ij}$$

Mechanically, three distinct components could change such that total expenditures would drop after a dollar store entry: (1) net drop in price of good j, (2) net drop in quantity of good j, and (3) change in product choices. In the following sections we explore if each of these three mechanisms contribute to the drop in expenditures. In section 6 we provide a theoretical framework to quantify how these changes translate into welfare. Previewing our results, we find no evidence that the households are buying the same consumption bundle at lower prices. Instead, the expenditure drop is driven by quantity changes: consumers are buying fewer amounts and shifting towards lower priced varieties.

Figure 7: Effect of First Dollar Store Entry on Households' Expenditure at Various Store Types



Notes: Figure reports event study estimates with 95% confidence intervals from Equation 5, using 2008-2019 Homescan data. The analysis uses a heterogeneity-robust estimator proposed by Callaway and Sant'Anna (2021). Observations are not weighted for national representativeness. Errors are clustered at the zipcode level.

5.1 Results - Relative price of the consumer bundle is unchanged

The null relative price index shown in Figure 4 implies that incumbent retailers are not changing prices on existing goods and consumers are not getting a price cut on existing purchases by switching to the dollar store.

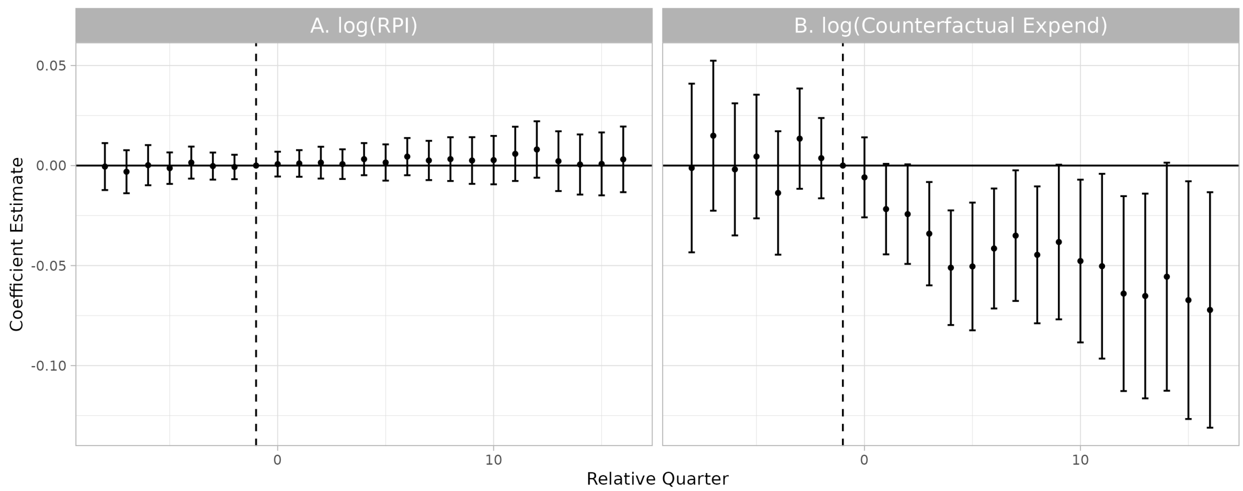
If households were purchasing the same goods in the post period as in the pre period, and dollar stores were offering cheaper prices, we should observe a drop in the relative price index post-entry. We repeat relative price index exercise, but with the reference price set at the county level so that we are comparing household expenditure to prices offered for the same good, but at the county average price. The precise null result we see in Figure 8 provides evidence that this is not the case.

That is, consumers are not enjoying the price cut from switching from a higher-priced good at an incumbent retailer to the exact same but lower-priced good at the dollar store (Table 1 shows that dollar store prices are 10% cheaper than grocery prices for the exact same product).[17] One possible explanation is that consumers are leaving money on the table by not switching to the dollar store for these cheaper products.

Instead, consumers use the dollar store to purchase new and cheaper goods and fewer varieties. We show this directly by computing the counterfactual expenditure (at the county level), which is the denominator from RPI Equation 6. The counterfactual expenditure is

[17] Note that a major difference between this result and the significant price differences we observed in Table 1 is that the price difference regressions focused solely on products sold across stores, while the RPI analysis pools all goods purchased both before and after dollar store entry.

Figure 8: Dollar Store Entry on Prices - County Average Reference Price



Notes: Figure reports event study estimates with 95% confidence intervals from Equation 5, using 2008-2019 Homescan data. The analysis uses a heterogeneity-robust estimator proposed by Callaway and Sant'Anna (2021). The dependent variable, the Relative Price Index (RPI), on the left side panel is defined in Equation 6. The dependent variable on the right side panel is the counterfactual expenditure, where the reference price is defined in Equation 7. Observations are not weighted for national representativeness. Errors are clustered at the zipcode level.

computed as the the household expenditure where prices of each good are replaced by county average prices. As shown in Figure 8, the counterfactual expenditure declines post-entry. In fact, this decline in the counterfactual expenditure mirrors the decline in total food expenditure shown in Figure 6.[18] Assuming that the reference price is unaffected by dollar store entry (said otherwise, assuming that dollar store entry does not affect average food prices at the county or state level), decreases in counterfactual expenditure suggest that decreases in expenditures are driven by quantity changes, variety changes, or both.

5.2 Results - Households reduce quantities

Next, we analyze whether the first dollar store causes households to purchase less quantity on net. Quantities could decrease if prior to the dollar store entry, the household lacked smaller-sized options and thus purchased more than the optimal amount of goods. In this case, the dollar stores' small-sized products would allow the household to re-optimize and thus reduce the quantity purchased. To measure quantity in observable units, we compare ounces consumed for different product groups before and after the first dollar store entry.[19] To give a complete picture of food shopping behavior, we measure quantity at the department level, the highest level of aggregation for NielsenIQ.

[18]The figure is almost the same when the reference price is at the state level.

[19]The majority of product sizes in the HMS dataset are measured in ounces. The liquid measurements are in "fluid ounces" and the weight measurements are in "ounces". We convert quarts and pounds into fluid ounces and ounces. When possible, we convert "counts" into ounces using an average measure – for example, one egg weighs 1.7 ounces. Data measured in counts that cannot be converted into a weight is excluded from the measurement.

Figure 9 shows the effect of dollar store entry on households' quantity purchased using the same event study analysis from Equation 5. No departments show increases in quantities following the entry of the first dollar store. Three departments – fresh produce, deli, and packaged meats – show no change in quantity, although the error bars are large ($\pm$ 10 percentage points) and so the result is noisy. The remaining three departments – dairy, dry grocery, and frozen food – show a 4% reduction in the average quantity consumed. While the drop in quantity is temporary for dairy and frozen foods, the reduction is persistent for dry groceries.

Households most reduce quantities for dry goods, frozen foods, and dairy (as shown in Figure 9), the three most popular departments at the dollar store by expenditure share (as shown in Figure A.6). Interestingly, while households decrease their overall expenditure in dry goods (by about 10 dollars per quarter), the household expenditure share shifts towards dry goods, as shown in Figure A.15. These results are all consistent with the hypothesis that before the dollar store, households were not optimizing on the size of the goods they were purchasing. The dollar stores' small-sized products allow household to reoptimize and thus reduce the quantity they purchase.

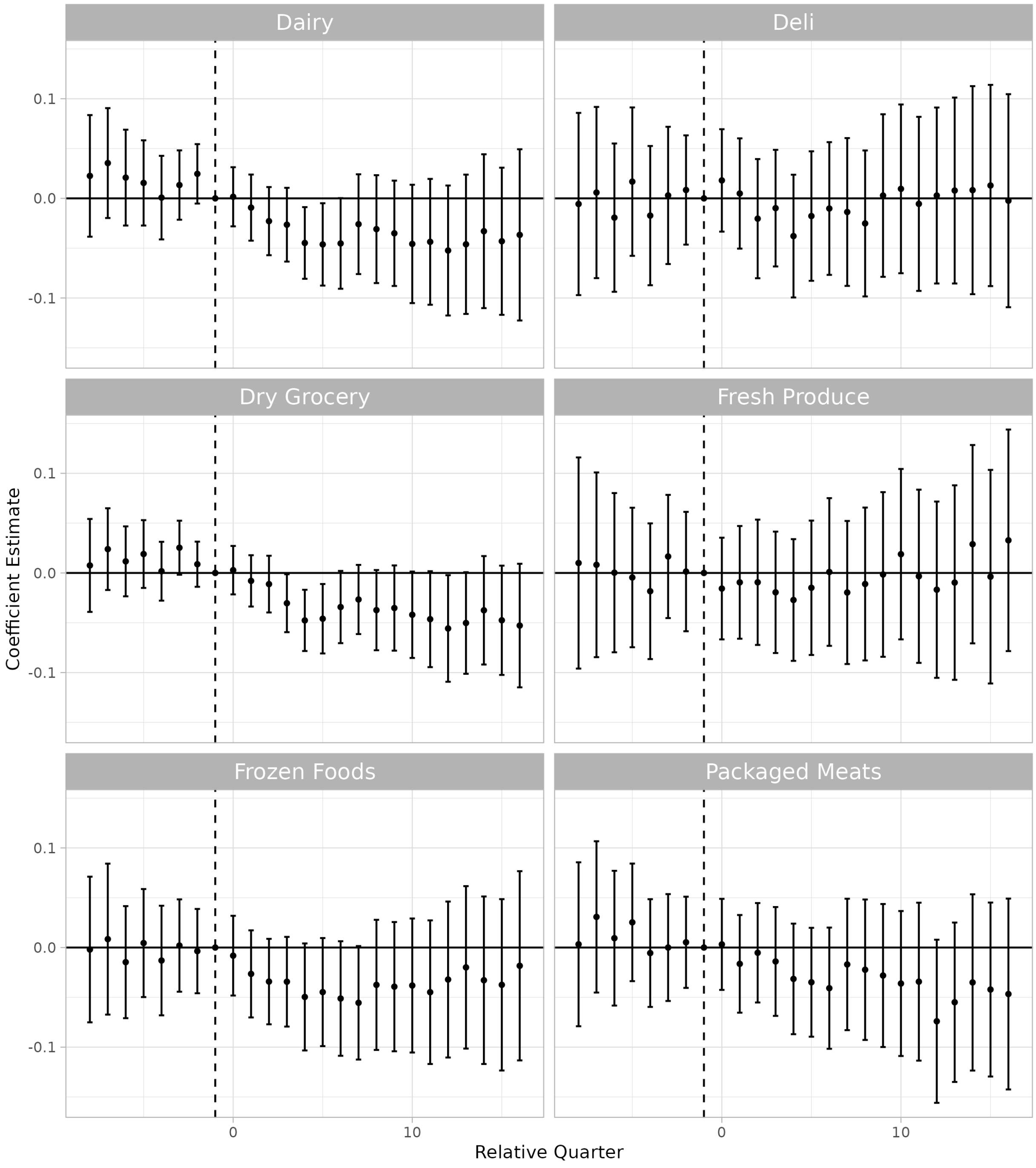
Important for policymakers is the result that households do not significantly change the quantity of fresh produce, speaking to concerns that the dollar store format causes unhealthy eating by inducing a substitution from broadly healthier categories (like fresh produce) to broadly less healthy categories. To investigate further, we also show results of the quantity analysis featuring the ten most popular product groups for dollar, grocery, and discount stores (the most popular categories are shown in Figure 2). Figure A.19 show null changes in quantity for all the selected product groups. These results hold both for more processed items that the dollar store specializes in (shown in purple), as well as for less processed items that are not commonly found at the dollar store (shown in green). These nulls suggests that if the first dollar store impacts consumer health, then the effect due to substitution towards away these broad product categories is small.[20]

5.3 Results - Households reduce varieties

Finally, we report the effect of the first dollar store on household variety in Figure 10. We investigate three different measures of aggregation: number of distinct UPCs purchased in one quarter, number of distinct modules purchased in one quarter, and number of distinct product groups purchased in one quarter. For all three levels of aggregations, pre-trends are flat in the lead up to dollar store entry, variety declines following dollar store entry, and the effect is persistent. From most disaggregated to most aggregated, UPC/barcode variety captures depth of variety, whereas the number of products groups captures breath of variety.

[20]Our "health" result is only a very crude approximation for health. Allcott et al. (2019) uses a Healthy Eating Index (HEI), a multi-dimensional measures that calculates the overall nutritional intake of each food. Further analyses on the nutritional content lies outside the scope of this study. In addition, we do not investigate within product-group changes in health.

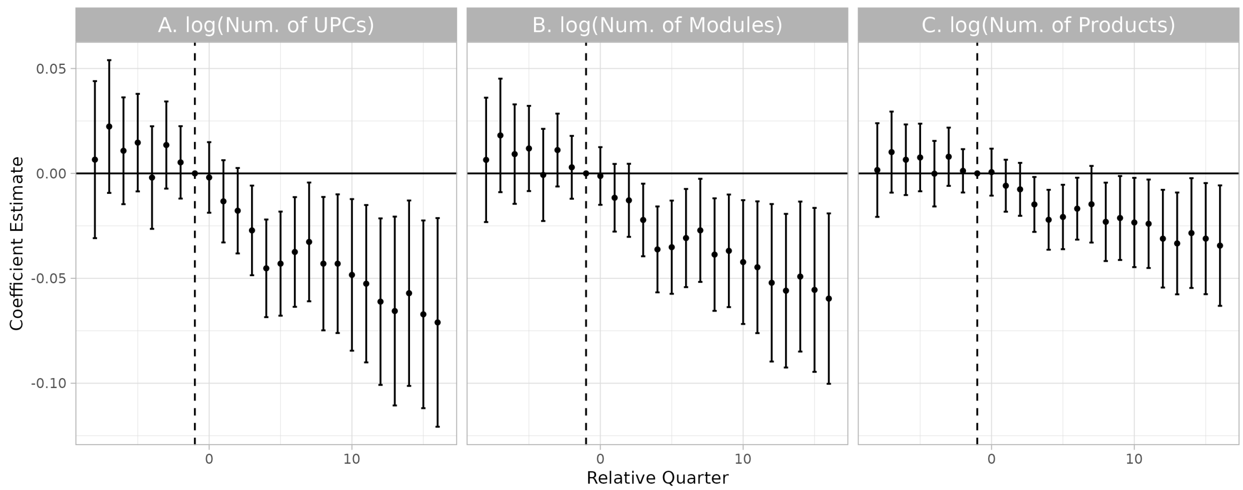
Figure 9: Effect of First Dollar Store Entry on Log Ounces of Each Department



Notes: Figure reports event study estimates with 95% confidence intervals from Equation 5, using 2008-2019 Homescan data. The analysis uses a heterogeneity-robust estimator proposed by Callaway and Sant'Anna (2021). Observations are not weighted for national representativeness. Errors are clustered at the zipcode level.

We find persistent and significant declines of unique varieties at all levels of aggregations: UPC/barcodes decline by 6%, product modules decline by 5%, and product groups decline by 1%.[21] That is, we observe that the dollar store shifts consumption towards lower-priced goods, at the expense of variety. We also observe that dollar stores are the store type with the least variety. We quantify how households value price, variety and other product characteristics in the demand estimation.

Figure 10: Effect of First Dollar Store Entry on Consumption Variety



Notes: Figure reports event study estimates with 95% confidence intervals from Equation 5, using 2008-2019 Homescan data. The analysis uses a heterogeneity-robust estimator proposed by Callaway and Sant'Anna (2021). The dependent variables here are different definitions for consumption bundle variety for the household at the quarter-year level. Observations are not weighted for national representativeness. Errors are clustered at the zipcode level.

6 Theoretical framework

Alone, the empirical results cannot quantify the effect of dollar store entry on consumer welfare or explain which aspects of the dollar store bundle have the largest effects. To quantify these effects, we estimate a model of consumer demand. We then use the model to better understand the policy concerns.

We model demand using a discrete-choice, random coefficient nested logit model[22]. In this

[21]For context, the average household in the reference period (k = 1) consumes 111 distinct UPCs, 64 distinct product modules, and 33 distinct product groups.

[22]Our model follows the existing literature but tailored to the setting in this paper. Allcott et al. (2019) model grocery demand as a choice of product groups using Cobb Douglass utility and measure consumption in calories. Handbury (2021) model product group choice using a combination of Cobb Douglass and log-logit preferences. Atkin et al. (2018) model households as first choosing a product group and then choosing a store within product group, with Cobb Douglass preferences over product groups and CES preferences over stores within product groups. Also, Atkin et al. (2018) use a Stone price index to aggregate from bar code to store product group. We follow Atkin et al. (2018) to aggregate from bar codes to product groups within stores, but use a nested logit model (instead of CES preferences) which allows for a reduction in total food

model, a household first chooses a store type to shop at – grocery, dollar, club, convenience, discount, or drug – and then chooses which product group to buy within store type: product groups correspond to different broad food categories, such as fresh produce and snacks. Preferences for a product group at a store type depend on price, variety, and product sizes. This specification allows us to quantify which aspect of the dollar stores are more or less valuable to consumers, as the household trades-off more expensive products, larger sizes, and more variety with cheaper products, smaller sizes, and less variety. Household indirect utility is written as

$$\begin{aligned} u_{ijst}^{m} = \alpha_0^m - \underbrace{\alpha_i^m \log p_{jst}^m}_{\text{price}} + \underbrace{\beta_i^m \log v_{jst}^m}_{\text{variety}} + \beta_2^m \left(\log v_{jst}^m\right)^2 + \underbrace{\gamma_i \log size_{jst}^m}_{\text{product size}} \\ + \gamma_2 \left(\log size_{jst}^m\right)^2 + \underbrace{\psi_j^m}_{\text{product group}} + \xi_{jst}^m + (1 - \underbrace{\lambda^m}_{\text{nest}})\epsilon_{ijst}^m \end{aligned} \tag{8}$$

where each household i of income group m in market t has utility u_{ijst}^m over product group j at retailer s. Household utility depends on the retailer's price p_{jst}^m, variety, v_{jst}^m, and size, $size_{jst}^m$. Additionally, utility varies with a market specific demand shock, ξ_{jt}^m, and idiosyncratic shock ϵ_{ijst}^m. The nest parameter, λ^m, indicates the degree of substitution between products within store type nest for income group m, where as $\lambda^m \to 0$, the nest structure reduces to a logit, and as $\lambda^m \to 1$, all substitution occurs within store type. To allow for more flexible substitution pattern within nest, prices, variety, and size coefficients all include a random coefficient term which is normally distributed and centered around the average value in the population: $\alpha_i^m \sim N(\alpha^m, \sigma^2_{\alpha m}), \beta_i^m \sim N(\beta, \sigma^2_{\beta m}), \gamma_i \sim N(\gamma^m, \sigma^2_{\gamma m})$.

The discrete-choice specification is chosen to accommodate the reductions in household expenditure without taking a stand on what the household does with the saved money. Within the scope of the model, a household can switch from a higher priced good with more varieties to a lower priced good with fewer varieties.

We focus on the level of good aggregation of interest to policymakers. When policymakers hypothesize that "less healthy" products at the dollar stores crowd out other "more healthy" products at the grocery store, they are referring to product groups such as fresh produce and snacks. As a result, the analysis is aggregated to the level of the policy concern, but is not so aggregated as to completely do away with variation in products.[23] So the inside goods comprise the top product groups by expenditure share, which are listed in Table A.4. The outside good comprises all the other less popular product groups, which are listed in Table A.5. Shares are then conditional on a food purchase, and shares of good j relative to the

expenditure following dollar store entry. The model can be represented either as a household choosing one product group within a store, or as a representative household that purchases shares of each product group, for details see Verboven (1996).

[23]For example, higher levels of aggregation group vegetable categories with other dry and frozen goods as opposed to with fresh produce.

outside good compares the quantity of a particular product group relative to all the other quantity purchased from the least popular, smaller product groups.

This aforementioned policy concern – dollar store crowding out grocery products – can happen through two channels: (1) grocery store closure, which we rule out in the empirical analysis and (2) close substitutability between different product groups across store types. This policy concern maybe highly relevant if estimates show close substitutability between different product groups across store types and if within-nest substitutability is fairly similar to cross-nest substitutability. In this case, the one solution might be to limit dollar store entry or to encourage dollar stores to shift their composition to mimic a smaller grocery store.[24] If however, the elasticity of substitution between product groups across store types is small, if dollar store market shares are small, and if the nest parameter indicates that substitution patterns are largely within-nest, then the policy recommendation is not to focus on the dollar store, but to instead focus on the composition of products within the store types that have the largest market share.

6.1 Aggregation from bar code to product group and store

To aggregate from individual household bar code purchases to a price index for each retailer-product-group, we assume that households' preferences follow a Stone price index, as in Atkin et al. (2018). This specification assumes that the household consumes all varieties within the product group, and pays an expenditure-weighted sum of log prices for these varieties that comprise the single product group:

$$\log p_{jst} = \sum_{b \in j} \phi_{bjs} \log \tilde{p}_{bjst} \tag{9}$$

where p_{jst} is the price of product j at store s in market t, which is comprised of bar codes b, ϕ_b is the household's expenditure on bar code b divided by the household's total expenditures on product j (product group g at store s) within a year, and $\tilde{p}_b$ is the price paid for bar code b. To recover $\log p_{jst}$ in a way that allows different store products to have different qualities, we regress expenditure weighted log bar code prices on store fixed effects and bar code fixed effects, and use the store fixed effects as the store price. We run a regression for each product-group market, so each price is the relative price in the product-group market, and is measured in log dollars.

Then, following this product definition, we compute variety v_{jts} as the average number of unique bar codes for product group g at store type s in market t and size $size_{jst}$ as the average size of the bar codes within a product group within a store. Since dollar stores offer small sizes and fewer varieties, we include second order terms to account for decreasing marginal returns and to test whether dollar stores are valued on this margin.

[24] Such policies have been suggested, for example, see here and here.

