Scalable Demand and Markups

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Abstract

We study changes in markups across 72 product markets from 2006 to 2018. A growing literature has documented a rise in markups over time using a production function approach; we instead employ the standard microeconomic method, which is to estimate demand and then invert firms' first-order pricing conditions to infer their markups. To make the method scalable, we propose estimating nested logit demand models, using household panel data to automate the assignment of products to nests. Our results indicate an overall upward trend in markups between 2006 and 2018, with considerable heterogeneity across and within product markets. We find that changes in firms' marginal costs and households' price sensitivity are the primary drivers of markup increases with changes in firm ownership playing a much smaller role.

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1 Introduction

An influential recent literature has documented a substantial rise in markups in U.S. industries over the past five decades.[1] To date, studies in this literature have been macroeconomic both in scope and method. The goal has been to characterize changes in markups across many firms and industries in order to understand whether the economy is broadly trending toward higher levels of market power and/or higher returns to scale in production. Consequently, studies have adopted empirical approaches that can be applied simultaneously to a large number of firms in a variety of industries, using optimization assumptions (such as cost minimization, or optimal utilization of a single input) to infer markups from firm-level data on revenues and input costs.

Microeconomists' contributions to this literature have been limited, in spite of the fact that estimating markups is a standard exercise in empirical microeconomics (especially industrial organization). The most obvious explanation for this gap is that conventional microeconomic approaches involve estimating demand and supply models that are narrowly tailored to a specific market. As Syverson (2019) notes in his review of the literature, this typically requires data on products' characteristics as well as a nuanced understanding of the institutional details of the market, making it an impractical method for analyses that span different markets and industries.

In this paper we propose a way to scale the microeconomic method for estimating markups so it can be tractably applied to firms operating in many different product markets. Using supermarket scanner data from Nielsen, we estimate markups for over 33,000 products sold in 22,000 stores in 72 distinct product markets between 2006 and 2018. We employ the method that has become standard in the empirical industrial organization literature, which is to estimate a discrete-choice model of demand and then invert the first-order conditions from the supply side pricing problem to get estimates of marginal costs and markups.

Studies employing this approach are typically focused on a single product market, so they usually specify the demand-relevant characteristics of each product in the market and estimate a mixed logit model that allows for rich patterns of substitution across products.[2] The flexibility of the substitution patterns enables more credible estimates of markups. However, estimating mixed logit models of demand in many markets simultaneously is not practical, as it would require incorporating detailed data on product characteristics peculiar to each market. Moreover, even if it were possible to collect such data, the computational demands would be substantial.

Since our aim is to estimate demand in a large number of distinct markets, we estimate nested logit demand models and propose a method for automating the assignment of products to nests.

[1] Notable examples include the studies of Gutiérrez and Philippon (2017); De Loecker, Eeckhout and Unger (2020); Barkai (2020); and De Loecker and Eeckhout (2021). See Basu (2019) and Syverson (2019) for insightful reviews of the literature.

[2] See Lancaster (1966) and Gorman (1980) for early discussions of the "characteristics approach" to demand estimation, and Berry, Levinsohn and Pakes (1995), Nevo (2001), and Petrin (2002) for seminal applications of the mixed logit method. See also Nevo (2013) for a review.

Our approach is scalable because the data requirements are not product-specific or market-specific, and because nested logit models are computationally easy to estimate (Berry, 1994). Moreover, our demand models still allow for flexible and sensible substitution patterns as long as the groupings of products into nests are appropriate.

We use Nielsen's household panel data to group products into nests. If panelists have preferences over products' characteristics and these preferences are stable over time, then temporary changes in relative prices will induce them to occasionally purchase substitutes for their preferred product. We therefore measure products' proximities by how commonly they are purchased by the same household, and then apply an agglomerative clustering algorithm to group the products into nests. We show examples indicating that the resulting product clusters are similar to those used in other (single market) studies where the groupings were based on the authors' judgments about products' characteristics. We also show that the nested logit demand models yield elasticity estimates that are close to published estimates from narrower studies of specific markets.

Consistent with the prior literature, the markups implied by our estimates exhibit an overall upward trend over our sample period. Median markups were higher in 2018 than in 2006 for 51 of the 72 product markets. Pooling across product markets, the median markup increased by approximately 10 percentage points. However, our results also indicate considerable heterogeneity in markup changes both across product markets and across products within a given market. For the typical product market, markups have become increasingly dispersed over the sample period.

For products or product markets where markups increased, what caused the increase? We explore candidate explanations in a series of counterfactual exercises. First, consumers' demand curves may have become more inelastic, perhaps because of an (unmodeled) change in demographic characteristics (Bornstein, 2021) or shifts in advertising behavior. Second, reshuffling of firms' product portfolios through merger or divestiture may have resulted in an increase in concentration. Third, it is possible that changes in the mix of products may have resulted in the removal of low-markup for high-markup products (Brand, 2020). Finally, the marginal costs of producing consumer packaged goods may have declined over time (similar to what Grieco, Murry and Yurukoglu, 2021, report for the automotive industry). We find that our measured changes in markups are mostly driven by changes in marginal costs and estimated demand elasticities, with changes in the set of products or in the assignment of products to firms playing a marginal role.

Compared to the above-mentioned macroeconomic studies of markups, our results represent a limited set of markets over a limited time period. For example, De Loecker, Eeckhout and Unger (2020) estimate markups for over 200,000 firms in a variety of different industries in the manufacturing, wholesale, and retail sectors between 1955 and 2016. We look only at products that are sold in supermarkets, and our data only cover a 13-year period. Nevertheless, we believe our results are an important complement to previously published estimates because they come from an entirely different method. The overall trends in our estimated markups align with previous findings, but the microeconomic view reveals considerable heterogeneity across products and markets.

Our work also complements two other recent studies that take a microeconomic approach to studying markups and concentration. Döpper et al. (2022) undertake an exercise very similar to ours, estimating demand in a large number of consumer packaged goods markets using scanner data and then inverting supply-side first order conditions to get markups. However, their approach to estimating demand differs from ours: whereas we estimate a nested logit model and employ standard instruments for prices, they estimate a random coefficients logit model and address the endogeneity of prices by imposing a covariance restriction, a method proposed by MacKay and Miller (2023). As we discuss in more detail below, their findings are quite similar to ours in spite of the different methodologies. The second related study is Benkard, Yurukoglu and Zhang (2021), which focuses on trends in product market concentration instead of trends in markups. Parallel to the above-cited macroeconomic literature on rising markups is a literature on rising concentration;[3] Benkard, Yurukoglu and Zhang (2021) re-examine that literature by taking a more microeconomic approach, defining product markets narrowly as they would be for antitrust purposes. Using consumer survey data to look at over 466 different markets between 1994 and 2019, the authors show that while concentration appears to be increasing if markets are defined broadly (e.g., by grouping related products into sectors), concentration is decreasing for narrowly defined product markets.