Market shares are computed by summing ounces (weights) of products consumed in each store-product-group. Intuitively, a market that consumes more snacks will have purchased a higher weight (in ounces) of snacks compared to a market that consumes fewer snacks. When the data is provided in a non-ounce unit (for example: pounds), the unit is converted to ounces; when the data is provided in counts (for example, a dozen eggs), the unit is converted to ounces whenever possible using the imputed weights in Table A.6.

6.2 Identification

Intuitively, variation in shares and prices across market will allow us to identify demand parameters. For example, comparing shares across markets with higher/lower prices allows us to identify the price coefficient and comparing markets with different amounts of variety and average package sizes across different retailers identifies the effect of product variety and package size size. To identify variance terms for price, variety, and size, we use interaction terms between product characteristics. However, quantity shares and prices are determined simultaneously in equilibrium, and, in particular, demand shocks are likely correlated both with prices and shares. To overcome this endogeneity, we employ several instruments: the average price of the same good in other markets for the same retailer (following Hausman et al. (1994)) and a "retail closing instrument".

The average retailer price instrument exploits the idea that local demand shocks are likely uncorrelated with prices in different markets. Intuitively, local pricing decisions can depend on both supply and demand factors, and the average retailer price instrument assumes that the average price in different markets captures the supply component without capturing the idiosyncratic demand in a market. The main threat to identification is that demand shocks may be correlated across several cities. However, since many retailers set prices at the national level (DellaVigna and Gentzkow (2019)), it is even more likely that prices do not reflect such local demand shocks[25]. Thus, we use average retailer price instrument to isolate changes in prices due to changes in cost, and not demand shifters, which in turns allows us to identify our demand parameters. We define the average retailer price instrument as the price from the save retailer averaged over all other counties.

6.2.1 Retail Closing Instrument

We introduce a "retail closing instrument" which exploits a plausibly exogenous shock that lowers the cost for a retailer to enter a zip code.[26] Throughout the 2000s and 2010s, technology shocks and other market forces caused a wave of bankruptcies that shut down several

[25]Even when retailers price uniformly, prices will still vary across markets in our setting as we measure relative prices across retailers in the same market, and different markets are composed of different retailers.

[26]We thank Fern Ramoutar for conceptualizing the use of retail bankruptcies as an instrument.

major brick and mortar retail chains.[27] These store closures created opportunities for other retailers such as dollar stores to enter. Then, stores such as a dollar stores would have easier access to now-vacant locations, both because the space was now available and because additional vacancies lower market rents, lowering the fixed costs of entry. In turn, the retailer bankruptcy can shift the shares and possibly prices in the market through the availability of stores and competition of new and existing stores. Therefore, we define the retail closing instrument as a binary variable equal to one if the county had a store that went through bankruptcy in the year(s) prior, and zero otherwise. The identifying assumption here is that non-food retail bankruptcies (such as the Blockbuster bankruptcy) only affects local food markets by creating a vacant storefront where another potentially food-providing store can locate.

In order to ensure that the timing of these bankruptcies is unrelated to the local demand for food, we focus on closures that occurred abruptly and bankruptcy that occurred at the national level. We also limit the set of retailers to retailers that don't sell food. We thus leverage bankruptcies of national retail chains that occurred during our study sample, which are listed in Table A.2. These bankruptcies occurred at different points in time, as illustrated in Figure A.12, and local markets had heterogeneous exposure to each bankruptcy.

To test for weak instruments, we regress the endogenous variables, prices and log shares of the nest on the instruments. The F-statistic for prices is 11,340 and for the log group share is 595 and is reported with the first stage in Table A.7.

6.2.2 Bankrupt Retailer Closings and Dollar Store Entry

We illustrate the variation we are exploiting with an exercise focused exclusively on dollar store entry. We show that the dollar store entry in a zip code is correlated with retailer bankruptcy in the same zip code only when the size of the bankrupt retailer suited the dollar store. First, we present anecdotal evidence which shows that dollar stores target stores of particular sizes (8,000-10,000 square feet):

> "If you want to be profitable, start with an 8,000-square-foot store." – Wally Lee, director of marketing and technology of supplier of dollar stores.[28]

> "Our stores predominantly range from 8,000 - 10,000 selling square feet" – Dollar Tree Annual Report, 2020

> "We lease the vast majority of our stores ... this leasing strategy [allows us] to pursue various expansion opportunities resulting from changing market conditions" – Dollar Tree Annual Report, 2020

[27] For anecdotal evidence of what is driving the "retail apocalypse", see the New York Times, Washington Post, and Wall Street Journal.

[28] Excerpt from New York Times article "The Dollar-Store Economy"

Then, we regress the first dollar store entry on a modified versions of the retail closing instrument described above. We estimate the probability a dollar store opens in a zip code on whether or not there was a store that experienced a national bankruptcy in the year(s) prior:

$$D_{it} = \Phi(\alpha + \sum_k \beta_k Z_{ik} + \lambda_t + \epsilon_{it}) \tag{10}$$

In this regression, D_{it} is an indicator variable for whether the first dollar store has entered zip code i by year t, Φ is the normal CDF, and Z_{ik} indicates the presence of a bankrupt retailer in the zip code i k years before that the first dollar store entry to the zip code. In practice, it can take several years after bankruptcy to shut down stores, and, it can take several years to open a new store in a vacant location. We thus include further lags of the bankruptcy instrument. We report two results: the first using only retailer bankruptcies that had average store footprints between 8,000 and 10,000 square feet and a second placebo check using only national retailers that had average store footprints smaller than 8,000 square feet.

We report results in Table A.8, which show that retail closings are positively correlated with dollar store entry when the size is appropriate and uncorrelated when the size of the store that went bankrupt is too small.

6.3 Supply

The model focuses entirely on demand and on the direct effects of the first dollar store entry. Had we observed a significant change in shopping trips, store count, or bundle price, we would have modeled the supply to decompose the change in welfare into the direct effect from the dollar store and the indirect effect from competing retailer response (for an example of this, see Atkin et al. (2018)).

7 Estimates

Demand parameters are estimated with general method of moments following Berry et al. (1995) and standard practices in Conlon and Gortmaker (2020). We report demand estimates from the random coefficients nested logit in Table 3, and the nested logit without random coefficients in Table A.9. First, all consumers dislike high prices, prefer variety, and larger package size, but there are diminishing returns for additional larger sizes and additional variety. The average household would be willing to pay .2-.5% for a 1% increase in variety, or would give up 4-5% of variety when the bundle price is 1% lower.[29] This willingness to

[29]The first, second, third, and fourth quartile by income would be willing to pay .29, .22, .56, and 1.14 percent more, respectfully, to increase variety by 1%, where variety is measured in number of upcs. In the

pay is consistent with the event study results showing that households reduce variety by 1% to reduce expenditures by 5%. Second, intuitively, lower-income households are more price sensitive than higher-income households. Price coefficients range from -1.9 for the lowest-income, most price-sensitive group to -.6 for the highest-income, least price-sensitive group, estimates which are largely comprable with the existing literature. In line with the descriptive evidence, lower-income households are thus more likely to shop at dollar stores. Third, compared to other store types, dollar stores benefit consumers predominantly through their low prices, as they carry a much more limited selection of product groups compared to these other store types. This contrasts with gains to consumers provided by large discount stores. A dollar store that enters a food desert provides consumers with low prices and novel variety. A dollar store that enters a crowded retail market provides consumers with lower prices but not the variety that the existing retailers already provide. In the crowded market, households may switch from the higher-priced higher-variety bundle to a lower-priced lower-variety bundle due to the distaste for higher prices and the decreasing marginal returns of additional variety and size. The estimates point to the unique role of these novel specialty stores in the existing retail market.

Crucial for those interested in expanding consumer access to product groups like fresh produce is the need to understand *why* dollar stores do not provide these product groups.[30] Put differently, given limited variety, why do dollar stores carry the selection of products they do? Products are selected due to either demand factors, supply factors, or both. If dollar stores select products that provide the highest utility, then the top groups purchased at the dollar store documented in Figure 2 – Candy, Snacks, Carbonated Beverages, Bread and Baked Goods, Cookies, and Juice – should reflect the household's most-preferred goods. This is not the case: the product group fixed effects which provide a measure household product group preference show that Candy, Snacks, Carbonated Beverages, Bread and Baked Goods, Cookies, and Juice are among the least preferred product groups. Estimates imply that product group selection are based on supply-side or costs considerations.

Those interested in expanding consumer access to fresh produce are also concerned that introduction of the dollar store will cause consumers to substitute away from popular products at preexisting grocers towards popular products at the dollar store, specifically from products like Fresh Produce to products like Candy, Snacks, and Carbonated Beverages. To evaluate the concern, we compare the substitution within- vs. across-nest and compute the elasticity of substitution between popular grocery products and popular dollar store products.[31] Since

pre-period, consumers purchased an average of 111 upcs total or 5.8 upcs per product group. The first, second, third, and foruth quartile by income would be willing to give up 3.94, 4.48, 5.23, and 4.90 per cent of upc variety, respectfully, to decrease prices by 1%.

[30] Dollar stores usually provide a very limited selection of fresh produce, and policymakers have been interested in expanding the fresh produce selection of dollar stores. See this report for work focused on expanding consumer access to fresh produce by corralling the dollar store to provide such products.

[31] Under the nested logit model, all products are substitutes. Products are by definition closer substitutes within nest than across nests, and the degree of substitution varies with the nest parameter. Product substitutability can vary from a logit model ($\lambda \to 0$), where all products have the same elasticity of substitution, to where the substitution within-nest is much higher than the substitution across nest, and all substitution occurs within the same nest ($\lambda \to 1$).

the nest parameter ranges between .81 and .99, we find that the elasticity of substitution is much higher within nest than across nests; almost all of the substitution patterns occur within-nest or within store type. Thus, demand estimates suggest that price changes have a much larger effect on substitution patterns within store type than price changes across store types. In the context of policy questions about the dollar store, product groups like fresh produce at the grocery store are poor substitutes for product groups like snacks at the dollar store relative to other products at the grocery store: for example, the average elasticity of substitution between grocery produce and dollar store snacks is .006. In fact, dollar store shares in the market are small at currently observed levels (documented in Figure A.7), and so changes in prices at the dollar store cause little substitution from the grocery store to the dollar store.

One large open question is explaining how dollar stores have proliferated so successfully across the United States. We find the following: (a) consumers dislike high prices, and dollar stores provide the lowest-priced products compared to other retailers (b) consumers prefer more variety and larger product sizes, which dollar stores do not provide compared to retailers (c) dollar stores choose their products due to cost considerations, not demand. Perhaps unsurprising given the name, we find that the demand-side driver of dollar store expansion is the dollar stores' low price point.

Table 3: Demand Estimates

Variable	Income Rank 1	Rank 2	Rank 3	Rank 4
Prices	-1.8953	-2.4173	-1.1059	-.5706
	(.3144)	(.3306)	(.4207)	(.3648)
Log Variety	.6673	.9986	1.7461	2.2131
	(.0111)	(.0655)	(.0708)	(.0732)
Log Avg. Size	2.7323	1.9591	1.5556	1.5644
	(.1037)	(.1153)	(.0496)	(.0542)
Log Variety^2	-.0315	-.1237	-.2975	-.3981
	(.0029)	(.0152)	(.0173)	(.0180)
Log Avg. Size^2	-.4542	-.3117	-.2515	-.2539
	(.0202)	(.0210)	(.0092)	(.0111)
Nest Parameter	.7697	.9900	.9900	.9881
	(.0196)	(.0354)	(.0359)	(.0447)
Intercept	-5.4053	-4.4294	-4.4111	-4.6925
	(.0946)	(.1185)	(.0925)	(.0946)
Product groups				
Candy	-.4555	-.6103	-.6590	-.7155
	(.0187)	(.0228)	(.0238)	(.0292)
Carbonated Beverages	.0119	-.1219	-.0214	-.0903
	(.0238)	(.0274)	(.0319)	(.0342)
Cereal	.1533	.1442	.1809	.1379
	(.0166)	(.0185)	(.0204)	(.0193)
Cheese	.2667	.3178	.2403	.1987
	(.0173)	(.0156)	(.0137)	(.0156)
Coffee	.1846	.1159	.1836	.1363
	(.0454)	(.0617)	(.0789)	(.0869)
Cookies	-.0018	.0149	.0569	.0473
	(.0186)	(.0221)	(.0332)	(.0357)
Eggs	.6332	.4986	.5092	.4941
	(.0178)	(.0179)	(.0154)	(.0181)
Fresh Produce	.1555	.1446	.0872	.0507
	(.0156)	(.0148)	(.0136)	(.0156)
Ice Cream, Novelties	.5087	.3783	.4141	.3841
	(.0238)	(.0333)	(.0418)	(.0369)
Juices, Drinks	.1457	.0185	.1388	.1301
	(.0218)	(.0246)	(.0266)	(.0313)
Meat	.1587	.1988	.1730	.1667
	(.0168)	(.0182)	(.0164)	(.0196)
Milk	.4718	.3175	.4028	.4077
	(.0219)	(.0212)	(.0196)	(.0211)
Prepared Food	.0210	.0019	-.0298	-.0558
	(.0149)	(.0175)	(.0159)	(.0165)
Snacks	-.2989	-.3033	-.3189	-.4072
	(.0158)	(.0159)	(.0142)	(.0159)
Soft Drinks: Non-Carbonated	-.0602	-.0592	.0635	.0539
	(.0410)	(.0592)	(.0695)	(.0638)
Soup	.1970	.1999	.2343	.1706
	(.0175)	(.0201)	(.0256)	(.0253)
Vegetables: Canned, Dried, Frozen	.0826	.0993	.1001	.0564
	(.0151)	(.0155)	(.0145)	(.0158)
Yogurt	.5769	.4566	.4126	.3273
	(.0186)	(.0225)	(.0247)	(.0224)
Non-Linear				
Log Price	.3629	.4663	.4853	.4088
	(.5413)	(.3272)	(.4293)	(.3816)
Log Variety	.0000	.4427	1.1109	1.5149
	(.0000)	(.0595)	(.0716)	(.0827)
Log Size	.7931	.4833	.3826	.3978
	(.0471)	(.0448)	(.0183)	(.0230)

Notes: Table reports coefficients from demand estimation where a market is a county-year-income group. We only use sales from dollar stores, discount stores, club stores, drug stores, convenience stores, and grocery stores. Data is based on consumer panel microdata for years 2008-2019. Income rank 1 is the lowest average income, income rank 4 has the highest average income.

7.1 Quantifying the value of the dollar store

To quantify the benefit of the first dollar store to the average household, we estimate the compensating variation, the dollar value which equates the utility of the average household in a zip with a dollar store and the utility of the same household in the same zip but without a dollar store.[32] To use consistent measures of expenditure throughout the paper, we measure the log compensating variation, which we interpret in percentage terms,

$$\log CV^m = \frac{1}{IT}\sum_{i,t}\frac{(1-\lambda^m)}{\alpha_i}\ln\left(\frac{\left(\sum_{j\in s^{dollar}} e^{(\delta^m_{jst}+\mu_{ijst})/(1-\lambda^m)}\right)^{1-\lambda^m}}{\sum_{s\in s^{no\ dollar}}\left(\sum_{j\in s} e^{(\delta^m_{jst}+\mu_{ijst})/(1-\lambda^m)}\right)^{1-\lambda^m}}+1\right) \tag{11}$$

where δ^m_{jst} is the average utility $\delta^m_{jt} = \alpha^m_0 + \beta^m_2(\log v^m_{jts})^2 + \gamma_2(\log size^m_{jts})^2 + \psi^m_{g(j)} + \xi^m_{jst}$ and μ_{ij} is the individual component $\mu_{ijst} = -\alpha_i \log p^m_{jst} + \beta_i \log v^m_{jst} + \gamma_i \log size^m_{jst}$.

Qualitatively, household welfare increases after the first dollar store entry because the household choice set is increased. In practice, the welfare effects will be small, since the share of food products sold by the dollar store compared to other store types are small, as shown in Figure A.7. We compute the compensating variation using parameters from the demand estimation and the prices, characteristics, and number of trips from the Neilsen data. We use data in the year after the first dollar store entry to compute the compensating variation.[33]

We report the welfare estimates in Table 4.[34] The benefit to the average household range from 2% for the lowest-income household in the top income rank to .1% for the highest-income household in the bottom income rank.

8 Heterogeneity by Income and Retail Environment

Dollar stores disproportionately locate in low-income neighborhoods (as well as non-metro areas), as shown in Figure A.3, and, on the flip side, dollar store customers are disproportionately low income, as shown in Figure A.5. Since dollar stores strategically locate in specific areas, households in these locations might experience the dollar store differently than the average consumer.[35]

[32] This is a standard measure of welfare for valuing new goods. For example, see Hausman and Leibtag (2007) in the context of Wal-mart's proliferation.

[33] Specifically, for each market we compute the average compensating variation across consumers using demand coefficients and price, variety, and size data. To compute welfare, we average log compensating variation across markets. We compute welfare using the first period after dollar store entry.

[34] To obtain standard errors, we use the parametric bootstrap (Horowitz (2001)). Specifically, we draw from the errors of the estimated parameters and re-compute average log compensating variation.

[35] The media has often highlighted that dollar stores shoppers are disproportionately low income and locate disproportionately in rural towns.

Table 4: Welfare Estimates

Variable	Income Rank 1	Rank 2	Rank 3	Rank 4
log CV	0.02137	0.00113	0.00174	0.00142
	(0.00082)	(0.00009)	(0.00560)	(0.00183)

Notes: Table reports coefficients from demand estimation where a market is a county-year-income group. We only use sales from dollar stores, discount stores, club stores, drug stores, convenience stores, and grocery stores. Data is based on consumer panel microdata for years 2008-2019. Income rank 1 is the lowest average income, income rank 4 has the highest average income. Standard errors are below estimates. Standard errors were estimated using 1000 bootstrap iterations.

In this section, we investigate how the first dollar store entry affects heterogeneous populations. We repeat our main analysis, but allow for heterogeneity by income as well heterogeneity for different retail environments. We consider two definitions of sparse retail environments: non metro areas (to capture the effect of dollar stores in rural areas) and food deserts. For each dimension of heterogeneity, we focus on the potentially most vulnerable population: the lowest income group and the sparsest retail environments.[36]

Then, we consider the effect of the first dollar store entry on expenditures, quantities, prices, and varieties. For expenditures, we consider both total, dollar store, and grocery store expenditures. We expect dollar store expenditures to increase more for low-income consumers, as well as as for consumers in sparse retail environments. To asses whether there maybe a competitive response from local retailers, we look at the effect on grocery expenditures and relative prices. Finally, we compute the effect on quantities and varieties to assess how heterogeneous effects compare to the average. For quantities, we consider the most policy-relevant department, fresh produce.

First, we consider heterogeneity by income. All income groups increase dollar store expenditures following the entry of the first dollar store, as shown in Figure A.21. However, households in the lowest income group react to the dollar store in a way which is different from other income groups and largely budget neutral. While other household groups react by reducing expenditures and varieties, the lowest income group barely reduces varieties and expenditures, and in a way that is not statistically significant, as shown in Figure A.25 and Figure A.21. Surprisingly, the second and third quantiles of income reduces quantities the most, by almost 5% and 8%, respectfully. . Similarly, the lowest income group's grocery store expenditure, shown in Figure A.23, do not decline significantly following dollar store entry. Intuitively, households in the lowest income group are not using the dollar store to save money, but are using the dollar store to re-optimize their choices at (approximately)

[36] We report effects for all groups, but specifically discuss the most likely vulnerable in the text. Additional dimensions of sparse retail environments include concentrated retail environments, or places where households shop at relatively few retailers.

the same budget constraint.[37] Meanwhile, the lowest income relative price index (RPI) increases marginally and not significantly (by .01 percentage points), as shown in Figure A.24. Finally, the lowest income households do not change the ounces of fresh produce following the first dollar store entry, as shown in Figure A.26. Overall, this paints a picture of the average household in the lowest income group which continues to operate at its previous budget constraint, and re-optimizes utility but in a way that is budget neutral and in a way that does not change the quantity of fresh produce consumed.

Unlike for the lowest income households, the shopping patterns for households in food deserts and non-urban areas mirror the average trend (although results are less precise due to data availability). That is, households in sparse retail environments increase dollar store expenditures, with household in food deserts spending an additional 15$ per quarter at the dollar store, well above the average. Similar to the average, households in food deserts and non-urban areas reduce expenditures, grocery expenditures, and variety, and experience the same lack of price change and lack of change in the quantity of fresh produce.

9 Conclusion

With over 35,000 dollar stores in the United States, the dollar store format has been subject to scrutiny regarding its effects on consumers. Much of this scrutiny has centered around three related concerns regarding (1) the types of goods supplied and how these goods differ from those provided by traditional retail formats, (2) the effect of dollar stores on local retail competition and the consumer choice set, and (3) the effect of the dollar store on consumer welfare. This paper addresses these questions in the context of the first dollar store entry. We quantify the effect of the dollar store on households and local retailers, and investigates the mechanisms that drive the supply and demand response.

First, we document the types of goods dollar stores carry and how they differ from goods supplied by other store types. We show that, relative to other store types, dollar store goods are characterized by their low prices, small sizes, and few varieties and we show that dollar store entry introduces mostly dry goods into the market. Even per unit, the dollar store prices are the lowest amongst all other store types. This low-price result voids the concern that dollar stores exploit cash-strapped consumers by charging low prices per good but high prices per unit by only offering small sizes.

However, this concern illustrates the uniqueness of the dollar store format. While dollar stores offer simultaneously the cheapest prices and the smallest sizes, grocery stores tend to exhibit an inverse relationship between price and size. This inverse relationship allows grocery stores to price discriminate across consumers and increase effective prices by shrinking package sizes. Thus, one possible strength of the dollar store is the ability to reverse the

[37]These seemingly disparate facts – that dollar store expenditures decrease while total expenditures do not change – is due to the fact that expenditures reduce marginally at other store types but in such a way that total expenditure is decreasing but not significantly.

traditional inverse relationship between size and price. It seems reasonable that dollar stores stock few varieties because they must guarantee a low price, and can only guarantee a low price per good and price per unit on a limited selection of goods.

In response to the first dollar store entry, we find a lack of supply-side response: while some store types (e.g. grocery stores) see declines in revenue following the first dollar store entry, stores do not change their prices and, on average, there is no grocery exit. On the demand side, in addition to not facing different prices at incumbent retailers, we show that households do not change the number of trips they take to other store types. Thus we conclude that the dollar store expands the household choice set.

Finally, we study the consumer response and quantify the welfare impact of the dollar store. We show that following the first dollar store entry, households reduce expenditures. This drop in expenditure is explained by a shift from a larger consumer bundle with higher prices but more variety to a smaller consumer bundle with lower prices but with less variety. The demand estimates suggest that this shift is driven by dollar store's low prices. We compute the value of the dollar store at 12% of food expenditure per year for the average household.

Our paper ties the literature on the expansion of non-traditional retail formats (such as big box stores) to the literature on how households re-optimize in the face of large product assortments. We show the importance of re-optimizing over varieties and how non-traditional retail formats allow households to purchase new goods and goods more efficiently.

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A Appendix

A.1 Tables

Table A.1: Product Size Effects of Dollar Store

Dependent Variable:	log(Size)
Variables	
Dollar Store	-0.2253
	(0.0027)
Discount	0.0487
	(0.0009)
Club	0.7244
	(0.0050)
Convenience	-0.2326
	(0.0060)
Drug	-0.1329
	(0.0053)
Fixed-effects	
county_product_month	Yes
Fit statistics	
Observations	483,480,789
R^2	0.82684
Within R^2	0.06925

Clustered (county_name) standard-errors in parentheses

Notes: Table reports coefficient from regressing log size of good on a store type variable. We only use sales from dollar stores, discount stores, club stores, and drug/convenience stores. Grocery stores are used as the reference group. Data is based on consumer panel microdata for years 2008-2018. We report coefficients with county by product module by month-year fixed effects. Standard errors are clustered at the county level.

Table A.2: Non-Food Retailers in the Retail Closing Instrument

Retail Chain	Bankruptcy Year	Dollar-Store Size?	Source
Blockbuster	2010	✓	SEC Form 10-K
Bon-Ton Stores	2018	Large	SEC Form 10-K
Borders	2011	Large	SEC Form 10-K
Charlotte Russe	2018	✓	SEC Form 10-K
Destination Maternity	2019	Small	SEC Form 10-K
Fashion Bug	2013	✓	SEC Form 10-K
Gymboree	2019	Small	SEC Form 10-K
HH Gregg	2017	Large	SEC Form 10-K
Hollywood Video	2010	✓	SEC Form 10-K
KB Toys	2008	Small	Michman and Mazze (2001)
Loehmann's	2014	Large	SEC Form 10-K
Mattress Firm	2018	✓	SEC Form 10-K
Mervyn's	2008	Large	CoStar
Movie Gallery	2010	✓	SEC Form 10-K
Rue 21	2017	✓	SEC Form 10-K
Shopko	2019	Large	SEC Form 10-K
Sports Authority	2016	Large	SEC Form 10-K
Tweeter	2007	✓	SEC Form 10-K

Notes: Table reports retailers went bankrupt, the bankruptcy year, and whether the typical store of that retailer would fit the size requirements for a dollar store. A store that is smaller than 5,000 square feet is considered too small, a store that is between 5,000 and 15,000 square feet is considered appropriately sized, and a store that is over 15,000 square feet is considered too large. Dollar stores are typically between 6,000 and 10,000 square feet. *Sources:* Square footage information comes from publicly-available form 10-K SEC filings for average store size of each retailer when available which can be found by searching here. For Mervyn's, the information comes from CoStar, one of the preeminent real estate information sources. The average dollar store size comes from SEC filings, as well as this Retail Dive and this New York Times article. The bankruptcy year for each retailer comes from Wikipedia.

Table A.3: Product Groups In Demand Estimation

Product Groups in Demand
Bread And Baked Goods
Candy
Carbonated Beverages
Cereal
Cheese
Coffee
Cookies
Eggs
Fresh Produce
Ice Cream, Novelties
Juices, Drinks
Meat
Milk
Prepared Food
Snacks
Soft Drinks-Non-Carbonated
Soup
Vegetables- Canned, Dried, Frozen
Yogurt

Notes: The table depicts the product groups in the inside group in demand estimation. The top 20 product groups by expenditure are included in the demand estimation, the top 19 groups by expenditure comprise the inside good, the remaining comprise the outside good.

Table A.4: Product Groups Combined in Demand Estimations

Combined Product Groups	Original Product Groups
Meat	Fresh Meat
	Packaged Meats - Deli
	Unprep Meat/Pultry/Seafood-frozen
Prepared Food	Prepared Food-Ready-To-Serve
	Prepared Food - Frozen
	Prepared Food - Dry Mixes
Juice, Drinks	Juice, Drinks - Canned, Bottled
	Juice, Drinks - Frozen
Vegetables - Canned, Dried, Frozen	Vegetables – Canned
	Vegetables and Grains - Dried
	Vegetables - Frozen
Snacks	Snacks
	Snacks, Spreads, Dips - Dairy
	Pizza/Snacks/Horse Devours-Frozen
	Pudding, Desserts - Dairy

Notes: Similar product groups are combined into the same product group for demand estimation.

Table A.5: Product Groups Comprising the Outside Good

Product Groups that Comprise the Outside Good
Baby food
Baked goods-frozen
Baking mixes
Baking supplies
Breakfast food
Breakfast foods-frozen
Butter and margarine
Condiments, gravies, and sauces
Cot cheese, sour cream, toppings
Crackers
Desserts, gelatins, syrup
Desserts/fruits/toppings-frozen
Dough products
Dressings/salads/prep foods-deli
Flour
Fruit - canned
Fruit - dried
Jams, jellies, spreads
Nuts
Packaged milk and modifiers
Pasta
Pickles, olives, and relish
Pizza/snacks/hors doeuvres-frozen
Pudding, desserts-dairy
Salad dressings, mayo, toppings
Seafood - canned
Shortening, oil
Snacks, spreads, dips-dairy
Spices, seasoning, extracts
Sugar, sweeteners
Table syrups, molasses
Tea

Notes: Product groups that comprise the outside group for demand estimation.

Table A.6: Conversion between counts and food weights in the Neilsen HMS data

Product Group Description	Weight (oz)
Egg	1.7
Fresh Apple	5.7
Fresh Cauliflower	32
Fresh Tomato	6
Fresh Potato	7.5
Fresh Mushroom	2
Fresh Onion	11.09
Fresh Kiwi	4
Fresh Grapefruit	8
Fresh Oranges	4.6
Fresh Lettuce	10.58
Fresh Garlic	1.41

Notes: Products that appear as counts in the data are converted into weights (ounces) to keep as much data in the analysis as possible.

Table A.7: First Stage for Hausman, Retail Closing Instruments

Dependent Variables:	Log Price	Log Group Share
Hausman Instrument	0.5978***	-1.204**
	(0.0443)	(0.4468)
Retail Bankruptcy Instrument	-0.0002*	-0.0289***
	(0.0001)	(0.0061)
Lagged Retail Bankruptcy	-0.0005**	-0.0150***
	(0.0002)	(0.0041)
Twice Lagged Retail Bankruptcy	-0.0004**	-0.0360***
	(0.0002)	(0.0049)
Log Variety	-0.0207***	0.5377***
	(0.0029)	(0.0474)
Log Average Size	0.0132**	0.5820***
	(0.0053)	(0.1409)
Log Variety^2	0.0039***	-0.0345***
	(0.0006)	(0.0116)
Log Average Size^2	0.0009	-0.0887***
	(0.0015)	(0.0255)
Fixed-effects		
Product Group	Yes	Yes
Fit statistics		
Observations	730,944	730,944
R^2	0.08458	0.18074
F-test (1st stage)	11,340.4	594.70

Clustered (product group) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: First stage estimates from regressions of log shares on prices, varieties, average package size, and group share instrumenting for prices and group shares with the retailer closing and Hausman instrument using 2008-2019 Homescan data.

Table A.8: Probability of Dollar Store Entry

	Dollar Open	
	(1)	(2)
Retail Closing Instrument	0.213***	
	(0.047)	
Retail Closing Placebo		0.055
		(0.224)
Fixed Effects		
year	Yes	Yes
Fit statistics		
Observations	14,278	14,278
Akaike Inf. Crit.	11,224.220	11,244.750

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: Table reports probit regression estimates with standard errors from Equation 10. The dependent variable is whether a dollar store enters a particular zip code. The dependent variables are whether the same zip code had store whose parent company underwent a national-level bankruptcy in the year prior. The Retail Closing Instrument subsets to bankruptcies of the correct size, the Retail Closing Placebo subsets to bankruptcies of stores that are too small for a dollar store to enter. The specification also includes a constant and year fixed effects.

Table A.9: Nested Logit Demand Estimates

Variable	Income Rank 1	Rank 2	Rank 3	Rank 4
Price	-2.17	-2.732	-1.889	-1.26
	(0.1254)	(0.1173)	(0.09672)	(0.09221)
Log Variety	0.5635	0.4698	0.4656	0.5293
	(0.01194)	(0.01478)	(0.01561)	(0.01987)
Log Avg. Size	0.7695	0.5645	0.6282	0.5828
	(0.029)	(0.03304)	(0.03284)	(0.04457)
Log Variety^2	-0.03205	-0.01891	-0.01571	-0.03324
	(0.002415)	(0.002287)	(0.002169)	(0.002266)
Log average size^2	-0.1069	-0.07418	-0.09221	-0.08762
	(0.004481)	(0.004826)	(0.004589)	(0.005534)
Nest Parameter	0.9385	0.99	0.99	0.99
	(0.01419)	(0.01864)	(0.02182)	(0.03178)
Intercept	-2.527	-1.957	-1.992	-1.921
	(0.09913)	(0.1294)	(0.1467)	(0.2211)
Product Groups				
Candy	-0.5657	-0.6836	-0.7156	-0.8189
	(0.02096)	(0.02225)	(0.02269)	(0.02951)
Carbonated Beverages	-0.02168	-0.09733	-0.05224	-0.1472
	(0.01917)	(0.01986)	(0.01891)	(0.02141)
Cereal	0.2045	0.1749	0.1846	0.137
	(0.01756)	(0.01818)	(0.01679)	(0.01835)
Cheese	0.3856	0.3702	0.3325	0.2818
	(0.01808)	(0.01907)	(0.01793)	(0.02138)
Coffee	0.2587	0.2639	0.3266	0.2815
	(0.02347)	(0.02387)	(0.02297)	(0.02586)
Cookies	0.02799	0.03683	0.09339	0.06513
	(0.01988)	(0.02059)	(0.02022)	(0.02287)
Eggs	0.6896	0.6582	0.6953	0.6654
	(0.01784)	(0.0184)	(0.01676)	(0.01829)
Fresh Produce	0.2198	0.1978	0.1857	0.1535
	(0.01604)	(0.01617)	(0.01495)	(0.01651)
Ice Cream, Novelties	0.5885	0.5129	0.5868	0.5511
	(0.0205)	(0.02159)	(0.02058)	(0.02222)
Juices, Drinks	0.1884	0.08125	0.167	0.141
	(0.01908)	(0.01957)	(0.01745)	(0.01904)
Meat	0.2334	0.2353	0.214	0.2298
	(0.01625)	(0.01663)	(0.01572)	(0.01854)
Milk	0.5298	0.4177	0.4743	0.4678
	(0.02101)	(0.02171)	(0.01993)	(0.02115)
Prepared Food	0.028	0.01096	0.02863	0.004749
	(0.01569)	(0.01629)	(0.01519)	(0.0169)
Snacks	-0.31	-0.3404	-0.318	-0.4149
	(0.01716)	(0.0175)	(0.01666)	(0.01837)
Soft Drinks-Non-Carbonated	0.1467	0.1392	0.1975	0.1778
	(0.02813)	(0.02717)	(0.02523)	(0.02947)
Soup	0.2758	0.2658	0.2955	0.2162
	(0.01783)	(0.01851)	(0.01729)	(0.01948)
Vegetables- Canned, Dried, Frozen	0.1263	0.1355	0.1533	0.1132
	(0.01565)	(0.01614)	(0.01504)	(0.01703)
Yogurt	0.7303	0.6518	0.6222	0.5351
	(0.01972)	(0.02117)	(0.01847)	(0.02079)

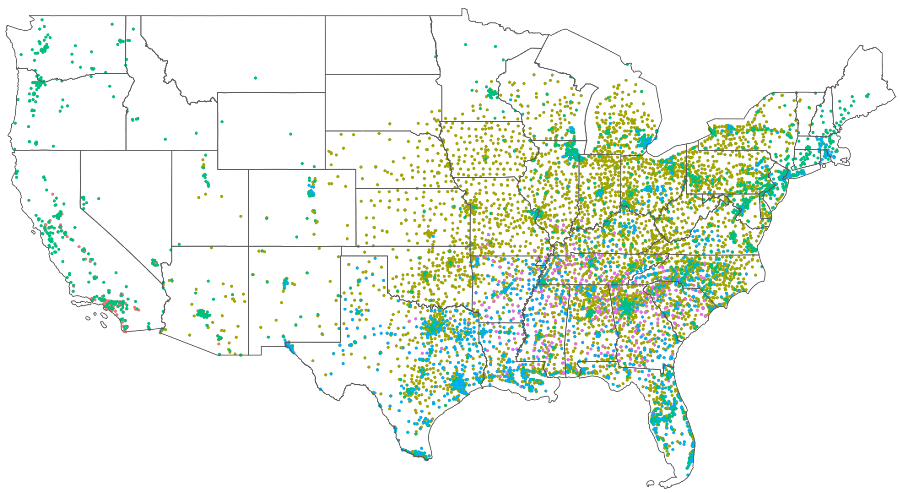
Notes: Table reports coefficients from nested-logit demand estimation where a market is a county-year-income group. The nests are the store types: dollar stores, discount stores, club stores, drug stores, convenience stores, and grocery stores. Data is based on consumer panel microdata for years 2008-2019. Income rank 1 is the lowest average income, income rank 4 has the highest average income.

A.2 Figures

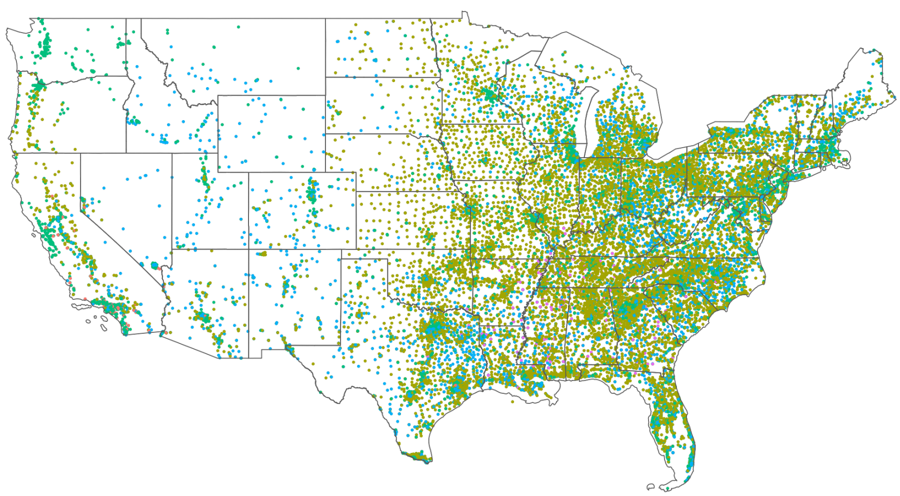
A.2.1 Descriptives

Figure A.1: Locations of Top 5 Dollar Store Chains, 2008 and 2019

(a) 2008

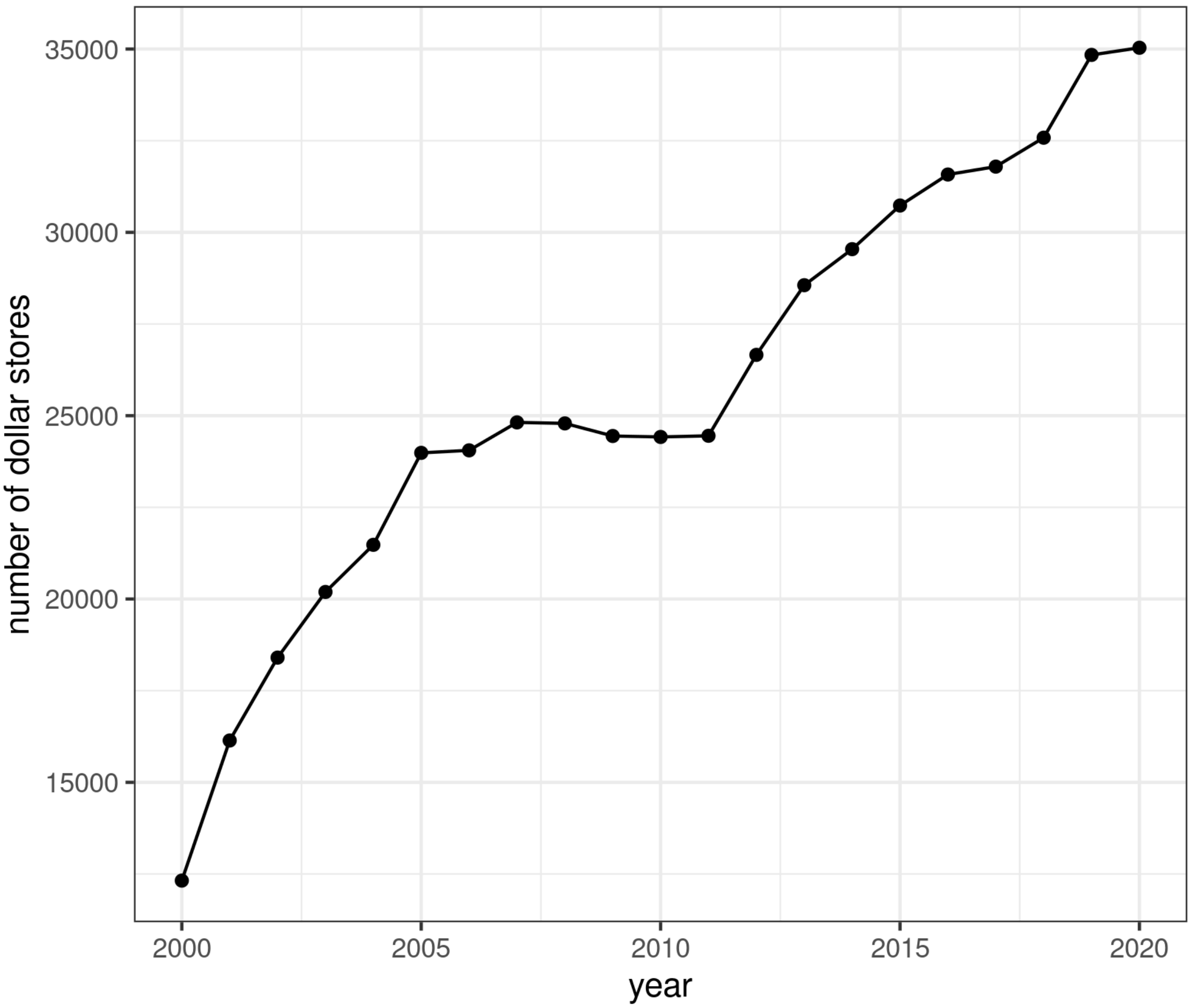


(b) 2019



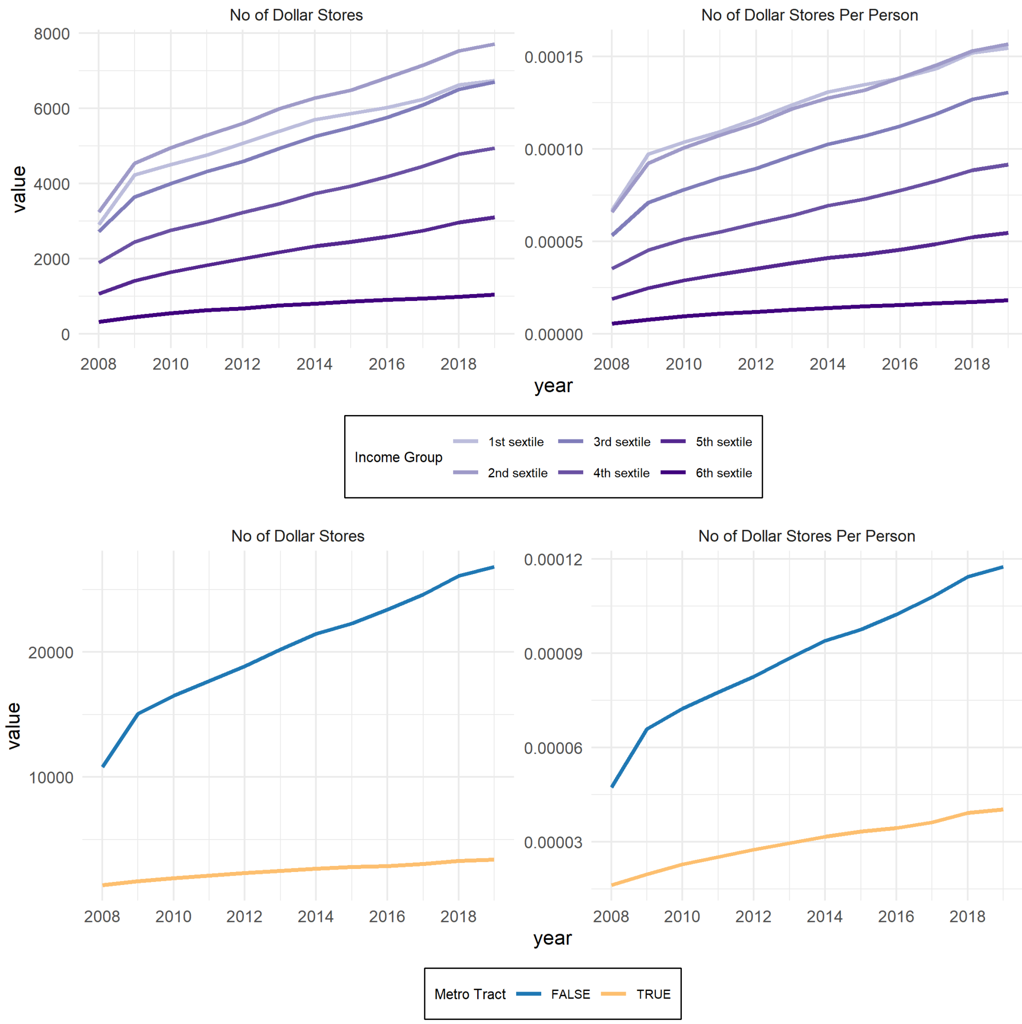
Notes: This figure shows the locations of dollar stores from the five largest chains in 2008 and 2019. The maps shows the contiguous United States. Each observation is a store, and each color corresponds to a different chain. Source: SNAP.