Our method also relates to other recent studies that use clustering algorithms to define markets or submarkets in imperfectly competitive industries. For example, Mercadal (2022) and Zhang (2016) apply clustering techniques to define submarkets in electricity distribution markets and discount retail markets, respectively. Closer to our work, Almagro and Manresa (2020) propose, as we do, using consumers' repeated choices to identify nests of similar products as a first stage in estimating demand equations. Unlike Almagro and Manresa (2020), we emphasize that this two-step approach can be applied in a scalable way, producing reasonable parameter estimates in a well-studied environment (consumer packaged goods).

The remainder of our paper is structured as follows. Section 2 discusses the source data and the construction of our sample. We outline the demand and supply models, which are fairly standard, in Section 3. Section 4 explains our method for automating the assignment of products to nests, and describes the outcomes of the procedure. Section 5 provides some details about how we estimate the demand models, including a discussion of instruments for price and nest shares. We briefly summarize the demand estimates in Section 6 before turning to the implications for markups in Section 7. Section 8 examines the likely sources of markup changes by computing counterfactual markups under different assumptions about households' demand elasticities, firms' ownership of different sets of products, and changes in marginal costs. Section 9 concludes.

[3] See, for example, Autor et al. (2020) and Covarrubias, Gutiérrez and Philippon (2020).

2 Data Sets, Sample Construction, and Descriptive Statistics

We use two main datasets for our analysis, both maintained by the Kilts Center at the University of Chicago Booth School of Business. We use the data on prices and quantities from the Nielsen Retail Scanner dataset to estimate demand, and we use the Nielsen Consumer Panel data to cluster products into groups (nests) for the demand estimation.

The Nielsen Retail Scanner dataset measures purchases in approximately 35 thousand supermarkets, drug stores, and other retailers. The dataset begins in 2006; measures sales, products, and other product characteristics; and has UPC-retail establishment-week triples as the unit of observation. For each product (UPC), we retrieve as best as we can the identity of the parent company manufacturing it in each year by manually searching the brand name associated with each UPC. We were able to determine that each distinct parent company produces, on average, approximately 17 UPCs under 3 brand names in a given year.

In order to facilitate comparability both across time and retailers, we restrict the sample to the set of supermarkets continuously present from 2006 to 2018. We further restrict the sample to the top selling products within each product market ("product modules" in Nielsen's parlance). For each product market, we restrict the data to the largest-selling products appearing in both the scanner and panel data that together comprise at least 85 percent of total sales in the market. Finally, we exclude markets with less than 50 products after making the first and second restrictions.

These sample selection criteria yield a sample of 33,652 products (UPCs) across 75 different product markets, sold in 22,306 different stores. Table 1 summarizes the ten largest product markets in our sample. The in-sample revenues for these ten markets range from $2.8 billion (for carbonated soft drinks in 2006) to $662 million (for refrigerated yogurt). The median product module (as of 2006) in our sample — breakfast sausages— is considerably smaller, with nominal revenue of $192 million. The table also characterizes the number of products and stores in the first and final years of our sample. In the median product market, there were approximately 120 products and 8,000 stores in each of these two years.

Table 1: Sample Description: 10 Largest Product Markets

Product Module	Stores		UPCs		Revenues		Nests
	2006	2018	2006	2018	2006	2018	
Soft Drinks - Carbonated	22247	21322	155	222	2779.20	2352.27	11
Soft Drinks - Low Calorie	21831	16773	111	239	1673.57	1269.90	4
Cigarettes	15647	18559	181	120	1444.62	1491.60	4
Water-Bottled	20924	19536	185	170	1302.81	1053.79	2
Cereal - Ready To Eat	10089	8293	172	212	1347.69	783.89	6
Light Beer (Low Calorie/Alcohol)	7477	9128	61	83	1094.57	751.57	8
Toilet Tissue	19553	15908	57	127	986.27	730.21	6
Fruit Drinks-Other Container	15994	16381	277	292	871.41	832.70	4
Dairy-Milk-Refrigerated	16984	17879	503	209	948.56	678.06	11
Yogurt-Refrigerated	7694	7985	159	308	662.48	809.65	3

Notes: This table presents summary statistics for the 10 largest product markets – ranked by the sum of total revenues in 2006 and total revenues in 2018 – in our sample. For the two endpoint years within our sample, we count the number of unique stores at which products were sold, the number of unique UPCs, and total revenues (in billions of dollars.). The final column lists the number of nests identified by our Section 4 clustering method. Table 9 in Appendix A provides the corresponding figures for all 75 product markets in our sample.

Products vary in their unit sizes, in unit measurements (e.g., ounces vs. liters vs. raw counts), and in the number of units that come within each package. Before estimating demand, we place each product on a common scale to make prices and quantities cleanly comparable across goods within a product market. To do so, we first deflate all prices using the consumer price index, so that all values are stated in 2010 dollars. Then, separately for each product market, we regress the logarithm of prices on (i) the logarithm of the size of the product, (ii) a fixed effect for the number of units per package, and (iii) fixed effects for the units in which sizes are denominated. Below, when considering the price of a product j in a particular market t, we set $\log p_{jt}$ to be the residual from this regression.[4,5] So that our normalization does not alter the expenditures spent on each product, our measure of quantities sold is the raw number of units of the product sold multiplied by predicted value from the aforementioned regression.

As we will describe in detail below, we use the Nielsen Consumer Panel dataset to cluster products *within* a product market into groups of similar (i.e., more easily substitutable) products.

[4] To motivate this procedure, consider first a scenario in which the unadjusted price of a product increases in proportion to its size. The log-log specification would deliver a coefficient of the term in point (i) equal to 1. Then, p_{jt} would equal the unadjusted price divided by the size of the product. Coefficients greater than 1 would indicate that larger products are sold at a discount. Including the fixed effects mentioned in points (ii) and (iii) places p_{jt} on a scale that is comparable across products with different numbers of units per package or different unit sizes.

[5] We also experimented with using the unit price per ounce as our measure of p_{jt}. This alternate strategy yielded similar results for markups and trends in markups, though with a slightly larger fraction of product markets with inadmissible parameter estimates.

This dataset tracks the retail purchases of a nationally representative panel of 40 to 60 thousand households, beginning in 2004 and extending to the present. After each shopping trip, surveyed households scan in the products (UPCs) they have purchased. For the clustering exercise, we use grocery store purchase data from 2004 to 2018 for 183,849 households that purchased at least one of the UPCs in our sample.