Figure A.2: Time Series of Dollar Stores



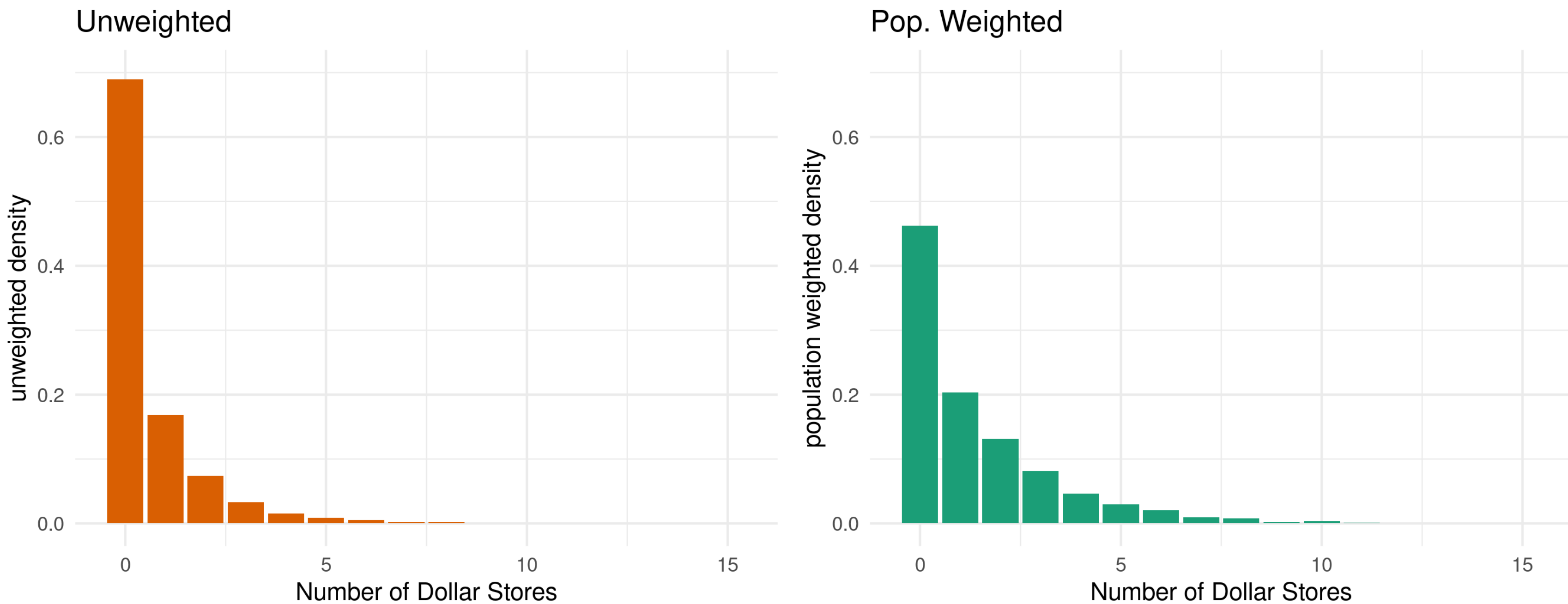
Notes: This figure shows the time series of dollar stores from the five largest chains in 2008 and 2019.

Figure A.3: Time Series of Dollar Store Growth by Income and Retail Environments



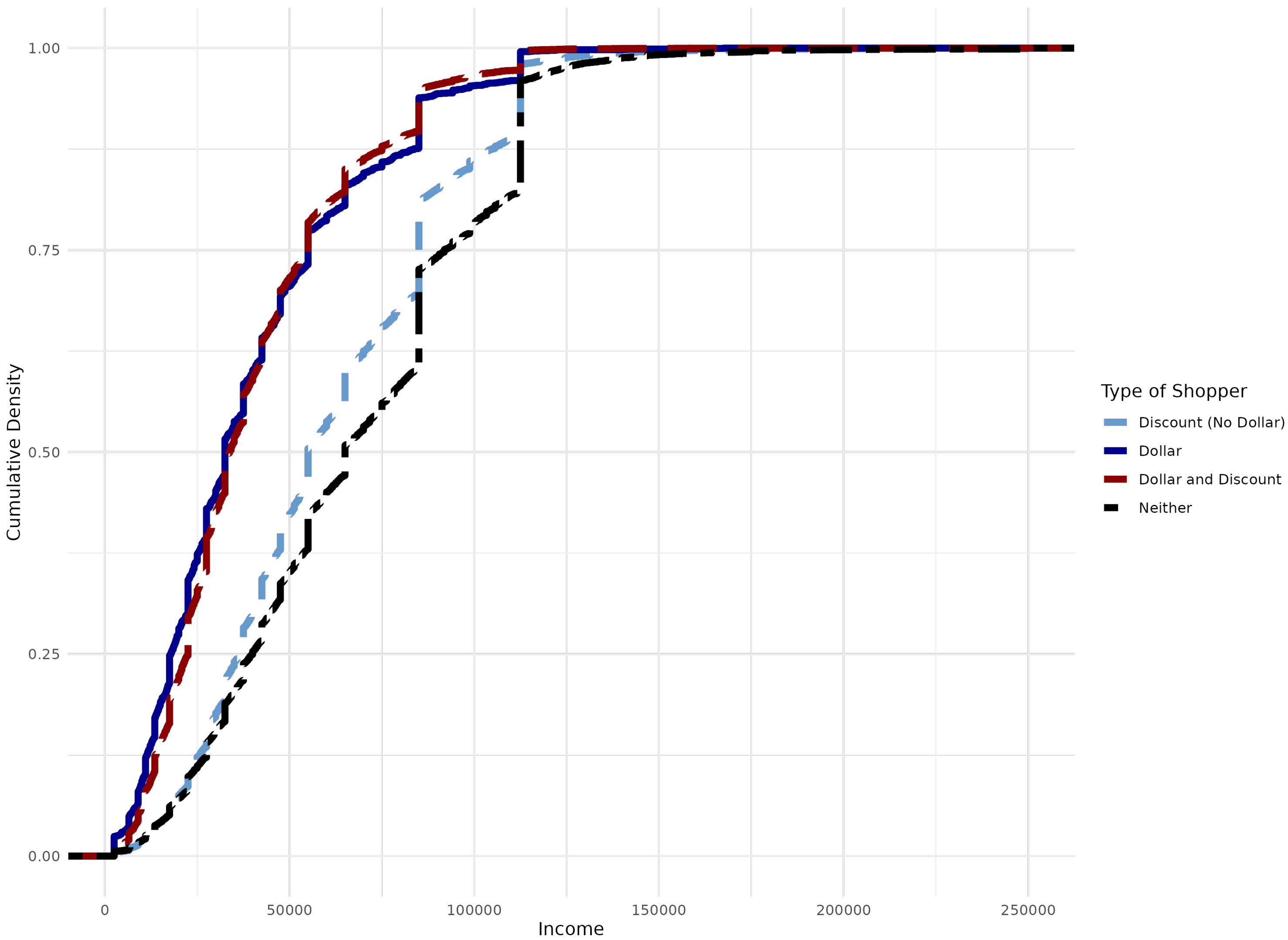
Notes: Growth of dollar stores over time by income and sparse retail environments. The top figure shows dollar store growth by income group. The bottom figure shows dollar store growth in metro and non-metro tracts.

Figure A.4: Dollar Store Density in Zip Codes



Notes: The figure plots current dollar store density unweighted (a) and weighted (b) by population. Each observation is a zip code. The modal zip code does not have a dollar store (69% of zip codes when zips are not populated-weighted, 45% of population-weighted zip codes). The modal zip code with at least one dollar store has only one dollar store (60% of unweighted zip codes, 36% of weighted zip codes).

Figure A.5: Income Distribution by Where Households Shop

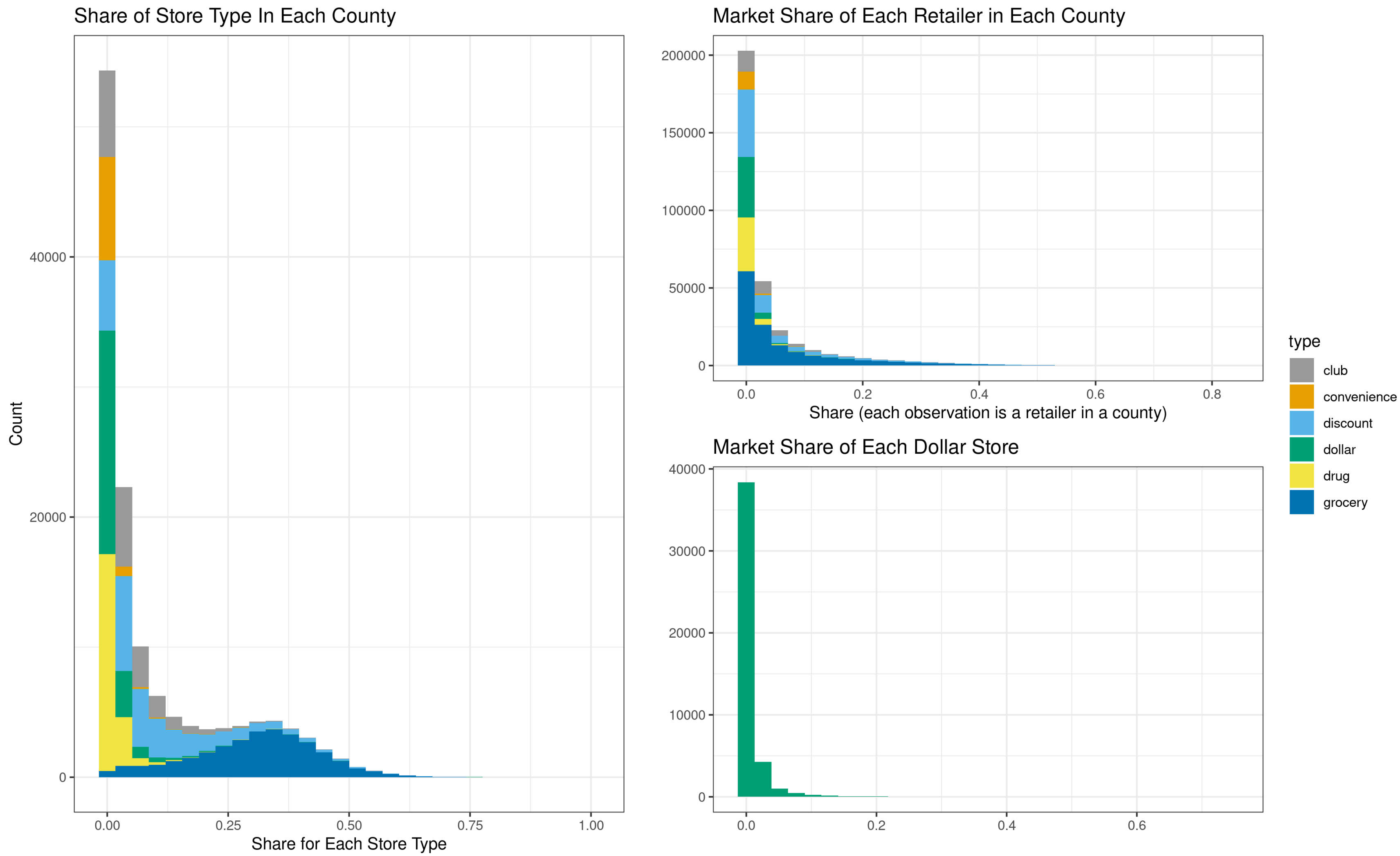


Notes: Figure reports CDF of the household income. The income distributions are broken out by shopper type. Dollar store shoppers are those that spent more than 5% of expenditures that year at dollar stores, and analogously for discount shoppers. Data is based on consumer panel microdata for years 2008-2019.

Figure A.6: Department Level Expenditure Shares by Store Type

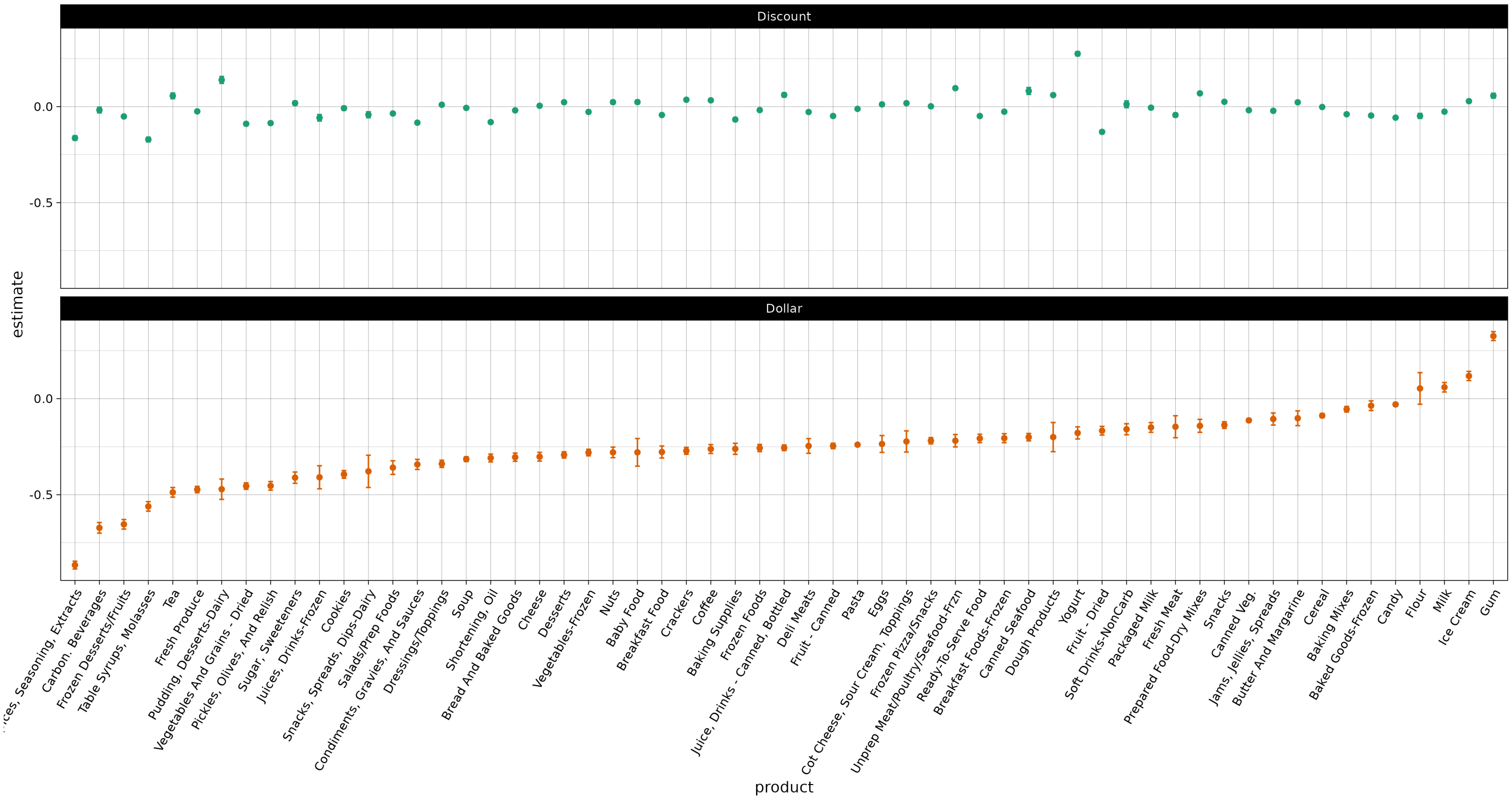
Notes: Figure reports shares by store type broken down by department, using 2008-2018 Homescan data.

Figure A.7: Share of Each Store Type in each County-Year



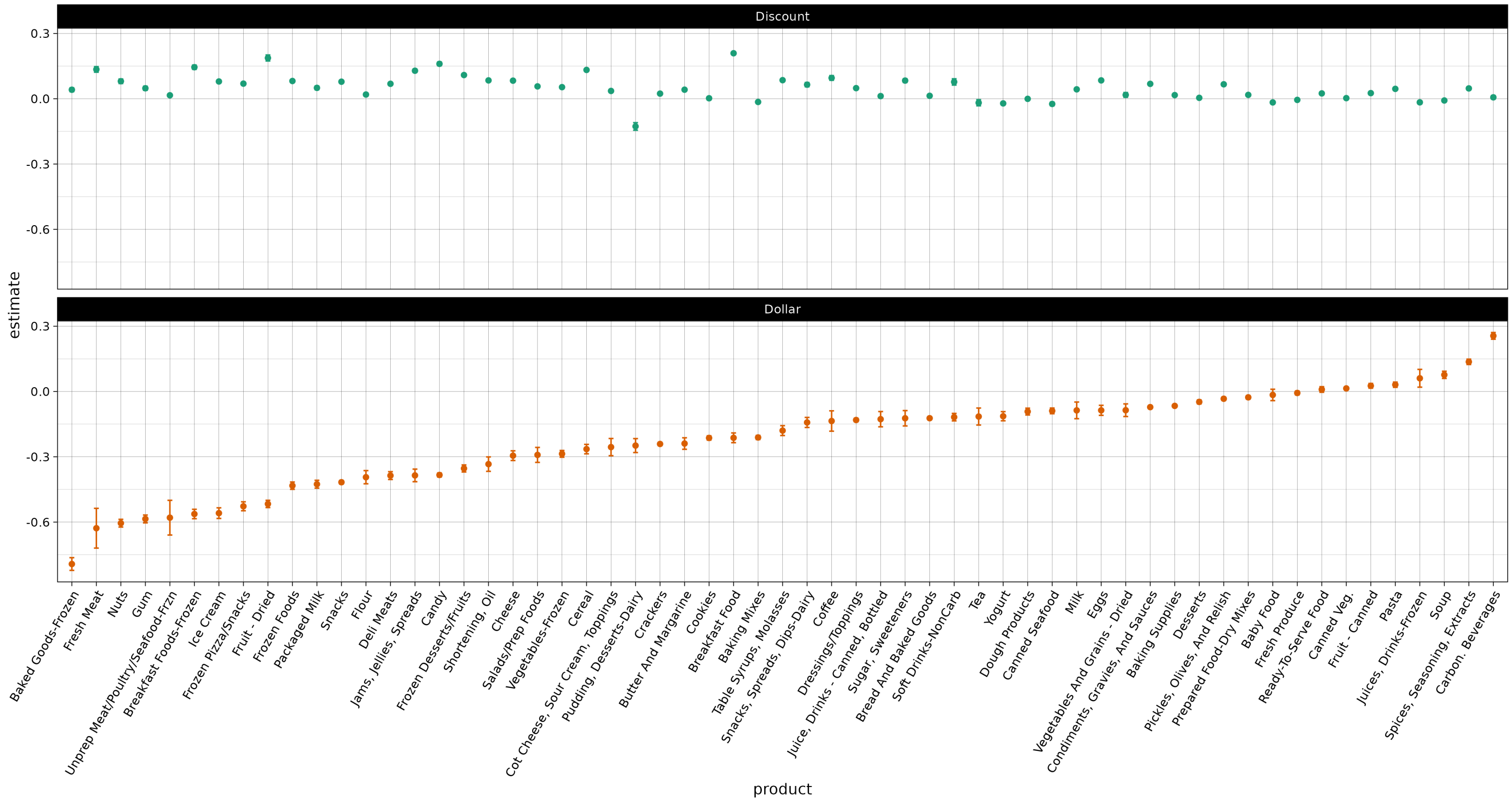
Notes: Total quantity shares for each store type in each county, as measured as ounces of product from one store type as a fraction of the total ounces of food products sold in the county. Data comes from the NielsenIQ Homescan panel (2008-2019).

Figure A.8: Price Per Unit Effects By Product Group



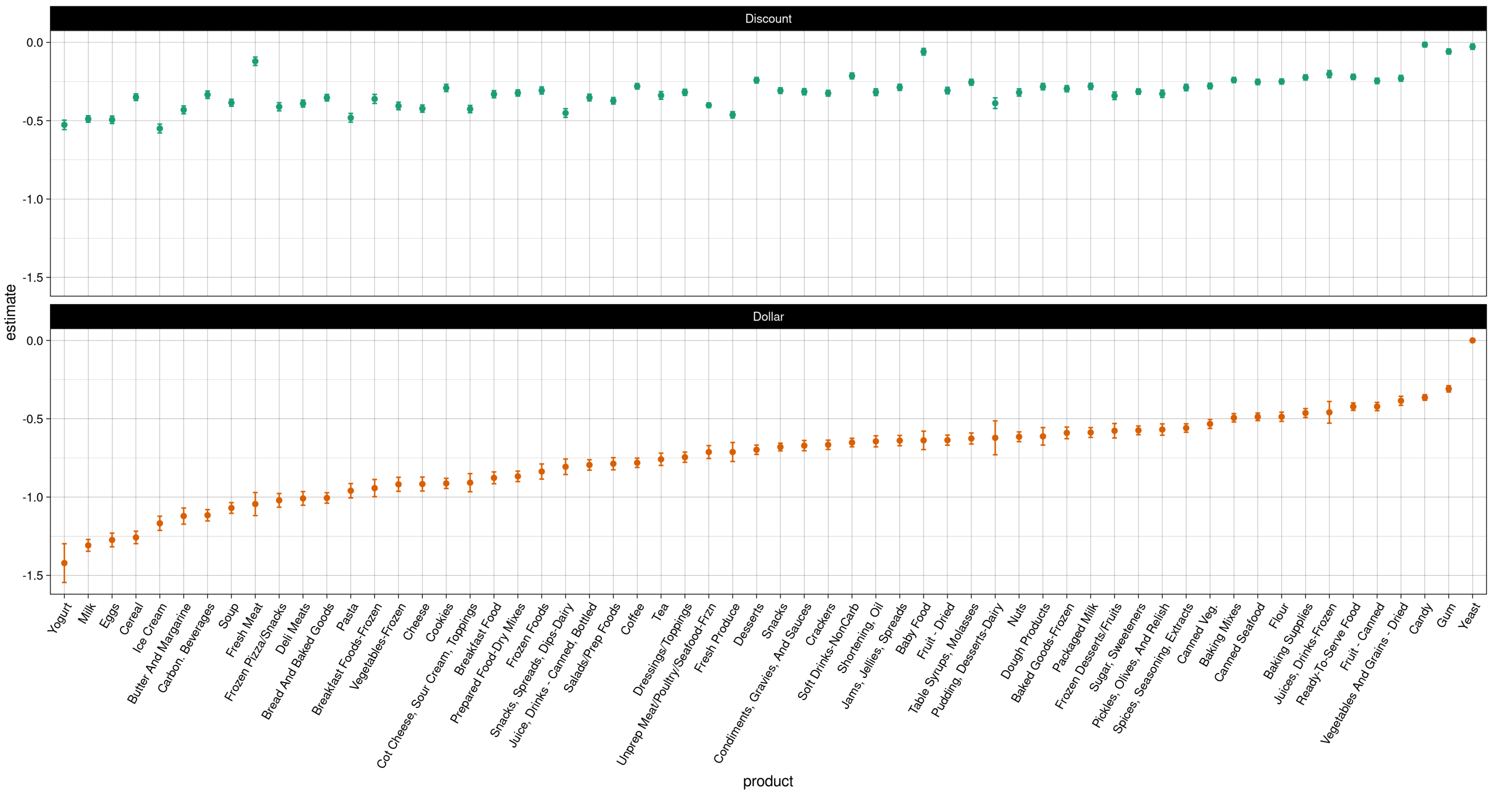
Notes: Figure reports coefficients and 95% confidence interval from regression of log price per unit of a good on store type, with county by product module by month-year fixed effects, broken out by product groups. We only use sales from dollar stores, discount stores, grocery stores, club/superstores, and drug/convenience stores. All stores other than dollar stores and discount stores are lumped into one group and used as the reference group for the regressions. Data is based on consumer panel microdata for years 2008-2018. Standard errors are clustered at the county level.

Figure A.9: Size Effects By Product Group



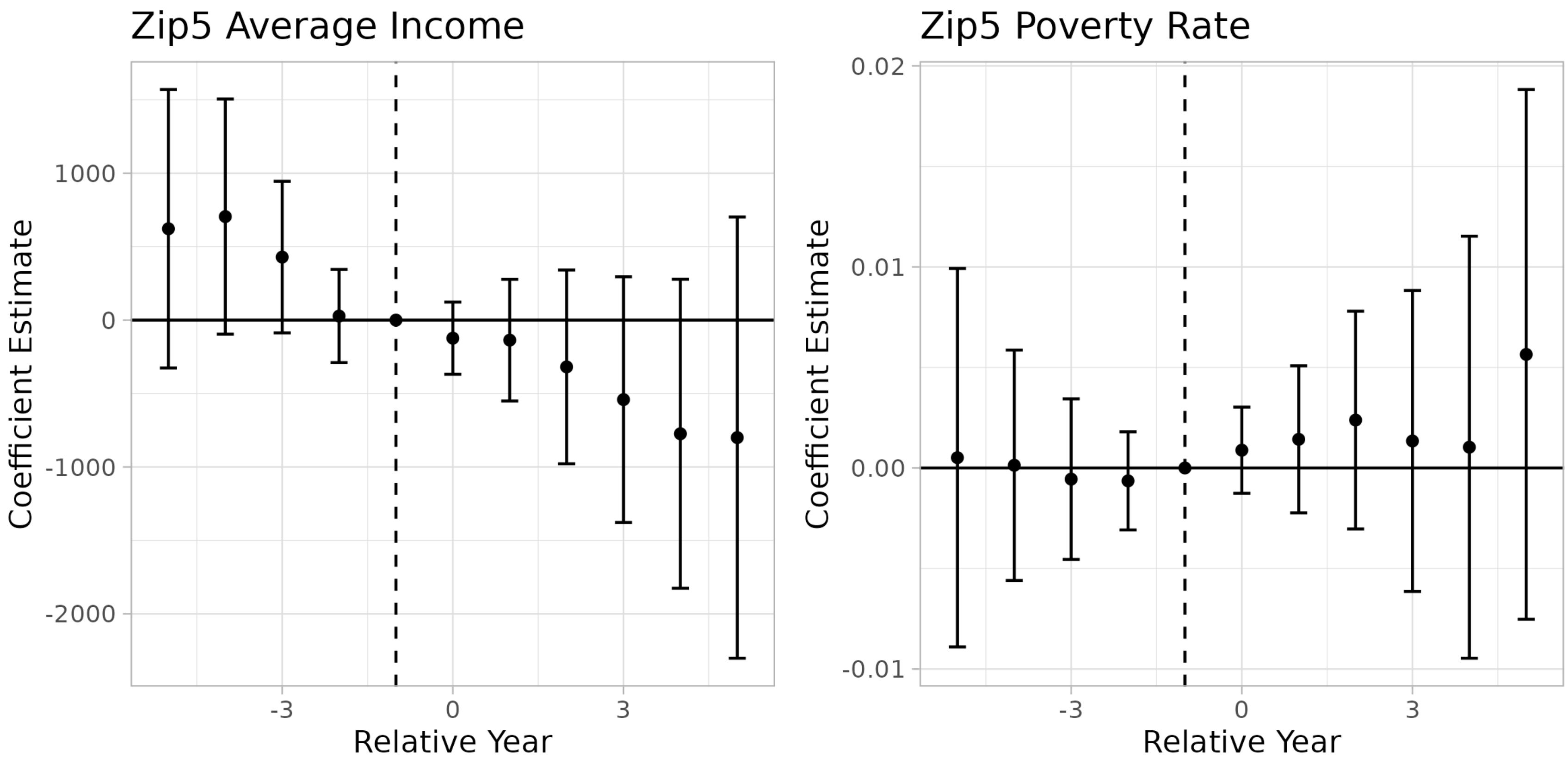
Notes: Figure reports coefficients and 95% confidence interval from regression of log size per unit of a good on store type, with county by product module by month-year fixed effects, broken out by product groups. We only use sales from dollar stores, discount stores, grocery stores, club/superstores, and drug/convenience stores. All stores other than dollar stores and discount stores are lumped into one group and used as the reference group for the regressions. Data is based on consumer panel microdata for years 2008-2018. Standard errors are clustered at the county level.

Figure A.10: Variety Effects By Product Group



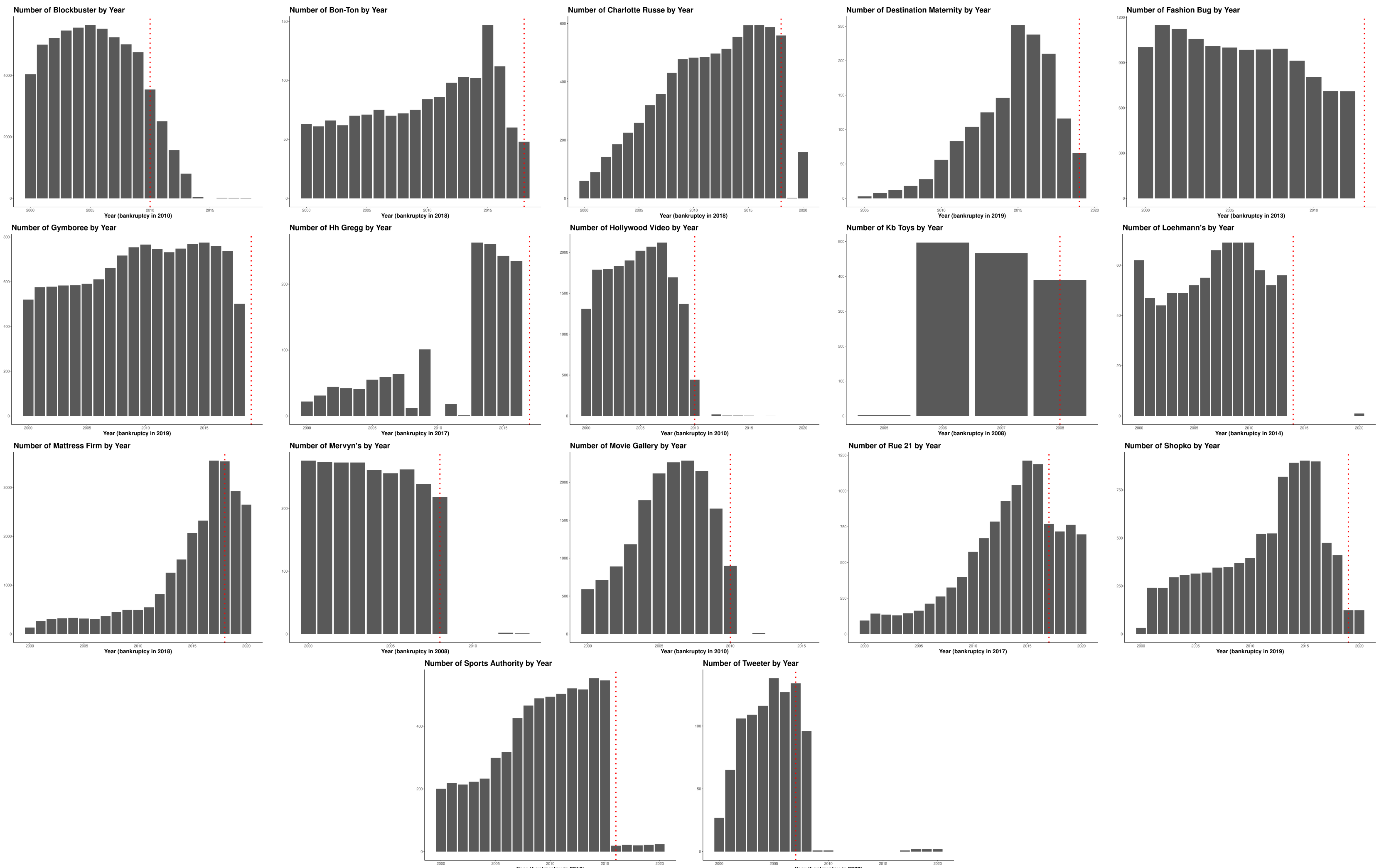
Notes: Figure reports coefficients and 95% confidence interval from regression of log size per unit of a good on store type, with county by product module by month-year fixed effects, broken out by product groups. We only use sales from dollar stores, discount stores, grocery stores, club/superstores, and drug/convenience stores. All stores other than dollar stores and discount stores are lumped into one group and used as the reference group for the regressions. Data is based on consumer panel microdata for years 2008-2018. Standard errors are clustered at the county level.

Figure A.11: Dollar Store Entry on Household Income



Notes: Figure reports event study estimates of impact on household income with 95% confidence intervals from Equation 5, using 5-year average zipcode income data using American Community Survey Data. The analysis uses a heterogeneity-robust estimator proposed by Callaway and Sant'Anna (2021). Observations are not weighted for national representativeness. Errors are clustered at the zipcode level.

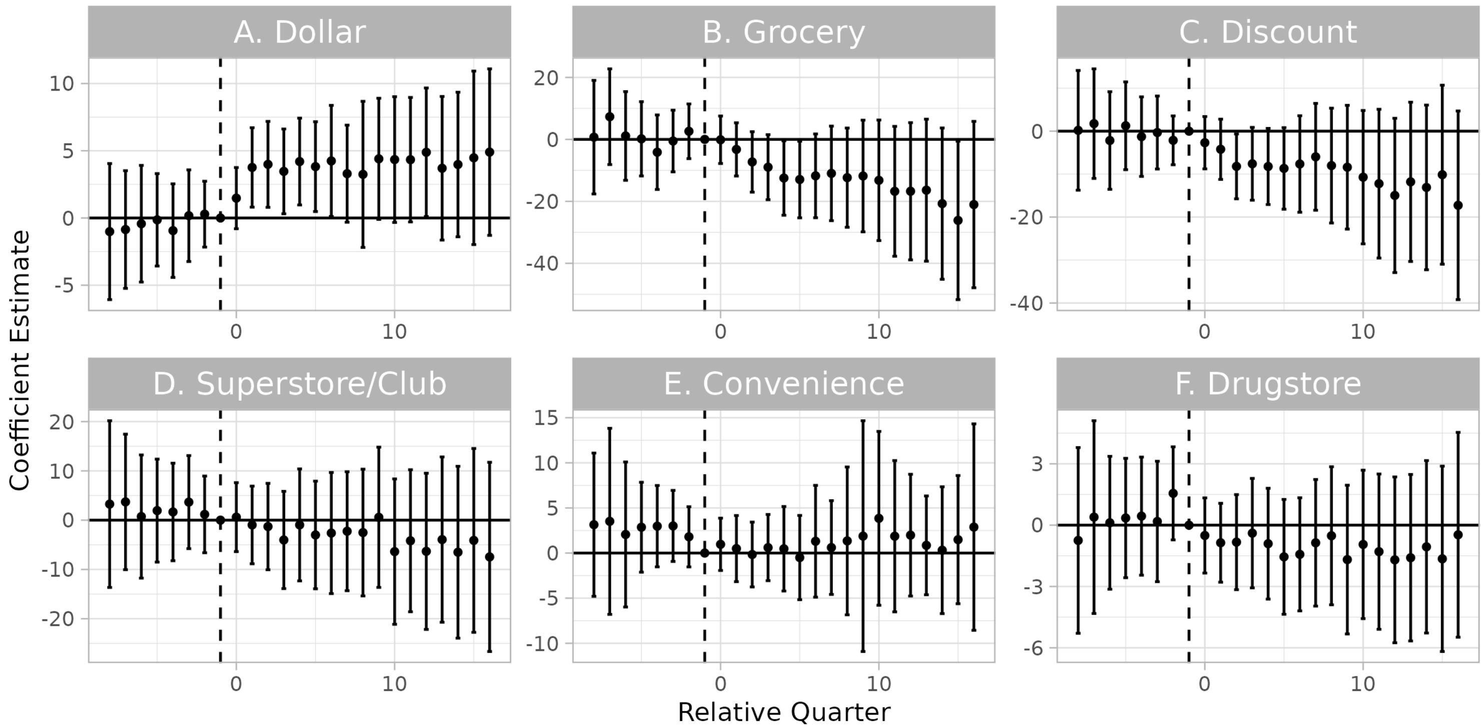
Figure A.12: Store counts by year for each retailer used to compute the retail bankruptcy instrument.



Notes: Figure reports store counts for non-food retailers that went bankrupt throughout the 2010s. Source: Infogroup Historic Data File, 2000-2020.

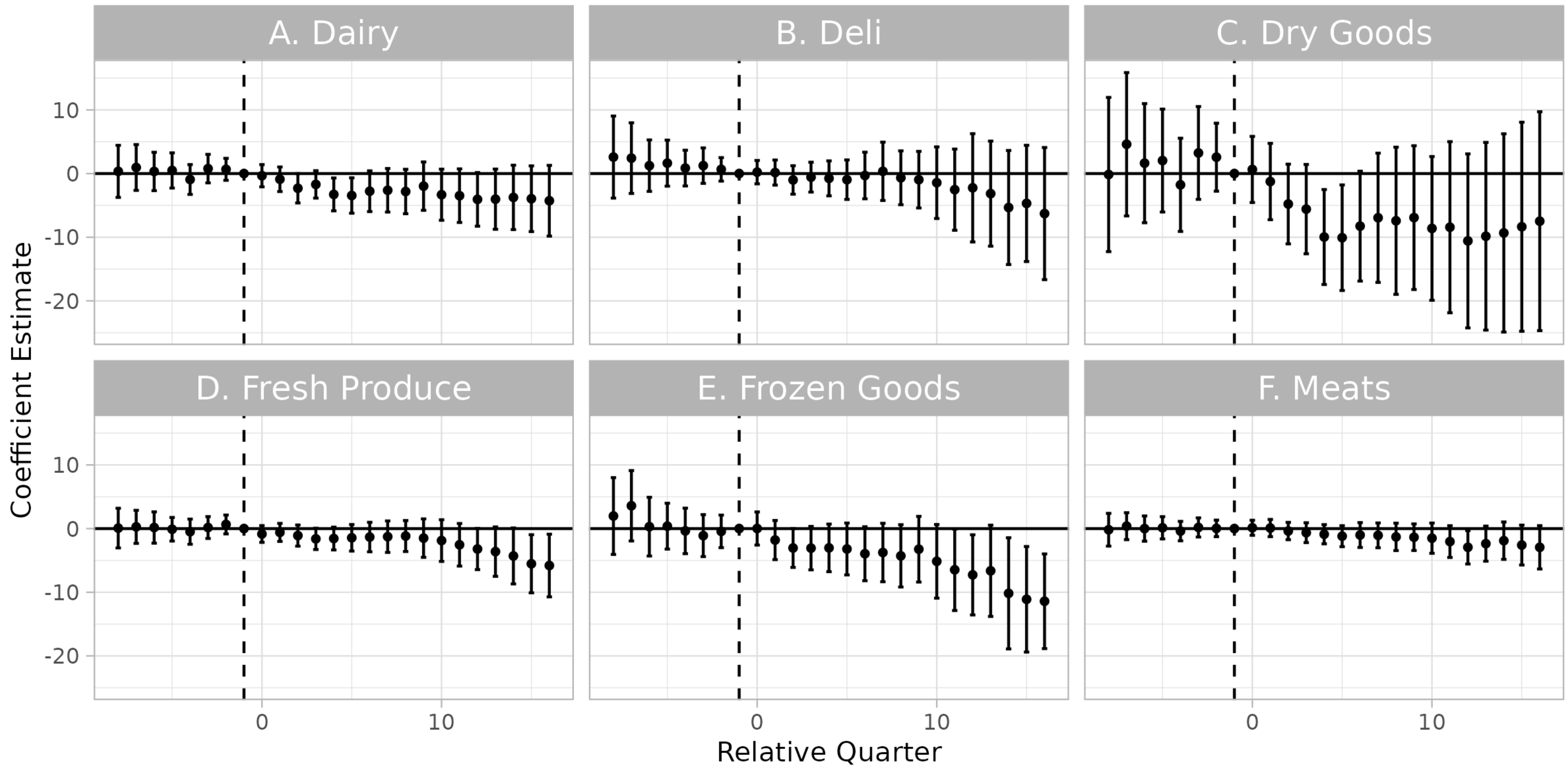
A.2.2 Effect of Dollar Store Entry on Expenditure, Prices, and Quantities

Figure A.13: Dollar Store Entry on Expenditures by Store Type



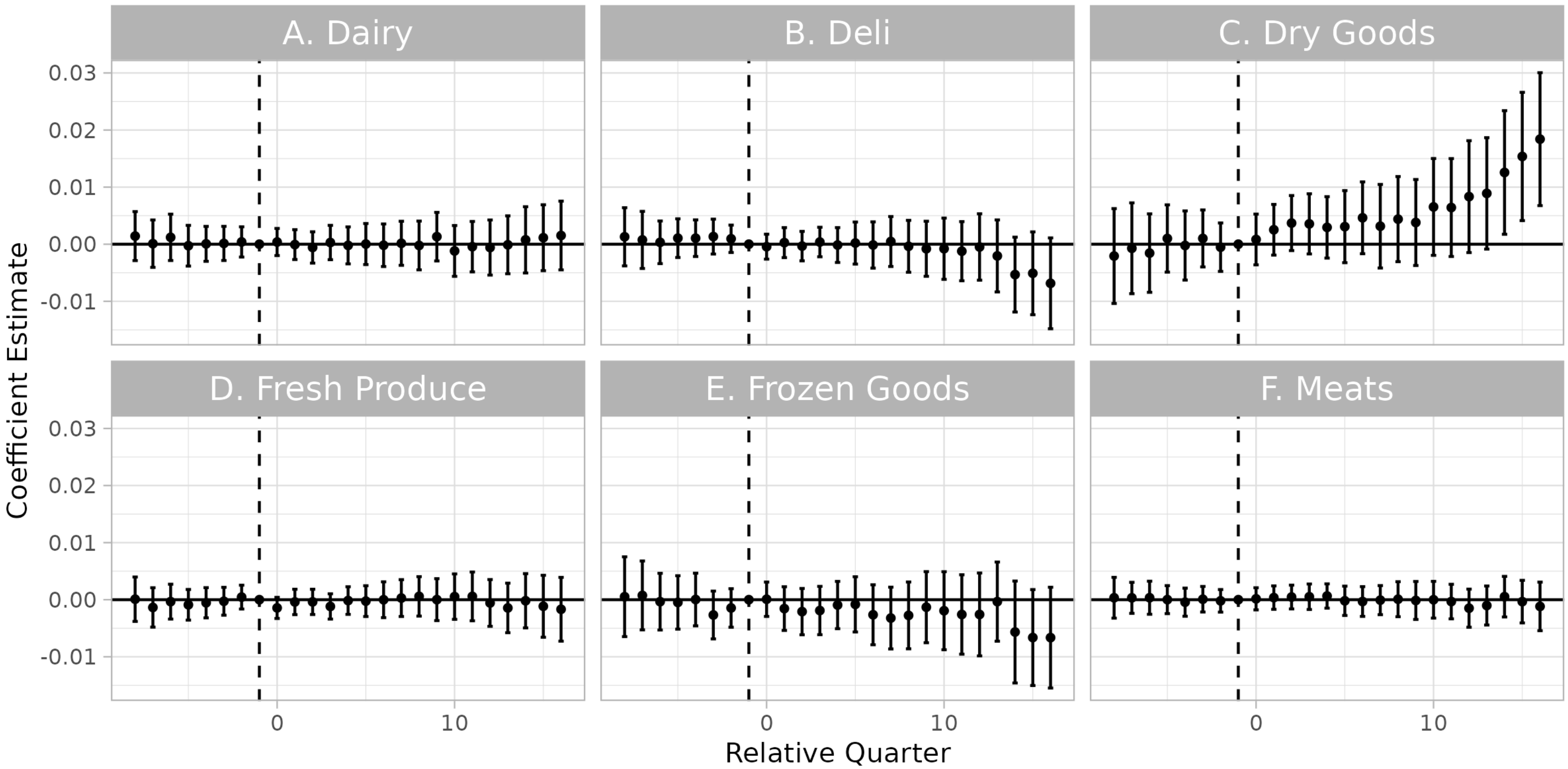
Notes: Figure reports event study estimates of impact on store-level expenditures with 95% confidence intervals from Equation 5, using 2008-2018 Homescan data. The analysis uses a heterogeneity-robust estimator proposed by Callaway and Sant'Anna (2021). Observations are not weighted for national representativeness. Errors are clustered at the zipcode level.