3 Model

3.1 Demand

We separately model demand for each product market, by adopting the framework from Berry (1994). For a given product market, let $t = (r, q)$ denote a market, which is a combination of store r and quarter q. Let $\mathcal{J}_t$ denote the set of products offered in market t. We further assume that products, within each product market, can be partitioned into G exhaustive and mutually exclusive nests, which are indexed by g. These partitions are stable across retailers and over time. Each consumer i in market t receives an indirect utility from purchasing product $j \in \mathcal{J}_t$ belonging to nest g according to:

$$u_{ijt} = \delta_{jt} + \zeta_{ig} + (1 - \sigma)\epsilon_{ijt} \; . \tag{1}$$

As is standard, δ_{jt} represents the mean utility for product j across consumers in market t, ζ_{ig} represents the taste that consumer i has for all products in nest g, and ϵ_{jt} is an idiosyncratic shock to consumer i's utility for product j in market t.

Following the literature, we assume that δ_{jt} has the following parametric form:

$$\delta_{jt} = \alpha p_{jt} + \xi_j + \xi_{b(j)d(r)q} + \xi_{jt} \; . \tag{2}$$

Here, p_{jt} is the price of product j in market t. Following Nevo (2001), we include product fixed effects ξ_j. Letting $b(j)$ represent the brand producing product j and $d(r)$ the DMA where store r is located we also include brand-DMA-quarter fixed effects, denoted $\xi_{b(j)d(r)q}$.[6] Unobserved market specific shocks to the utility of product j, which are common across consumers, are captured by ξ_{jt}.

To close the model we make additional standard assumptions. We define an outside option $j = 0$ in each market t, which represents not purchasing any product in $\mathcal{J}_t$. We assume that this product belongs to its own nest $g = 0$. We normalize consumer i's utility from the outside option as $u_{i0t} = \epsilon_{i0t}$ so that $\delta_{0t} = 0$. The shocks ϵ_{ijt} and ϵ_{i0t} are assumed to be distributed i.i.d. Type I

[6] For example, Coca-Cola is sold in both 2 liter bottles and 12 packs of 12-ounce cans. These would be separate products, j, belonging to the same brand, $b(j)$.

extreme value. Finally, ζ_{ig} is assumed to follow the conjugate distribution to the Type I extreme value distribution defined in Cardell (1997). With this assumption, $\zeta_{ig} + (1-\sigma)\epsilon_{jt}$ is distributed Type I extreme value for all $\sigma \in (0,1)$.

Assuming that each consumer purchases one unit of the product that gives her the highest utility in market t, the market share of product j in market t can be written as a function of the mean utility δ_{jt} and the nesting parameter σ:

$$s_{jt} = \frac{\exp(\delta_{jt}/(1-\sigma))}{D_{gt}} \frac{D_{gt}^{(1-\sigma)}}{\sum_g D_{gt}^{(1-\sigma)}} \ , \tag{3}$$

where $D_{gt} = \sum_{j \in \mathcal{J}_{gt}} \exp(\delta_{jt}/(1-\sigma))$ and $\mathcal{J}_{gt}$ is the set of products in nest g offered in market t. The first fraction on the right hand side of the market share equation corresponds to the share of product j within nest g in market t and the second fraction corresponds to the total market share of nest g.

Discussion of the Demand Model: Given the aim of our paper to scalably estimate demand, and therefore markups, we use a nested logit model within each product market for pragmatic reasons. As we discuss below, with this framework, preferences can be estimated quickly for any one product market via two-stage least squares. And, it is simple to write code that can scale the estimation to many markets.

When considering markets of consumer packaged goods, a standard approach incorporates the random coefficients demand model from Berry, Levinsohn and Pakes (1995) (BLP) to model demand. If a researcher observes a rich set of characteristics, then the random coefficients model can lead to a rich set of substitution patterns. However, determining the important product characteristics for a large set of markets and then collecting and cleaning the relevant data would be prohibitively time-consuming. Also, the BLP model can be computationally intensive to estimate for one market, let alone 75. Furthermore, in many contexts, the nested logit model delivers similar substitution patterns to a BLP model. Berry (1994) shows that similarity of the indirect utility specification in nested logit models to that in a random coefficients models.[7] Finally, while the BLP model provides accurate substitution patterns when the researcher has access to all (or at least most) product characteristics relevant for consumers' decision-making, in practice this may not always be the case. In this latter scenario, the model is mis-specified and the resulting substitution patterns may be misleading. The method we describe below uses household purchase data

[7] When product characteristics are discrete (or can be discretized), ζ_{ig} can be thought of as a Cardell distributed random preference for product nest g, formed as a unique combination of the product characteristics. If consumers have Cardell distributed preferences for each characteristic, then ζ_{ig} is simply the sum of the preferences across the characteristics of products in nest g (Cardell, 1997). While BLP models more commonly assume preferences are normally distributed, Grigolon and Verboven (2014) show that the distributional differences have little effect on the estimated substitution patterns.

to form nests and estimate substitution patterns in a way that is agnostic about the characteristics that determine substitution.

3.2 Supply

Considering still each product market separately, suppose F_t manufacturers offer products in market t and denote $\mathcal{J}_{ft} \subset \mathcal{J}_t$ as the subset of products in market t offered by manufacturer f. We denote the variable profits to firm f in market t as

$$\pi_{ft} = \sum_{j \in \mathcal{J}_{ft}} M_t s_{jt}(p_{jt} - c_{jt}) \ , \tag{4}$$

where c_{jt} represents the marginal cost to the manufacturer of selling product j in market t and M_t is the market size. Following the literature on consumer packaged goods (e.g.: Nevo (2001), Miller and Weinberg (2017), Backus, Conlon and Sinkinson (2021)), we maintain two assumptions. First, we assume that manufacturers simultaneously set retail prices in market t to maximize profits. This is consistent with a vertical model in which retailers charge manufactures a fixed fee for shelf space and retail margins are zero. Under this assumption, c_{jt} represents the combined marginal cost of production, distribution, and retail.

Second, we rule out economies of scale and scope by assuming that the marginal cost of product j in market t is constant across units sold, that it does not depend on the sales of product j in other markets t, and that it does not depend on the sales of other products produced by firm f in any product market. With this assumption, the decision of firm f to set prices in market t does not depend on any other market. Thus, the Nash Bertrand equilibrium prices are denoted by a system of first order conditions:

$$p_t = c_t - \left(\Omega_t \circ \frac{ds_t{}'}{dp_t} \right)^{-1} s_t \ , \tag{5}$$

where p_t and s_t are $\mathcal{J}_t$ vectors stacking the prices and shares of the products in market t and $\frac{ds_t}{dp_t}$ is the $\mathcal{J}_t \times \mathcal{J}_t$ matrix of price derivatives. The ownership matrix is Ω_t, whose $(j,k)^{\text{th}}$ element equals one if products j and k are sold by the same manufacturer and zero otherwise. The $\circ$ operator represents element by element multiplication.

Discussion of the Supply Model: Our objective is to scalably recover markups for each product in a market, defined as $\frac{p_{jt} - c_{jt}}{p_{jt}}$. Assuming that manufacturers set retail prices according to a model of Bertrand competition serves that objective: once we estimate demand, we can analytically recover marginal cost by inverting Equation (5). Evidence in support of these assumptions in consumer packaged goods is mixed. For example, while Miller and Weinberg (2017) and Sullivan

(2020) find evidence of price collusion in beer and superpremium ice cream, respectively, Nevo (2001) and Backus, Conlon and Sinkinson (2021) conclude for Bertrand conduct in the market for cereal. Duarte et al. (2023) test several standard vertical models in the market for yogurt sold in supermarkets. They reject several models including those involving double marginalization and collusion. The only model they fail to reject is the zero retail margin model. However, if some markets are indeed collusive, then the markups we recover will be smaller than the truth.[8]

4 Assigning Products to Nests

A key input into Equation (1) is the assignment of products to nests. The nested logit model relaxes the IIA assumption underpinning logit demand in a way that enhances the substitution of products within a nest, so the objective for researchers hoping to obtain realistic substitution patterns is to place products that are closer substitutes in the same nest. In standard applications, the researcher has a prior on which observable characteristics are most important for substitution and uses that institutional knowledge to define nests.

Such an approach is not feasible in our setting. Because we aim to measure markups in 75 distinct product markets with each typically having over 200 products, any method that relies on human judgment as its primary input would be impractical. Instead, we develop a procedure that uses auxiliary data on household purchases to uncover sets of products that consumers view as close substitutes. Our approach does not require data on product characteristics, which is important because utility-relevant characteristics are different in each product market, so collecting data on characteristics across many markets would be prohibitively costly. Moreover, data on characteristics may not even be available, since in many product markets (for example, soda) the characteristics relevant to consumers' substitution choices are not easily quantified.

The central idea of our approach is to use the Consumer Panel data to determine sets of products that are ever purchased by the same household across a large number of shopping trips, and to gauge the substitutability of a given pair of products by how commonly the two products are purchased by the same household. The underlying premise is that if individuals within each household have preferences over products' characteristics and these preferences are stable over time, then temporary changes in relative prices or availability (e.g., due to periodic sales or stockouts) will induce consumers to occasionally purchase substitutes for their preferred product. For example, if a household sometimes purchases Pepsi and sometimes purchases Coke, but never purchases Mountain Dew, the implication is that Coke is a closer substitute to Pepsi than Mountain Dew for

[8] Given the recent literature on testing conduct (Berry and Haile, 2014; Backus, Conlon and Sinkinson, 2021; Duarte et al., 2023), future work could use our scalable methods for estimating demand to test different models of firm conduct across a set of consumer packaged goods markets. However, testing conduct requires collecting instruments that satisfy the falsifiable restriction in Berry and Haile (2014) and are strong for testing as defined in Duarte et al. (2023). This could be time intensive across many markets.

that household.

To operationalize this idea, we begin by calculating pairwise purchase correlations between products. If there are N households in the Consumer Panel (indexed by i) and J products in a given product market (indexed by j), let b_{ij} be an indicator for whether household i ever purchased product j, and let b_j be the $N \times 1$ vector of these indicators. We compute the pairwise purchase correlation $\rho_{jj'}$ between products j and j' as the sample correlation between b_j and $b_{j'}$, which reflects the likelihood that products j and j' are purchased by the same household—i.e., how likely a household is to have ever purchased product j' conditional on having ever purchased product j. We then construct a dissimilarity matrix $\mathbf{D}$ with $1 - \rho_{jj'}$ as its $(j, j')^{th}$ element, and then divide products into nests by applying a clustering algorithm to the dissimilarity matrix $\mathbf{D}$. We use agglomerative clustering with Ward's linkage method,[9] and choose the number of clusters for each product market using the Duda-Hart rule.[10] Our approach thus uses purchase patterns from the Consumer Panel to learn nests of close products without needing any data on product characteristics nor any human judgments about which characteristics are most relevant to consumers' substitution choices.

The important question is whether this automated method results in group assignments that make sense. A natural way to evaluate this is to compare our clustering results to those from previous studies where products were grouped based on the authors' judgments about products' likely substitutes. For example, Nevo (2001) is a canonical paper in industrial organization that provides a nesting structure for breakfast cereal. Nevo groups 25 leading brands of cereal into four nests: "all family/basic," "taste enhanced," "simple health," and "kids." In Table 2, we compare his grouping to the results from our clustering. Our algorithm groups cereals into the seven nests shown in the table.[11] For any brand that appears in Nevo (2001) we report his grouping as well. While our clusters do not perfectly match Nevo's, they are broadly consistent: our nests 4 and 5 contain cereals Nevo defined as kids' cereals, and most of the cereals Nevo defined as "all family/basic" are in our nest 1.

Another study we can use as a comparison is Mariuzzo, Walsh and Whelan (2003), in which carbonated soft drinks are grouped along three dimensions: diet versus regular, flavor (regular, lemon, citrus, and fruit), and size. Our approach separates diet and regular soft drinks into different nests by default, since the Nielsen database puts them in separate product markets. Within the

[9]In this context, an agglomerative method begins by treating all J products in the market as separate clusters, then finds the two nearest products and combines them into a cluster, leaving $J - 1$ clusters, and so on. The meaning of "nearest" depends on the linkage method. Ward's linkage method combines clusters at each iteration by finding the pair of clusters that lead to the smallest increase in within-cluster variance after merging.

[10]For each splitting of one group into two subgroups, the Duda-Hart rule calculates an index $Je(2)/Je(1)$, the ratio of the sum of squared errors for the two subgroups to the sum of squared errors for the initial group. The chosen number of splits (groups) is the one that minimizes the pseudo-T^2 associated with this index.

[11]We assigned the descriptive labels like Basic, Healthy, and Kids after examining the groupings. Some brands appear in multiple nests because the algorithm assigns UPCs (not brands) to nests, so for instance different sizes of the same brand might land in different nests.