Figure A.14: Dollar Store Entry on Department Expenditure



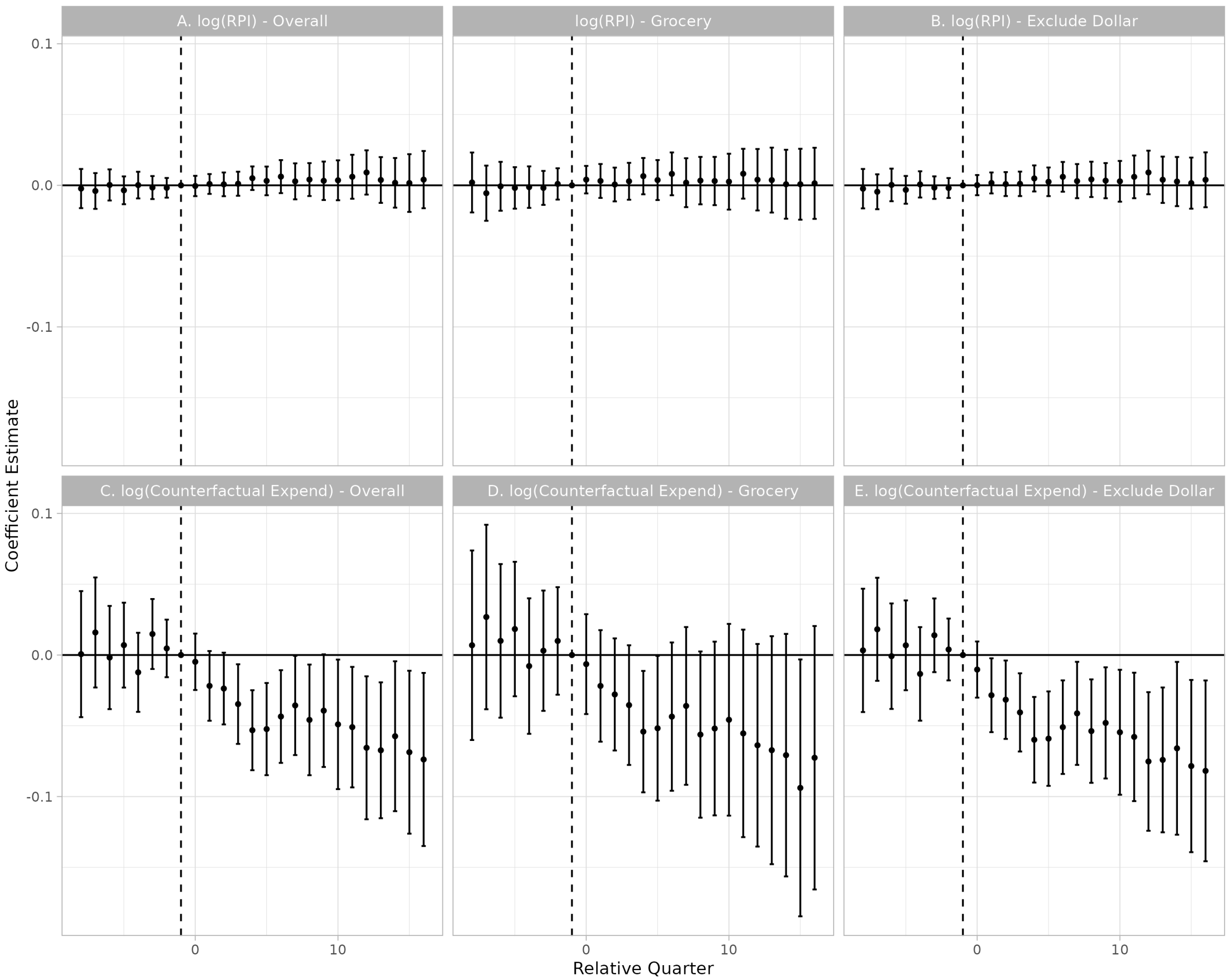
Notes: Figure reports event study estimates with 95% confidence intervals from Equation 5, using 2008-2018 Homescan data. The analysis uses a heterogeneity-robust estimator proposed by Callaway and Sant'Anna (2021). The dependent variables here are different definitions for consumption bundle variety for the household at the quarter-year level. Observations are not weighted for national representativeness. Errors are clustered at the zipcode level.

Figure A.15: Dollar Store Entry Fraction of Department Expenditure



Notes: Figure reports event study estimates with 95% confidence intervals from Equation 5, using 2008-2018 Homescan data. The analysis uses a heterogeneity-robust estimator proposed by Callaway and Sant'Anna (2021). The dependent variables here are different definitions for consumption bundle variety for the household at the quarter-year level. Observations are not weighted for national representativeness. Errors are clustered at the zipcode level.

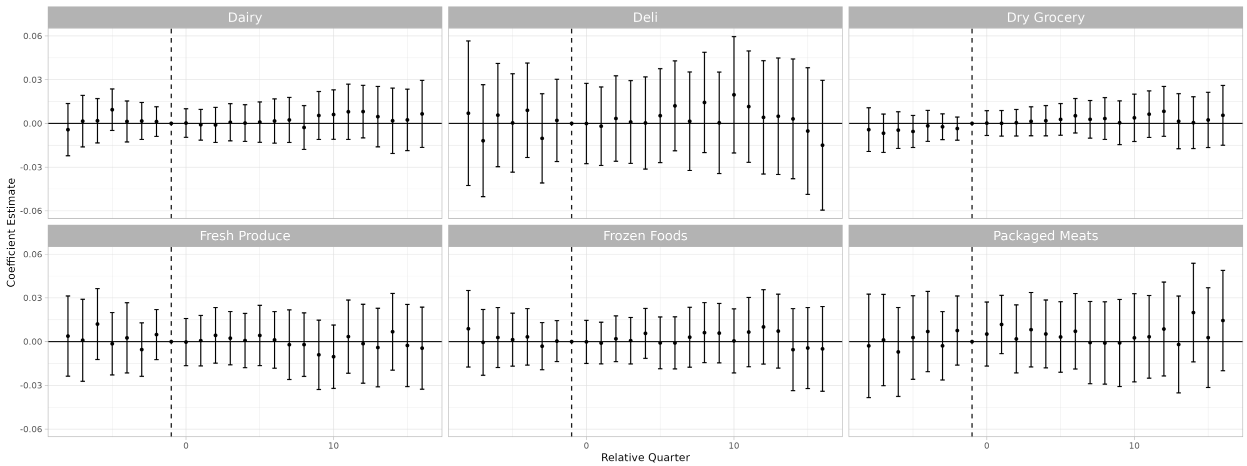
Figure A.16: Effect of Dollar Store Entry on Log Relative Price Index and Counterfactual Expenditure



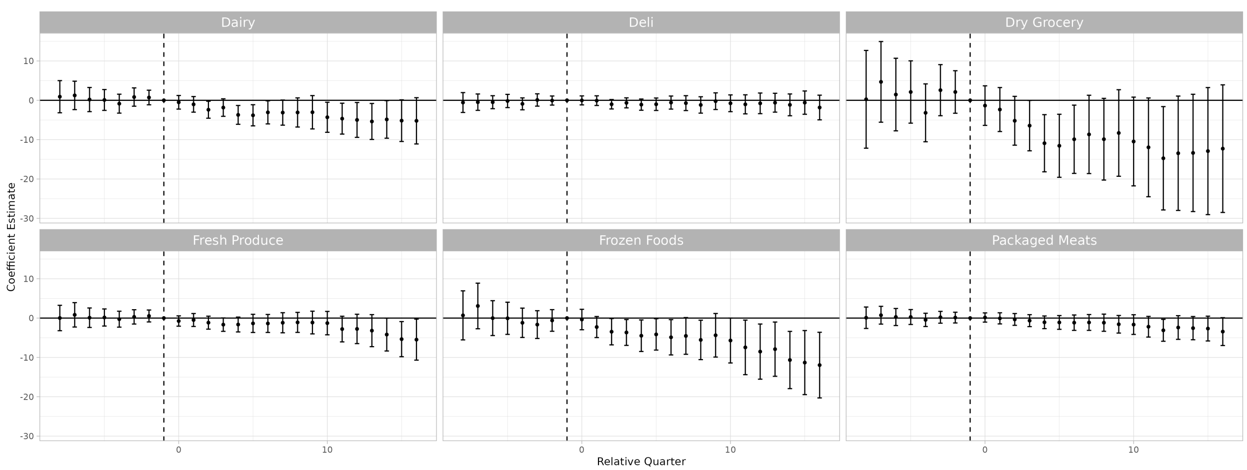
Notes: Figure reports event study estimates with 95% confidence intervals from Equation 5, using 2008-2019 Homescan data. The analysis uses a heterogeneity-robust estimator proposed by Callaway and Sant'Anna (2021). Observations are not weighted for national representativeness. Errors are clustered at the zipcode level. The state is used to calculate the average reference price.

Figure A.17: Effect of Dollar Store Entry on Department Relative Price Index and Counterfactual Expenditure

(a) Relative Price Index

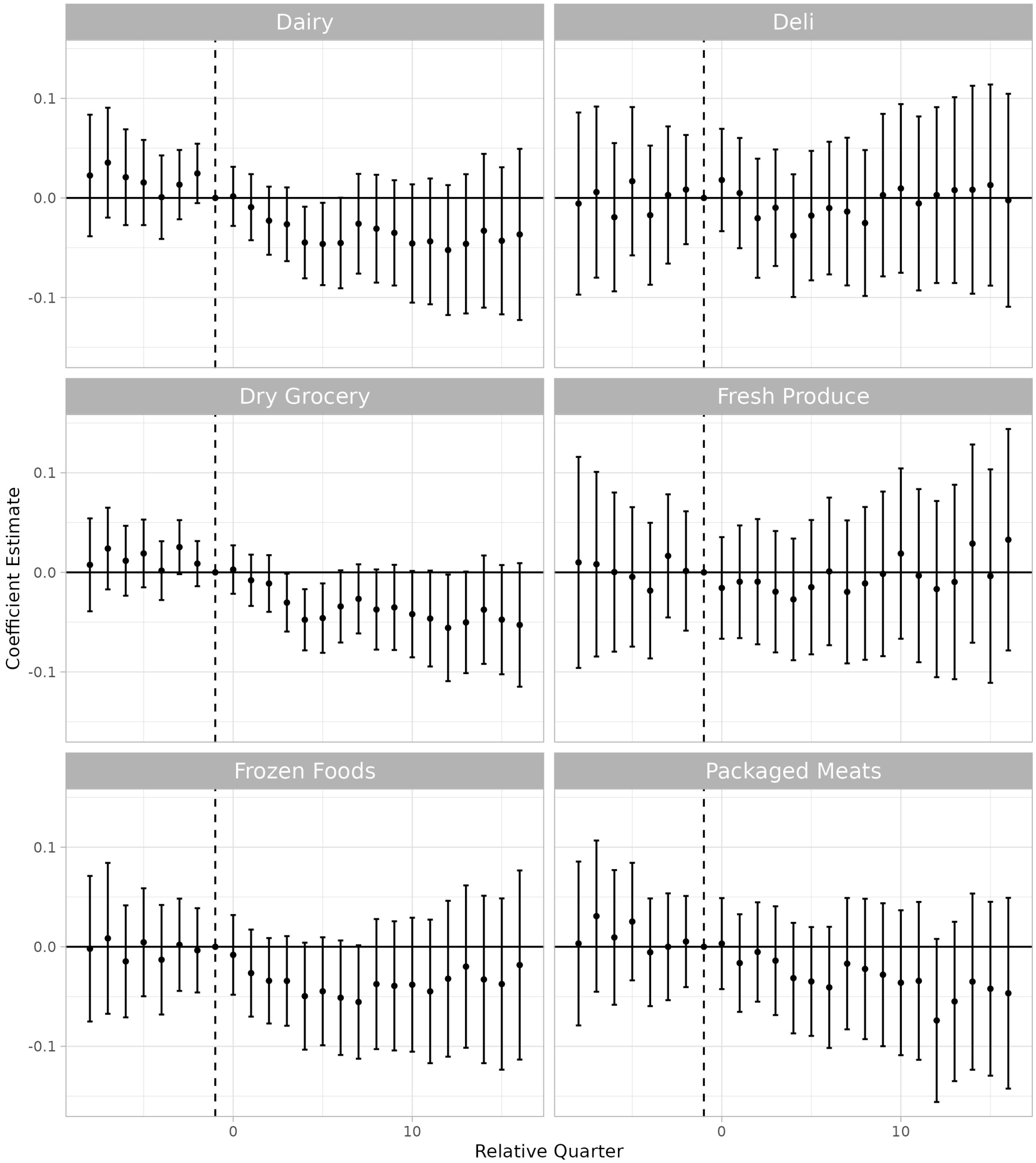


(b) Counterfactual Expenditure



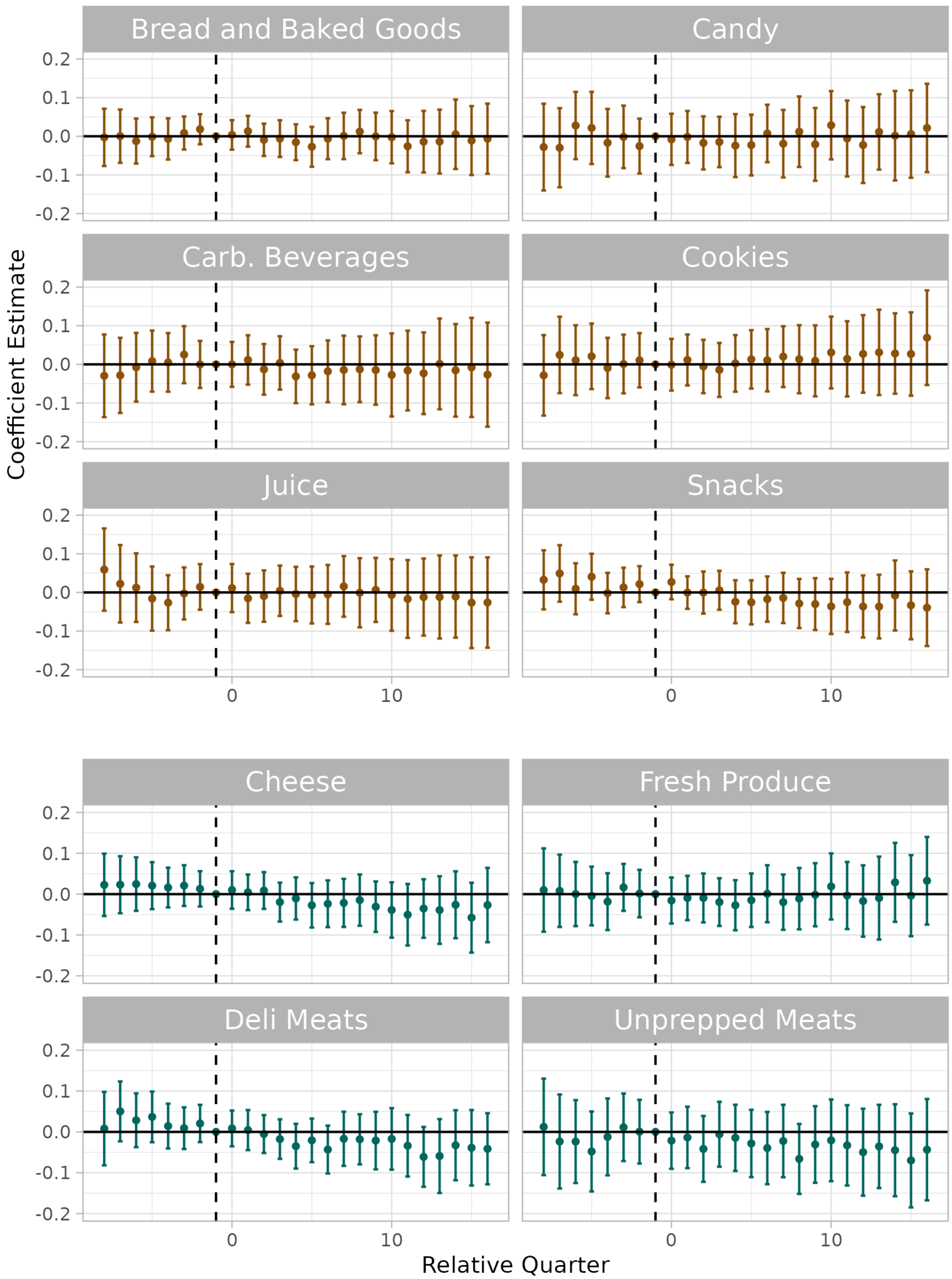
Notes: Figure reports event study estimates with 95% confidence intervals from Equation 5, using 2008-2019 Homescan data. The analysis uses a heterogeneity-robust estimator proposed by Callaway and Sant'Anna (2021). Observations are not weighted for national representativeness. Errors are clustered at the zipcode level. The county is used to calculate the average reference price.

Figure A.18: Effect of Dollar Store Entry on Department Log Ounces



Notes: Figure reports event study estimates with 95% confidence intervals from Equation 5, using 2008-2019 Homescan data. The analysis uses a heterogeneity-robust estimator proposed by Callaway and Sant'Anna (2021). Observations are not weighted for national representativeness. Errors are clustered at the zipcode level.

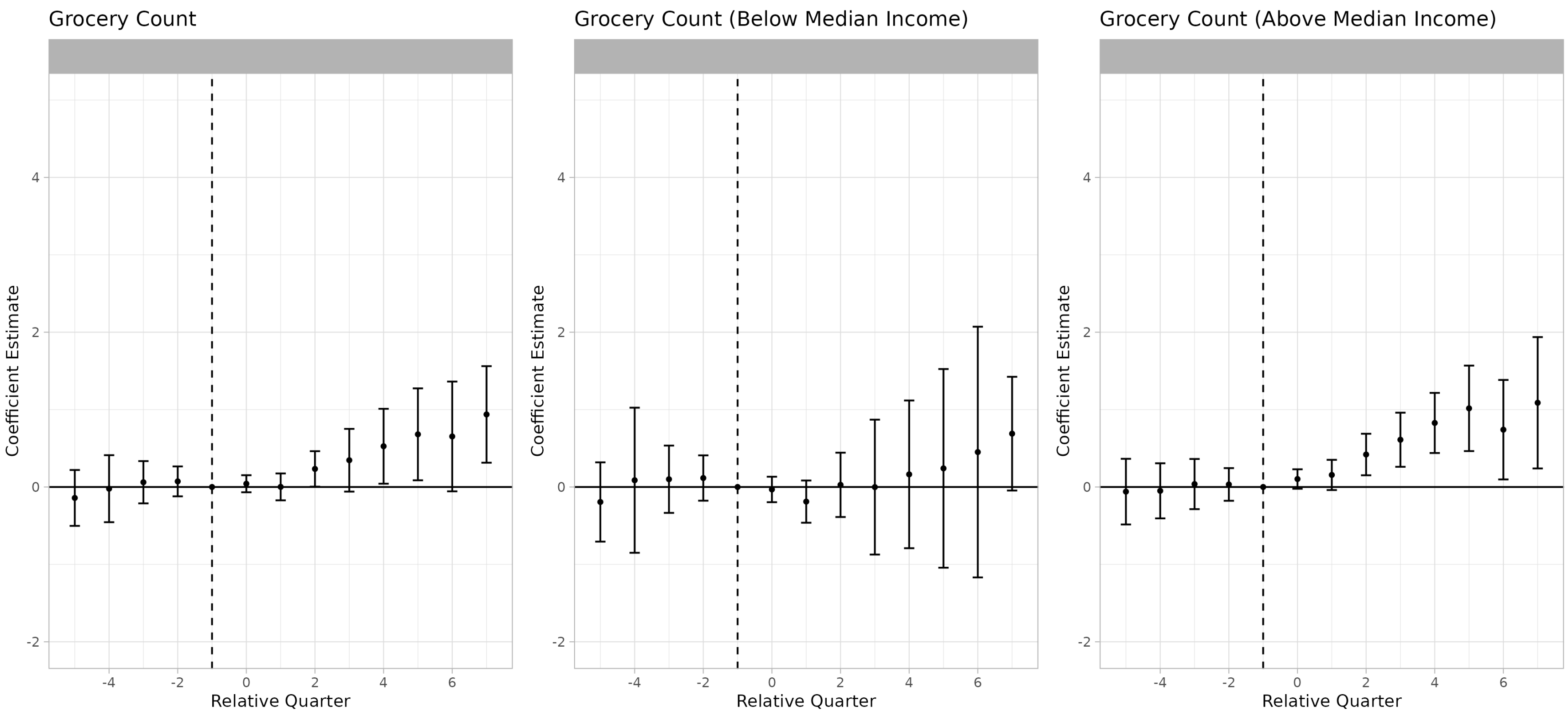
Figure A.19: Effect of Dollar Store Entry on Product Group Log Ounces



Notes: Figure reports event study estimates with 95% confidence intervals from Equation 5, using 2008-2019 Homescan data. The analysis uses a heterogeneity-robust estimator proposed by Callaway and Sant'Anna (2021). Observations are not weighted for national representativeness. Errors are clustered at the zipcode level.