TABLE 2: Clustering Results for Ready-to-Eat Cereal

Nest 1 - Basic		**Nest 2 - Enhanced**		**Nest 3 - Healthy**	
APPLE CINNAMON CHEERIOS		CINNAMON CHEX		ALL-BRAN	
CHEERIOS	B	CINNAMON LIFE		CINNAMON LIFE	
CHOCOLATE CHEERIOS		CRACKLIN' OAT BRAN		FIBER ONE	
CINNAMON CHEX		FROSTED FLAKES	K	FIBER ONE HONEY CLUSTERS	
CORN CHEX		GREAT GRAINS		GRAPE-NUTS	H
CORN FLAKES	B	HONEY NUT CHEX		HONEY BUNCHES OF OATS	T
CRISPIX	B	LIFE	K	OAT CLUSTER CHEERIOS CRNCH	
FRUITY CHEERIOS		OATMEAL SQUARES		SELECTS CRAN ALMD CRUNCH	
HNY. NUT CHEER. MEDLEY CRUNCH		SPECIAL K CHOC. DELGHT		SELECTS GREAT GRAINS	
HONEY NUT CHEX		SPECIAL K VANILLA ALMOND		SHREDDED WHEAT 'N BRAN	
KIX	K	GRAPE NUTS TRAIL MIX CRUNCH		SHREDDED WHEAT	H
KRAVE				SPECIAL K	H
MULTIGRAIN CHEERIOS				SPECIAL K CHOC. DELGHT	
MULTIGR. CHEERIOS PEANUT BTR.				SPECIAL K CINNAMON PECAN	
RAISIN BRAN	T			SPECIAL K FRUIT & YOGURT	
RAISIN BRAN	T			SPECIAL K RED BERRY	
RICE CHEX				SPECIAL K VANILLA ALMD.	
RICE KRISPIES	B			TOTAL WHOLE GRAIN	
WHEAT CHEX					

Nest 4 - Kids		**Nest 5 - Kids**		**Nest 6 - Kashi**	
APPLE JACKS		APPLE JACKS		KASHI GO LEAN	
CAP'N CRUNCH CRNCH BRERRY		CAP'N CRUNCH	K	KASHI GO LEAN CRISP!	
CAP'N CRUNCH OOPS! ALL BERRY		CAP'N CRUNCH CRNCH BERRY		KASHI GO LEAN CRUNCH!	
CAP'N CRUNCH P.B. CRN		CHEERIOS	B	KASHI HEART TO HEART	
CINNAMON TOAST CRUNCH	K	CINNAMON TOAST CRUNCH	K		
COCOA KRISPIES		COCOA KRISPIES			
COCOA PEBBLES		COCOA PEBBLES			
COCOA PUFFS		COOKIE-CRISP			
COOKIE-CRISP		FROOT LOOPS	K		
CORN POPS	K	FROSTED FLAKES	K		
FROOT LOOPS	K	FROSTED MINI-WHEATS	T		
FROOT LOOPS MARSHMALLOW		FRUITY CHEERIOS		**Nest 7 - Single Serving**	
FROSTED FLAKES	K	FRUITY PEBBLES		APPLE JACKS	
FRUITY PEBBLES		HONEY NUT CHEERIOS	K	FROOT LOOPS	K
GOLDEN CRISP		HONEY SMACKS		FROSTED FLAKES	K
GOLDEN GRAHAMS		HONEY-COMB		HONEY NUT CHEERIOS	K
HONEY NUT CHEERIOS	K	LUCKY CHARMS	K	LUCKY CHARMS	K
HONEY SMACKS					
HONEY-COMB					
LUCKY CHARMS	K				
REESE'S PUFFS					
TRIX	K				

Notes: The table reports our clustering results for the ready-to-eat cereal product market. We report the brands with at least one UPC in each of the seven nests, restricting attention to UPCs with average annual sales exceeding 300,000 units. For the brands that also appear in Nevo (2001), we report his grouping of them: B = all family/basic, T = taste enhanced, H = simple health, K = kids.

regular (non-diet) market, our algorithm divides products into 14 nests. Table 3 shows the five highest-revenue UPCs in each nest, along with the nests they would have been assigned to in Mariuzzo, Walsh and Whelan (2003).[12] Although the nest assignments do not perfectly match what Mariuzzo, Walsh and Whelan (2003) would have chosen, the groupings are quite reasonable overall. Some of the nests are based on size (e.g., 12-packs of 12oz cans, or 2L bottles), while others are based on flavor (e.g., ginger ale) or type (e.g., energy drinks).

As a third example, Table 4 shows how our algorithm groups the top-revenue beer brands in our

[12] We mimic Mariuzzo, Walsh and Whelan (2003) by placing products in nests based on size group and flavor. The size groups are (Sm) if the product is sold as single bottle/can of less than or equal to 12.5 ounces; (Med) if the product is sold as a single bottle/can of size greater than 12.5 ounces and less than or equal to 33.8 ounces; (Lrg) if the product is sold as a single bottle/can of size greater than 33.8 ounces; (Multi) all other products. We place products into flavor groups based on strings that appear in the UPC description: (Lemon) for strings "* ln*", "* ln/lm*", "* lm/ln*"; (Citrus) for "*citr*", "* or *", "* gft *", "* lm *"); (Fruit) for "*grape*", "* ch/*", "* ch *", "* strby *", "* frt *"; and (Regular) for all others.

Table 3: Clustering Results for Carbonated Soft Drinks

Nest 1 - 20oz bottles		**Nest 2 - Mini cans**	
Coca-Cola 20oz bottle	Med/Reg	Coca-Cola 8-pack 7.5oz cans	Multi/Reg
Pepsi 20oz bottle	Med/Reg	Coca-Cola 8-pack 12oz cans	Multi/Reg
Dr. Pepper 20oz bottle	Med/Reg	Pepsi 8oz can	Sm/Reg
Coca-Cola 32-pack 12oz cans	Multi/Reg	7-UP 8oz can	Sm/Lemon
Sprite 20oz bottle	Med/Lemon	Coca-Cola 6-pack 7.5oz cans	Multi/Reg
Nest 3 - Ginger ale		**Nest 4 - Polar water**	
Canada Dry Ginger Ale 2L bottle	Lrg/Reg	Polar Raspberry-Lime Seltzer 1L bottle	Med/Reg
Canada Dry Ginger Ale 12-pack 12oz cans	Multi/Reg	Polar Seltzer Lemon 1L bottle	Med/Lemon
Pepsi 2L bottle	Lrg/Reg	Polar Seltzer 1L bottle	Med/Reg
Schweppes Ginger Ale 2L bottle	Lrg/Reg	Polar Seltzer Lime 1L bottle	Med/Citrus
Schweppes Ginger Ale 12-pack 12 oz cans	Multi/Reg	Polar Seltzer Cranberry-Lime 1L bottle	Med/Reg
Nest 5 - European sparkling water		**Nest 6 - La Croix**	
San Pellegrino 1L bottle	Med/Reg	La Croix Lime 12-pack 12oz cans	Multi/Citrus
San Pellegrino 750mL glass bottle	Med/Reg	La Croix Grapefruit 12-pack 12oz cans	Multi/Citrus
Perrier 1L bottle	Med/Reg	La Croix Lemon 12-pack 12oz cans	Multi/Lemon
Perrier Citron 1L bottle	Med/Reg	La Croix Cran-Raspberry 12-pack 12oz cans	Multi/Reg
Perrier 6-pack 500mL bottles	Multi/Reg		
Nest 7 - Energy drinks		**Nest 8 - Red Bull**	
Monster Energy 16oz can	Med/Reg	Red Bull 12oz can	Sm/Reg
Rockstar Energy 16oz can	Med/Reg	Red Bull 250ml can	Sm/Reg
Red Bull 4-pack 250 mL can	Med/Reg	Red Bull 16oz can	Med/Reg
Rockstar Punched 16oz can	Med/Reg	Red Bull 4-pack 250ml can	Sm/Reg
Amp 16oz can	Med/Reg	Red Bull Yellow 12oz can	Sm/Reg
Nest 9 - Kickstart		**Nest 10 - 12-packs**	
Mt. Dew Kickstart Orange Citrus 16oz can	Med/Citrus	Coca-Cola 12-pack 12oz cans	Multi/Reg
Mt. Dew Kickstart Fruit Punch 16oz can	Med/Fruit	Pepsi 12-pack 12oz cans	Multi/Reg
Mt. Dew Kickstart Black Cherry 16oz can	Med/Fruit	Dr. Pepper 12-pack 12oz cans	Multi/Reg
Mt. Dew Kickstart Limeade 16oz can	Med/Fruit	Sprite 12-pack 12oz cans	Multi/Lemon
Mt. Dew Kickstart Midnight Grape 12oz can	Sm/Fruit	Pepsi 24-pack 12oz cans	Multi/Reg
Nest 11 - Mostly Single Cans		**Nest 12 - Mt. Dew/Pepsi**	
Vanilla Coke 12-pack 12oz cans	Multi/Reg	Mountain Dew 12-pack 12oz cans	Multi/Citrus
Sunkist Orange Soda 12oz can	Sm/Citrus	Mountain Dew 2L bottle	Lrg/Citrus
A&W Root Beer 12oz can	Sm/Reg	Mountain Dew 24-pack 12oz cans	Multi/Citrus
7-UP 12oz can	Sm/Lemon	Mountain Dew 20oz bottle	Med/Citrus
Vault Citrus soda 20oz bottle	Sm/Citrus	Pepsi 2L bottle	Lrg/Reg
Nest 13 - Plastic bottle 6-packs		**Nest 14 - 2L bottles**	
Coca-Cola 6-pack 500mL bottles	Multi/Reg	Coca-Cola 2L bottle	Lrg/Reg
Coca-Cola 8-pack 12oz bottles	Multi/Reg	Pepsi 2L bottle	Lrg/Reg
Pepsi 6-pack 500mL bottles	Multi/Reg	Sprite 2L bottle	Lrg/Lemon
Dr. Pepper 6-pack 500mL bottles	Multi/Reg	7-UP 2L bottle	Lrg/Lemon
Mountain Dew 6-pack 500 mL bottles	Multi/Citrus	A&W Root Beer 2L bottle	Lrg/Reg

Notes: The table reports clustering results for the carbonated soft drinks product market. We report the five highest-selling UPCs in each of the 14 nests that our algorithm generated. For comparison, the nest assignment from the approach of Mariuzzo, Walsh and Whelan (2003), based on size and flavor, is indicated to the right of each product name.

sample.[13] Low-quality beers end up grouped together, as do imported beers. Imports from Mexico are mostly placed in their own separate nest, and there are two nests dominated by Budweiser and Miller Genuine Draft, respectively.

While these groupings may not be exactly what a market expert would come up with, overall these examples indicate that our algorithm delivers sensible clusters of similar products. A full listing of the number of clusters for all 75 product markets is available in the Appendix.

[13] Light beers are not shown in the table because they have their own separate product market.

Table 4: Clustering Results for Beer

Nest 1 - Tallboys	Nest 2 - Inexpensive	Nest 3 - A Cut Above
BUD ICE	BUD ICE	BECK'S
BUDWEISER	BUDWEISER	COORS BANQUET
BUDWEISER & CLAMATO CHELADA	BUSCH	HEINEKEN
BUSCH	BUSCH ICE	LABATT BLUE PILSNER
COORS BANQUET	HURRICANE HIGH GRAVITY LAGER	LABATT ICE
CORONA EXTRA	ICEHOUSE	MOLSON ICE
CORONA FAMILIAR	ICEHOUSE EDGE	MULTIPLE VALUE
FOSTER'S	KEYSTONE ICE	PABST BLUE RIBBON
HEINEKEN	MILLER HIGH LIFE	ROLLING ROCK
MILLER GENUINE DRAFT	MILWAUKEE'S BEST	SAMUEL ADAMS BOSTON LAGER
MILLER HIGH LIFE	MILWAUKEE'S BEST ICE	SAMUEL ADAMS SEASONAL
MODELO ESPECIAL	NATTY DADDY	SHINER BOCK
MODELO ESPECIAL CHELADA	NATURAL ICE	STELLA ARTOIS
PABST BLUE RIBBON	PABST BLUE RIBBON	YUENGLING AMBER LAGER
ROLLING ROCK	STEEL RESERVE 211 HIGH GVTY LG	
SAPPORO DRAFT		
TECATE		
Nest 4 - Mostly Mexican	**Nest 5 - Budweiser**	**Nest 6 - MGD**
CORONA EXTRA	BUDWEISER	MILLER GENUINE DRAFT
CORONA EXTRA CORONITA		
DOS EQUIS ESPECIAL LAGER		
HEINEKEN		
MODELO ESPECIAL		
PACIFICO		
TECATE		

Notes: The table reports clustering results for the beer product market. We report the brands with at least one UPC in each of the six nests, restricting attention to UPCs with average annual sales exceeding 100,000 units.

5 Estimation

To obtain estimates of the demand parameters, we follow Berry (1994) by estimating the linear regression

$$\log\left(\frac{s_{jt}}{s_{0t}}\right) = \alpha_{y(q)} p_{jt} + \sigma_{y(q)} \log(s_{jgt}) + \xi_j + \xi_{b(j)d(r)q} + \xi_{jt} \ , \tag{6}$$

where s_{jgt} is the share of product j within nest g in market t, with markets defined as combinations of product market/store/quarter. To allow substitution patterns to vary over the 13 years in our sample, we estimate year-specific values of the parameters: $\alpha_{y(q)}$ and $\sigma_{y(q)}$, where $y(q)$ is the year associated with quarter q. The linearity of this equation makes for computationally easy estimation of the demand parameters, but an important issue remains: prices and nest shares are endogenous, so consistent estimation of α and σ requires valid instruments—i.e., instruments that are uncorrelated with demand shocks ξ_{jt}.

Our choice of instruments is complicated by our desire to be scalable. In particular, we do not define any product characteristics x, instead capturing their effect through the included product fixed effects. Thus we cannot use BLP-style instruments generated from rivals' product characteristics. Other standard instrument choices including rivals' cost shifters and changes in market structure are also impractical, as they would require collecting these data for each product market.