A.2.3 Effect of Dollar Store Entry on Local Retail

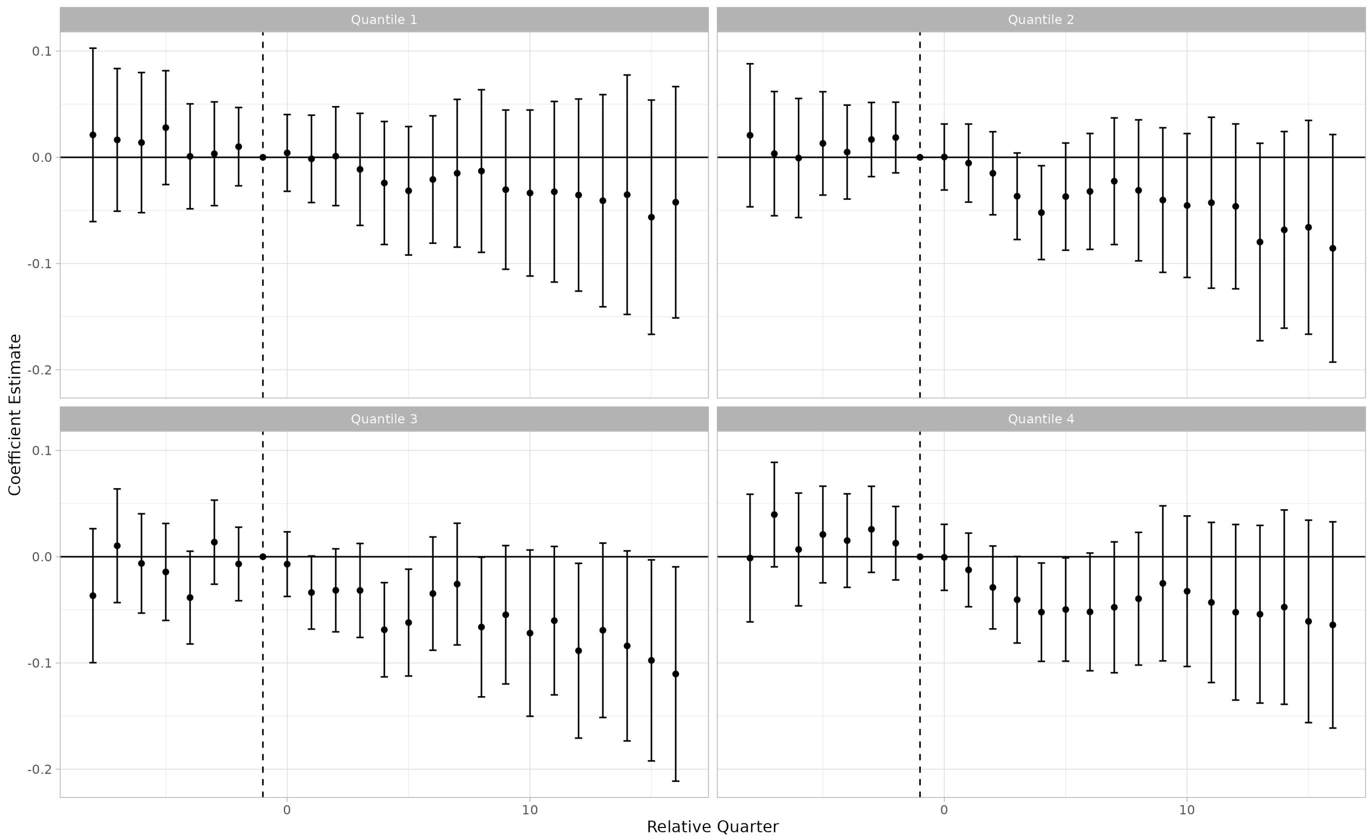
Figure A.20: Dollar Store Entry on Grocery Count: No Demographic Controls



Notes: Figure reports event study estimates with 95% confidence intervals from Equation 4, using 2008-2018 SNAP and ZBP data. The analysis uses a heterogeneity-robust estimator proposed by Callaway and Sant'Anna (2021). The figure reports the grocery count as the outcome variable. Errors are clustered at the zip code level.

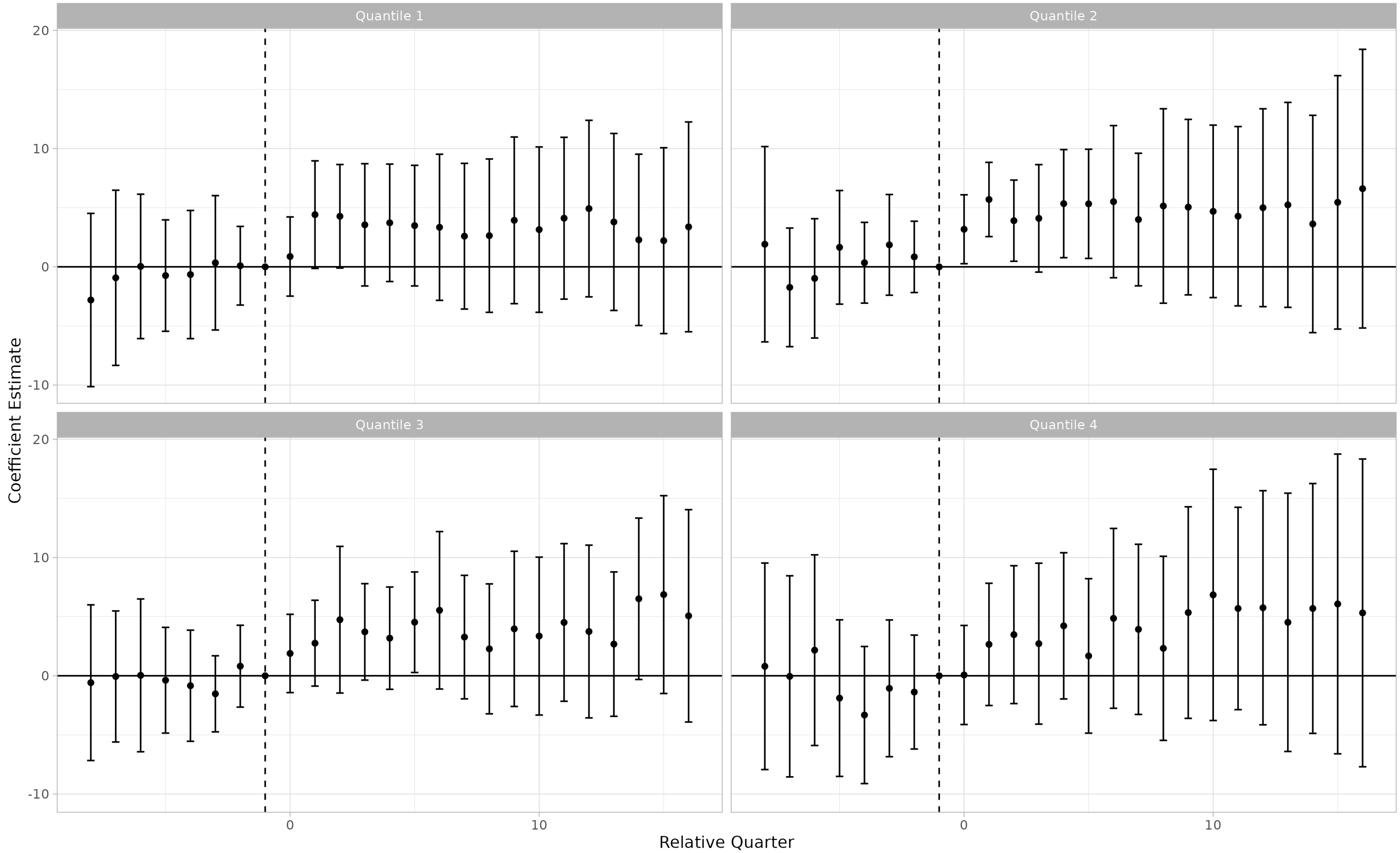
A.2.4 The Effect of Dollar Store Entry by Income Group

Figure A.21: Log Total Expenditure by Income



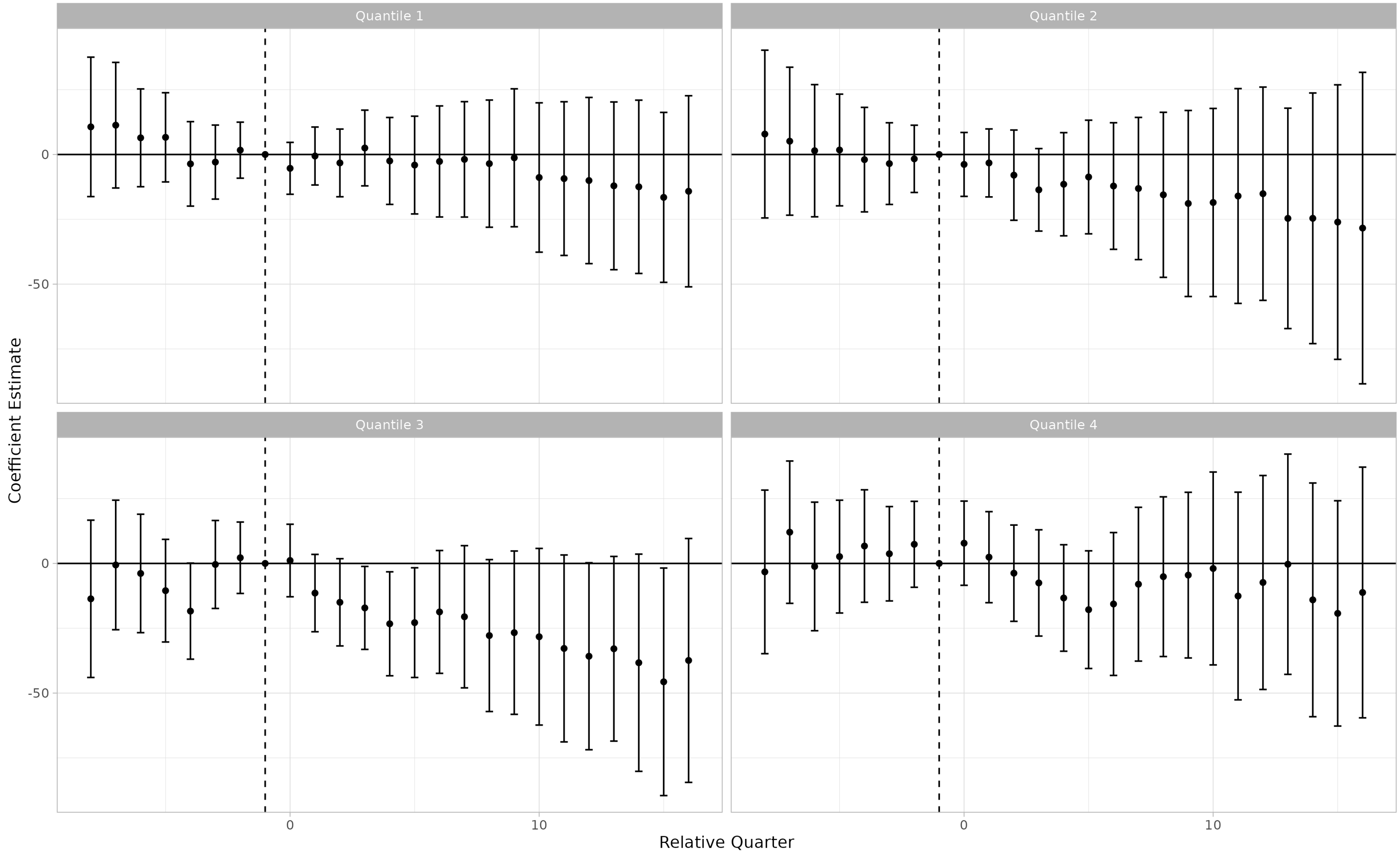
Notes: Figure reports event study estimates with 95% confidence intervals from Equation 5, using 2008-2019 Homescan data. The analysis uses a heterogeneity-robust estimator proposed by Callaway and Sant'Anna (2021). Observations are not weighted for national representativeness. Errors are clustered at the zipcode level. Income Rank 1 is the lowest income, Rank 4 is the highest income.

Figure A.22: Dollar Store Log Total Food Expenditure by Income



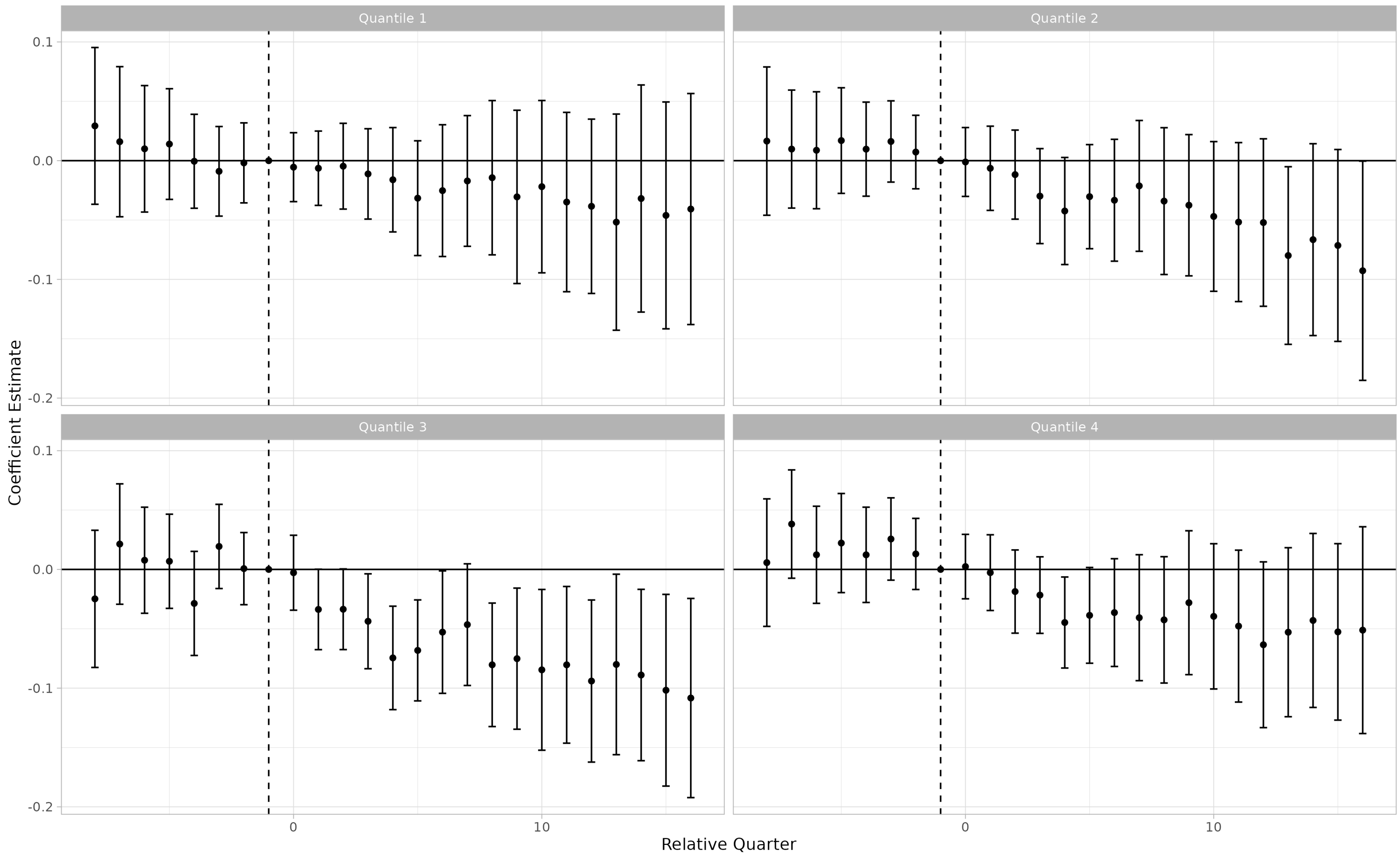
Notes: Figure reports event study estimates with 95% confidence intervals from Equation 5, using 2008-2019 Homescan data. The analysis uses a heterogeneity-robust estimator proposed by Callaway and Sant'Anna (2021). Observations are not weighted for national representativeness. Errors are clustered at the zipcode level. Income Rank 1 is the lowest income, Rank 4 is the highest income.

Figure A.23: Grocery Store Log Total Food Expenditure by Income



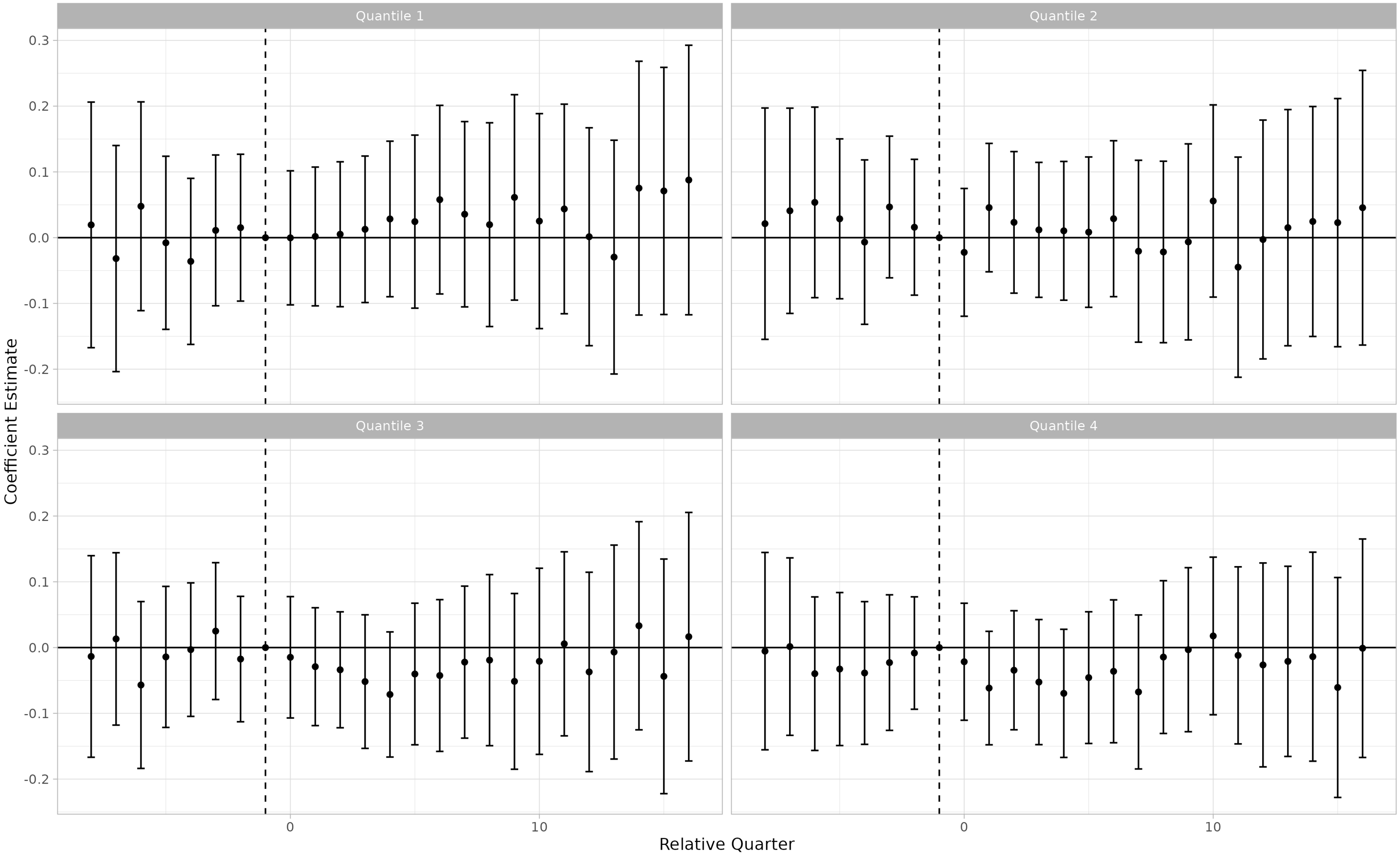
Notes: Figure reports event study estimates with 95% confidence intervals from Equation 5, using 2008-2019 Homescan data. The analysis uses a heterogeneity-robust estimator proposed by Callaway and Sant'Anna (2021). Observations are not weighted for national representativeness. Errors are clustered at the zipcode level. Income Rank 1 is the lowest income, Rank 4 is the highest income.