Alternatively, instruments formed from the number of products or prices in other markets can be quickly computed in each market from the scanner data. Under the standard timing assumption that products are chosen before the demand shocks are observed by the manufacturers, the number of products both within a market and within a nest offer exogenous sources of variation which we use as instruments. In particular, the number of products both within and across nests changes the degree of competition faced by a firm, affecting its pricing. Furthermore, adding or dropping a product from the nest identifies σ, the degree to which consumers substitute within or across nests. We also follow Nevo (2001) and use Hausman instruments for price. In particular, we instrument for the price of a given product in a DMA with the average price of a product within that region of the United States, excluding that DMA. A threat to Hausman instruments is that the ξ_{jt} might be correlated across markets, say via national or regional advertising campaigns. To mitigate this problem, we include a robust set of fixed effects intended to control for the component of demand shocks common across markets.

Given our set of instruments, we can estimate the parameters in Equation (6) via two-stage least squares. This procedure is scalable and fast in standard statistical software packages such as STATA. Once demand is estimated, we recover estimates of markups in market t as:

$$\mu_t \equiv \frac{p_t - c_t}{p_t} = -\left(\Omega_t \circ \frac{ds_t(\alpha_{y(q)}, \sigma_{y(q)})'}{dp_t}\right)^{-1} s_t \oslash p_t \ , \tag{7}$$

where the operator $\oslash$ represents element by element division.

6 Demand Estimates

Our estimation procedure yields estimates of price sensitivity (α) and nest substitutability (σ) for each of the 75 markets in each of 13 years. Overall, the results indicate that our method yields credible estimates of demand. For example, estimates of the price sensitivity parameter are negative in all years for all but a few product markets. The only exceptions are cigarettes, wet cat food, and non-chocolate candy, for which the estimate of α is positive in multiple years; and soup mixes, cottage cheese, and sugar-free chewing gum, each of which has a single year in which the estimated α is positive (in the years 2007, 2016, and 2017, respectively). Estimates of the nest parameter are between 0 and 1 in 972 of 975 (=13 ×75) cases, with only two product markets having exceptions (ground and whole bean coffee in 2006 and 2007, and non-chocolate candy in 2016).

Another way to check the credibility of our demand estimates is to compare with those of other published studies. In Table 5 we compare our estimated own-price and cross-price elasticities in the breakfast cereal product market to those from Nevo (2001). Even though we are using data from 2006-2018 (vs. 1992 in Nevo (2001)), the estimates in the two papers align well with one another: the mean own-price elasticity is -3.45 in our paper, compared to -2.88 in Nevo (2001), and the mean cross-price elasticities are 0.07 versus 0.08, respectively. Moreover, the elasticity estimates in the two papers are positively correlated: the own-price elasticities in our paper and in Nevo (2001) have a correlation of 0.26, and the cross-price elasticities have a correlation of 0.40.[14]

TABLE 5: CPE Comparison for Cereal

Panel A: Our Demand Estimates	1	2	3	4	5	6	7	8	9
1. K Corn Flakes	-3.523	0.023	0.144	0.020	0.141	0.016	0.019	0.111	0.020
2. K Frosted Flakes	0.046	-3.046	0.043	0.204	0.064	0.031	0.159	0.040	0.232
3. K Rice Krispies	0.179	0.030	-3.710	0.035	0.195	0.027	0.032	0.132	0.030
4. K Froot Loops	0.023	0.108	0.031	-3.455	0.038	0.019	0.128	0.022	0.084
5. GM Cheerios	0.376	0.095	0.469	0.103	-3.458	0.074	0.096	0.276	0.087
6. GM Total	0.009	0.010	0.012	0.011	0.011	-4.330	0.011	0.009	0.011
7. GM Lucky Charms	0.039	0.124	0.035	0.169	0.040	0.025	-3.621	0.034	0.115
8. P Raisin Bran	0.073	0.017	0.062	0.015	0.053	0.010	0.016	-2.801	0.019
9. Q CapN Crunch	0.018	0.073	0.017	0.050	0.022	0.013	0.050	0.020	-3.071
Panel B: Nevo (2001) Demand Estimates	1	2	3	4	5	6	7	8	9
1. K Corn Flakes	-3.379	0.212	0.197	0.014	0.202	0.097	0.012	0.013	0.038
2. K Frosted Flakes	0.151	-3.137	0.105	0.069	0.129	0.079	0.061	0.013	0.138
3. K Rice Krispies	0.195	0.144	-3.231	0.031	0.241	0.087	0.026	0.031	0.055
4. K Froot Loops	0.019	0.131	0.042	-2.340	0.072	0.025	0.107	0.027	0.149
5. GM Cheerios	0.127	0.111	0.152	0.034	-3.663	0.085	0.030	0.037	0.056
6. GM Total	0.096	0.108	0.087	0.018	0.131	-2.889	0.017	0.017	0.029
7. GM Lucky Charms	0.019	0.131	0.041	0.124	0.073	0.026	-2.536	0.027	0.147
8. P Raisin Bran	0.027	0.037	0.068	0.044	0.127	0.035	0.038	-2.496	0.049
9. Q CapN Crunch	0.043	0.218	0.064	0.124	0.101	0.034	0.106	0.026	-2.277
Panel C: Inside/Outside Nest Demand Estimates	1	2	3	4	5	6	7	8	9
1. K Corn Flakes	-3.572	0.066	0.059	0.064	0.065	0.047	0.059	0.046	0.054
2. K Frosted Flakes	0.143	-3.141	0.139	0.182	0.167	0.097	0.162	0.102	0.150
3. K Rice Krispies	0.080	0.083	-3.724	0.080	0.083	0.070	0.080	0.069	0.075
4. K Froot Loops	0.077	0.098	0.076	-3.441	0.085	0.054	0.084	0.058	0.078
5. GM Cheerios	0.197	0.217	0.205	0.196	-3.670	0.192	0.207	0.182	0.185
6. GM Total	0.026	0.026	0.026	0.026	0.027	-4.297	0.026	0.025	0.025
7. GM Lucky Charms	0.096	0.120	0.106	0.114	0.118	0.073	-3.616	0.081	0.103
8. P Raisin Bran	0.039	0.042	0.040	0.040	0.043	0.029	0.041	-2.811	0.038
9. Q CapN Crunch	0.046	0.052	0.047	0.051	0.051	0.031	0.051	0.037	-3.047

Notes: The table reports average brand level own- and cross-price elasticities. Each cell corresponds reports the percentage change in the row brand's quantity due to a one-percent change in the price of the column brand. Panel A is computed using our demand estimates and reports the mean elasticities across markets. Panel B reproduces the the relevant parts of Table VII in Nevo (2001). Panel C reports estimates from a model with all inside products placed in a single nest. Brand names begin with initials K (Kellogg), GM (General Mills), P (Post), and Q (Quaker).

[14] The Spearman rank correlations are 0.38 and 0.44, respectively.