Figure A.25: Log Number of Unique Varieties by Income



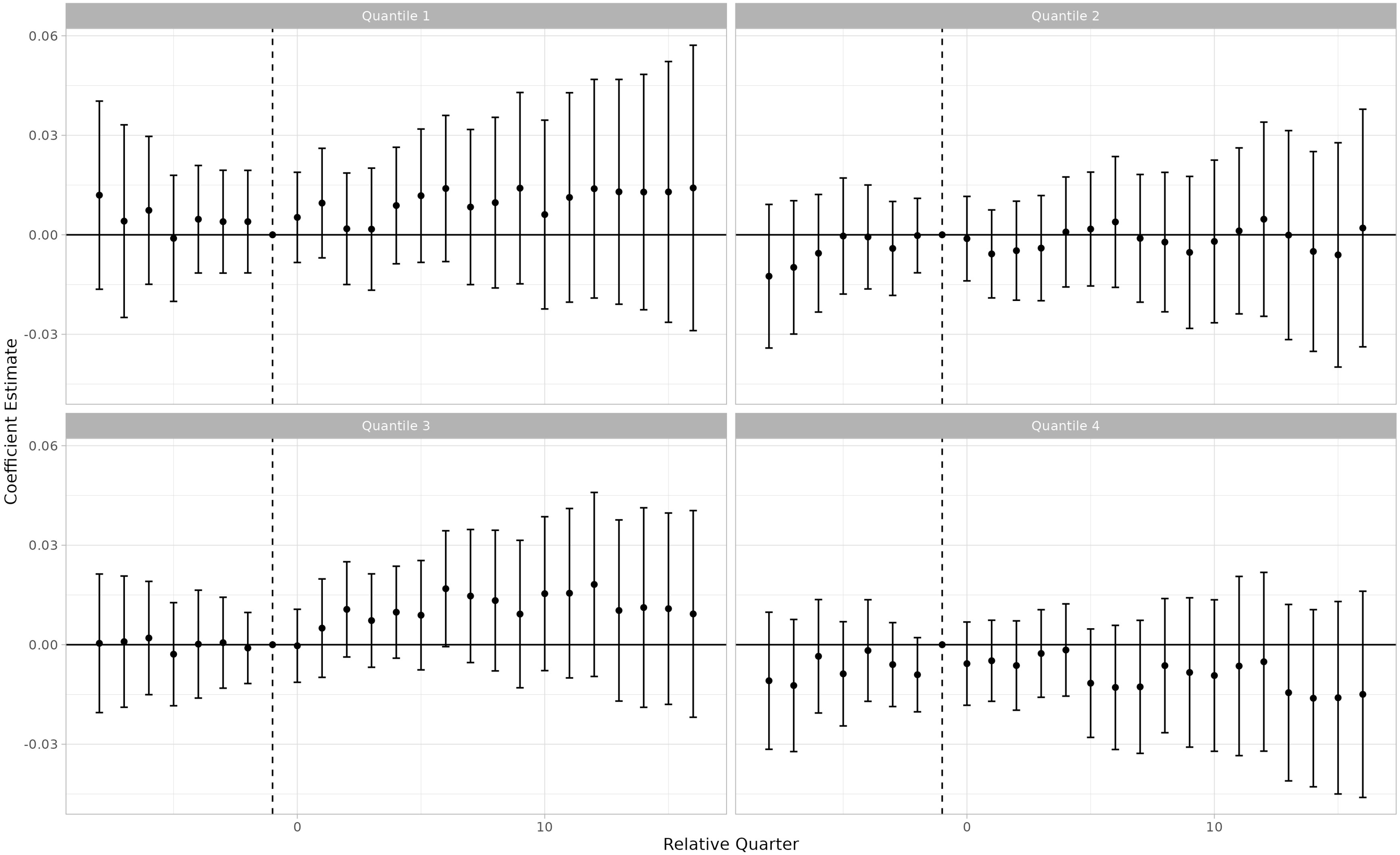
Notes: Figure reports event study estimates with 95% confidence intervals from Equation 5, using 2008-2019 Homescan data. The analysis uses a heterogeneity-robust estimator proposed by Callaway and Sant'Anna (2021). Observations are not weighted for national representativeness. Errors are clustered at the zipcode level. Income Rank 1 is the lowest income, Rank 4 is the highest income.

Figure A.26: Log Quantity of Fresh Produce by Income



Notes: Figure reports event study estimates with 95% confidence intervals from Equation 5, using 2008-2019 Homescan data. The analysis uses a heterogeneity-robust estimator proposed by Callaway and Sant'Anna (2021). Observations are not weighted for national representativeness. Errors are clustered at the zipcode level. Income Rank 1 is the lowest income, Rank 4 is the highest income.

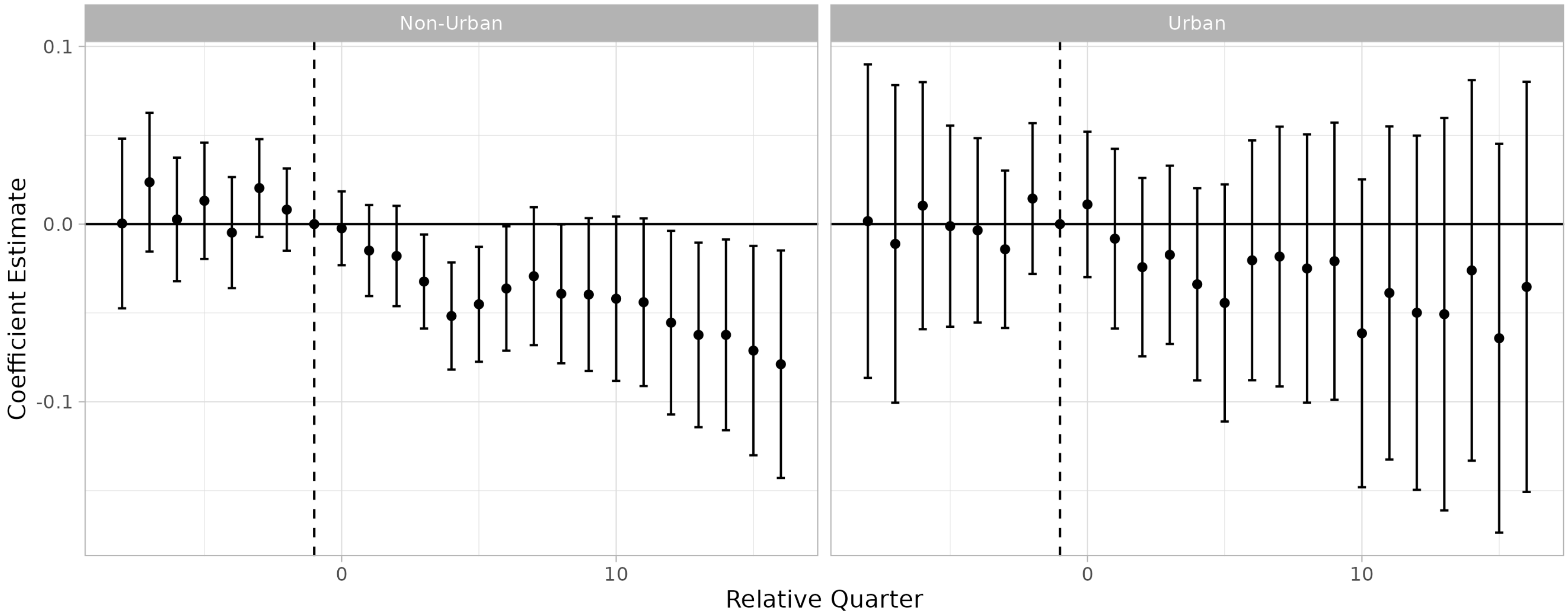
Figure A.24: Log Relative Price Index by Income



Notes: Figure reports event study estimates with 95% confidence intervals from Equation 5, using 2008-2019 Homescan data. The analysis uses a heterogeneity-robust estimator proposed by Callaway and Sant'Anna (2021). Observations are not weighted for national representativeness. Errors are clustered at the zipcode level. Income Rank 1 is the lowest income, Rank 4 is the highest income.

A.2.5 The Effect of Dollar Store Entry by Urban and Non-Urban Group

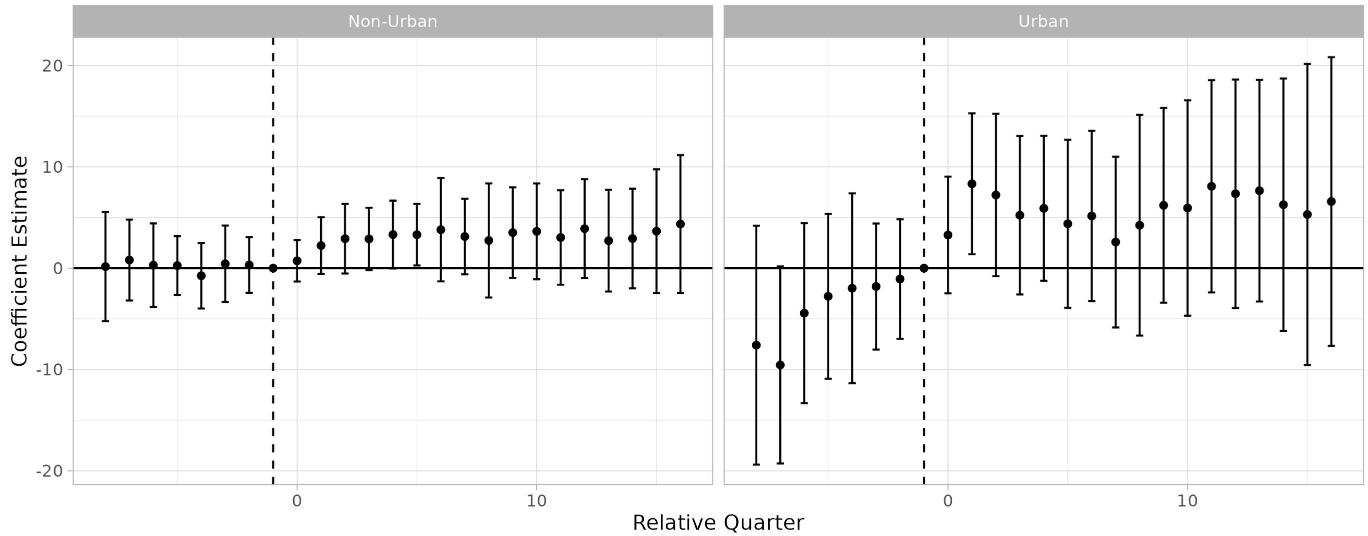
Figure A.27: Log Total Expenditure for Non-Urban and Urban



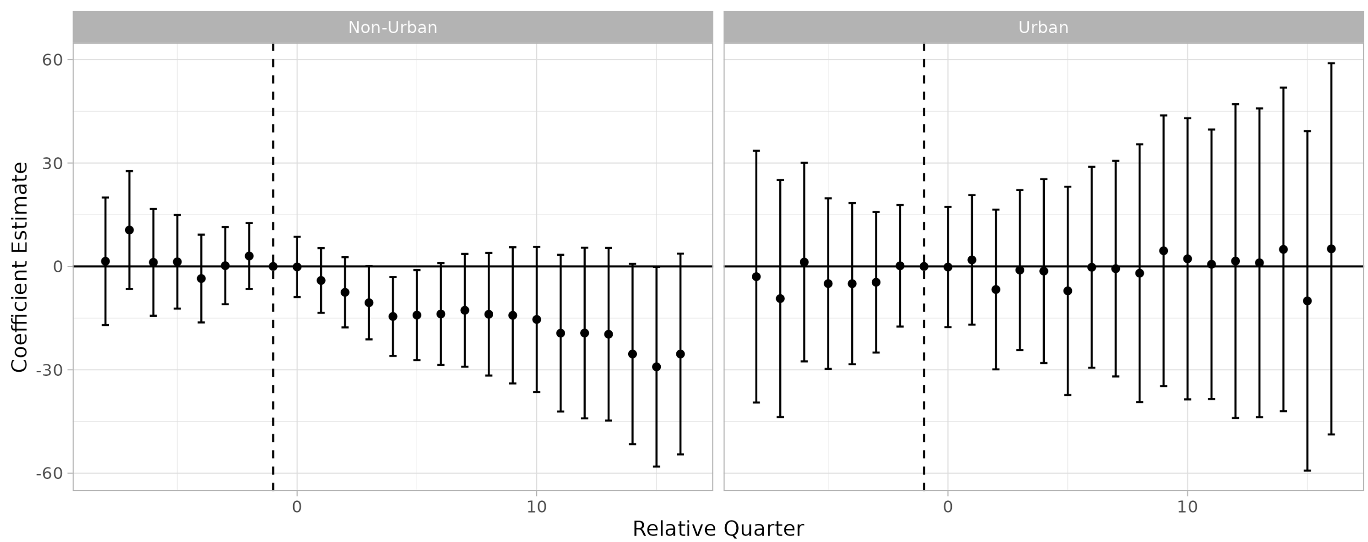
Notes: Figure reports event study estimates with 95% confidence intervals from Equation 5, using 2008-2019 Homescan data. The analysis uses a heterogeneity-robust estimator proposed by Callaway and Sant'Anna (2021). Observations are not weighted for national representativeness. Errors are clustered at the zipcode level.

Figure A.28: Heterogeneity by Non-Urban and Urban Households

(a) Dollar Store Total Expenditure



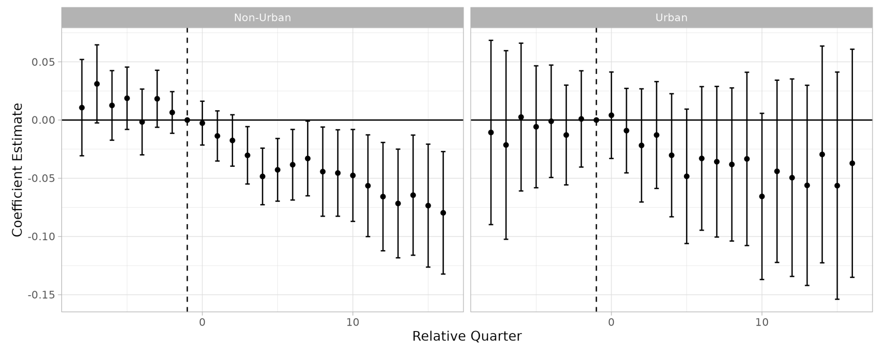
(b) Grocery Store Total Expenditure



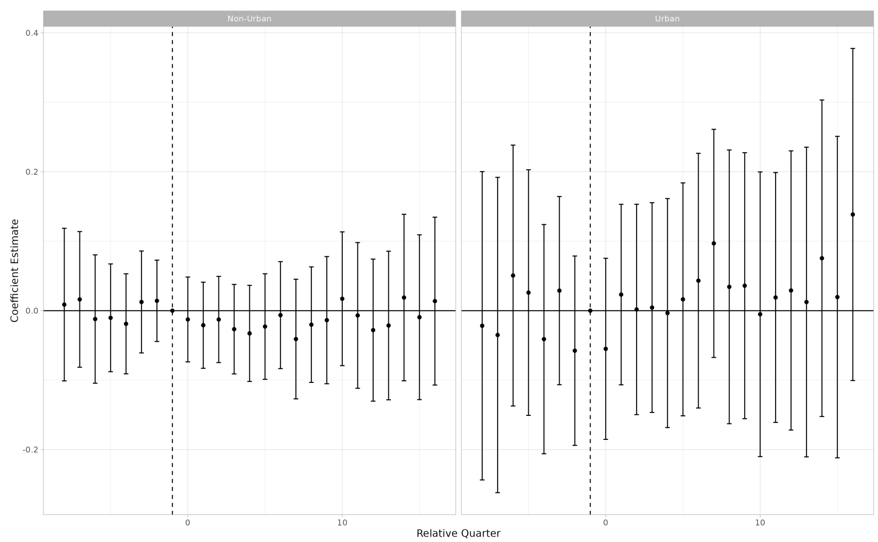
Notes: Figure reports event study estimates with 95% confidence intervals from Equation 5, using 2008-2019 Homescan data. The analysis uses a heterogeneity-robust estimator proposed by Callaway and Sant'Anna (2021). Observations are not weighted for national representativeness. Errors are clustered at the zipcode level.

Figure A.29: Heterogeneity by Non-Urban and Urban Households

(a) Log Number of Unique Varieties



(b) Log Quantity of Fresh Produce

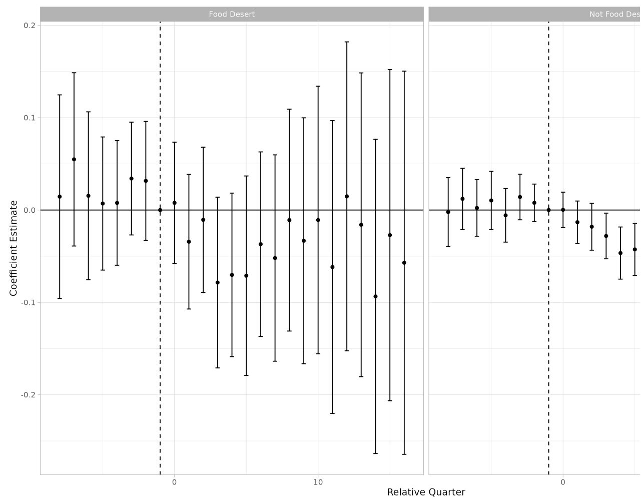


Notes: Figure reports event study estimates with 95% confidence intervals from Equation 5, using 2008-2019 Homescan data. The analysis uses a heterogeneity-robust estimator proposed by Callaway and Sant'Anna (2021). Observations are not weighted for national representativeness. Errors are clustered at the zipcode level.

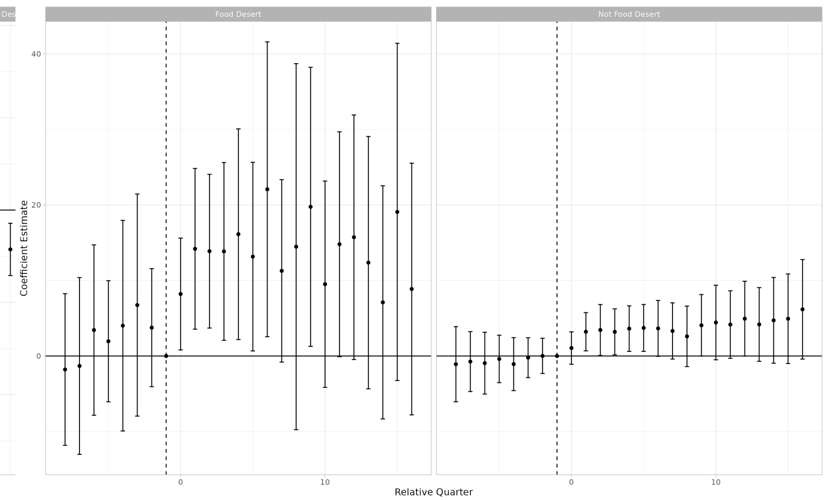
A.2.6 The Effect of Dollar Store Entry by Food Desert vs Non Food Desert

Figure A.30: Heterogeneity by Food Desert and Non-Food Desert

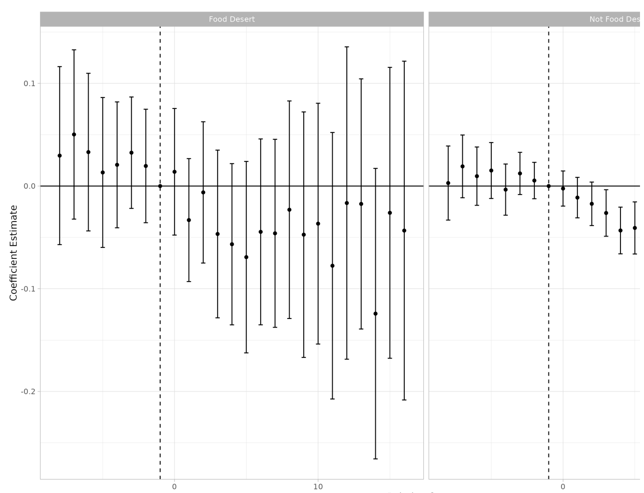
(a) Total Expenditure



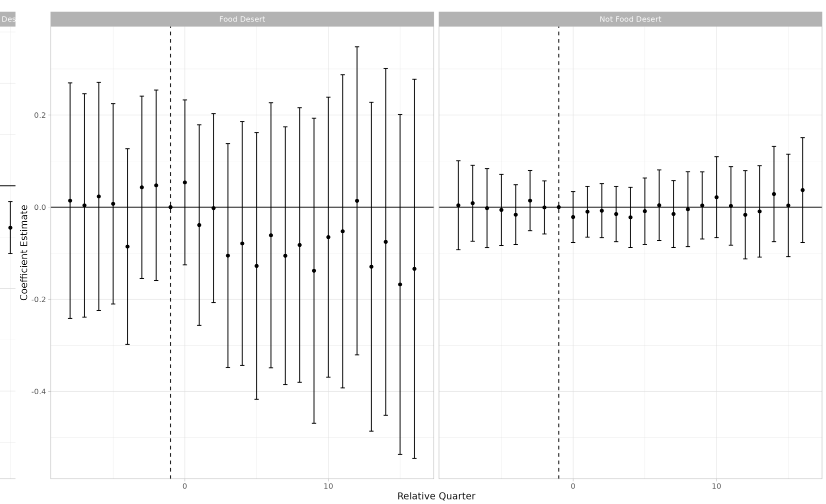
(b) Dollar Store Total Expenditure



(c) Log Number of Unique Varieties



(d) Log Quantity of Fresh Produce



Notes: Figure reports event study estimates with 95% confidence intervals from Equation 5, using 2008-2019 Homescan data. The analysis uses a heterogeneity-robust estimator proposed by Callaway and Sant'Anna (2021). Observations are not weighted for national representativeness. Errors are clustered at the zipcode level.