To highlight the usefulness of our automated nesting procedure, we computed alternative demand estimates for a model in which all products in a market are included in a single nest, with a second nest consisting only of the outside good. Under this approach, the resulting demand estimates are generally *not* credible: all of the product markets have at least one year in which the price sensitivity parameter is positive, and 71 of the 75 product markets have instances where the nesting parameter is outside the $[0, 1]$ range. We report the elasticity estimates for this demand system in Panel C of Table 5. Price increases cause consumers to disproportionately substitute to the cereal brands with the highest sales - namely Cheerios and Frosted Flakes.

Table 6 reports our estimates of α and σ for the ten largest product markets for the first, middle, and final years of our sample. Among the nine product markets with credible estimates (cigarettes being the exception), α has increased for every market but light beer. Evidently, households have become less price sensitive over our sample period. For σ, the parameter characterizing how correlated households' tastes are among the products within each nest, there seems to be an increasing trend within most markets. Over our sample, σ has increased for carbonated soft drinks, bottled water, ready-to-eat cereal, light beer, and refrigerated yogurt; decreased for low-calorie soft drinks and toilet tissue; and displayed no clear trend in fruit drinks (other container) and refrigerated milk. These patterns pertain to our broader sample as well. Among all 75 product markets in our sample, $\alpha_{2018} > \alpha_{2006}$ for 63 product markets, while $\sigma_{2018} > \sigma_{2006}$ for 53 markets; see Table 10 in Appendix A.

TABLE 6: Demand Parameter Estimates

Product Module	α_{2006}	α_{2012}	α_{2018}	σ_{2006}	σ_{2012}	σ_{2018}	$\alpha_{2018} - \alpha_{2006}$
Soft Drinks - Carbonated	-4.37	-2.21	-1.63	0.68	0.85	0.92	2.73
Soft Drinks - Low Calorie	-3.01	-2.43	-2.09	0.67	0.64	0.60	0.92
Cigarettes	3.90	9.10	6.65	0.52	0.21	0.42	2.75
Water-Bottled	-1.35	-1.44	-0.79	0.74	0.77	0.81	0.56
Cereal - Ready To Eat	-2.59	-1.99	-2.15	0.29	0.54	0.57	0.44
Light Beer (Low Calorie/Alcohol)	-6.52	-7.93	-7.31	0.13	0.34	0.53	-0.79
Toilet Tissue	-4.17	-4.12	-2.52	0.45	0.32	0.32	1.66
Fruit Drinks-Other Container	-1.52	-0.78	-1.27	0.79	0.84	0.82	0.25
Dairy-Flavored Milk-Refrigerated	-2.58	-3.29	-0.90	0.67	0.84	0.65	1.67
Yogurt-Refrigerated	-4.04	-1.84	-1.58	0.24	0.46	0.57	2.47

Notes: For the set of product markets listed in Table 1, we present estimates of α_y and σ_y for $y \in \{2006, 2012, 2018\}$. The final column presents $\alpha_{2018} - \alpha_{2006}$. Table 10 in Appendix A presents estimates for all 75 product markets in our sample.

Building off of Table 6, Table 7 presents average own-price elasticities for the largest product markets in our sample. Elasticities tend to become smaller in magnitude when $\alpha_{2018} > \alpha_{2006}$ or when $\sigma_{2018} < \sigma_{2006}$. For certain product markets—like carbonated soft drinks—demand is more elastic even though $\alpha_{2018} < \alpha_{2006}$, while for others—like low calorie soft drinks or refrigerated yogurt—demand is more inelastic. Overall, own-price elasticities have increased in magnitude for 47 out of the 72 product markets—including six out of the top nine product markets—with permissible demand estimates.

Table 7: Own-Price Elasticity Estimates

Product Module	Unweighted				Sales-Weighted			
	2006	2010	2014	2018	2006	2010	2014	2018
Soft Drinks - Carbonated	-10.40	-14.32	-5.67	-16.62	-10.49	-13.51	-5.37	-14.72
Soft Drinks - Low Calorie	-7.22	-9.46	-4.20	-4.71	-7.33	-8.86	-4.17	-4.57
Water-Bottled	-5.79	-6.54	-3.54	-4.21	-5.67	-6.13	-3.14	-3.61
Cereal - Ready To Eat	-3.47	-3.72	-3.74	-4.00	-3.40	-3.66	-3.67	-3.87
Light Beer (Low Calorie/Alcohol)	-6.84	-8.66	-8.90	-11.96	-6.86	-8.49	-8.05	-10.06
Toilet Tissue	-6.45	-5.66	-3.86	-3.58	-6.25	-5.69	-3.84	-3.58
Fruit Drinks-Other Container	-7.93	-9.25	-2.23	-7.61	-7.40	-8.50	-1.95	-6.87
Dairy-Milk-Refrigerated	-7.46	-4.02	-6.17	-5.77	-8.52	-4.44	-6.62	-6.38
Yogurt-Refrigerated	-4.46	-3.40	-3.42	-4.38	-4.45	-3.45	-3.50	-4.20
Median	-5.09	-4.95	-4.26	-4.37	-4.83	-4.72	-4.06	-4.06

Notes: For the set of product markets listed in Table 1, with the exception of the Cigarettes product markets, we present estimates of the revenue- weighted and unweighted average own-price elasticity for each market-year pair for 2006, 2010, 2014, and 2018 (estimates from other years are omitted to make the table readable.) The row labeled Median refers to the median across the 72 product markets for which we compute own-price elasticities. See Table 11 in Appendix A for estimates for the full sample.

In the following sections, where we use our demand estimates to infer and analyze markups, we exclude from the analyses three product markets: cigarettes, wet cat food, and non-chocolate candy. For these three product markets the demand estimates were obviously problematic, as they implied upward-sloping demand curves in one or more years.[15]

7 Trends in Markups

This section summarizes changes in markups between 2006 and 2018.

With our demand estimates from the previous section, we compute markups for each product-store-quarter combination using Equation (7); in total this gives us over 154 million markup esti-

[15]The coffee and bacon product markets each had years for which the estimate of σ was slightly less than zero, but the elasticity estimates in these years were still negative with reasonable magnitudes.

mates. To summarize changes in markups at the product level, we focus on the median markup for that product across stores in a given year, which we will denote $\tilde{\mu}_{jy}$.

Table 8 summarizes the distributions of these median markups for the largest product markets in our sample, and shows comparisons of these distributions at the beginning and end of our sample period. Percentiles and means in the top panel of the table are unweighted; in the bottom panel, products are weighted by their revenues in the corresponding year.

Table 8: Markups By Year

Panel A: Unweighted								
Product Module	Percentiles/Mean in 2006				Percentiles/Mean in 2018			
	25th	50th	75th	Mean	25th	50th	75th	Mean
Soft Drinks - Carbonated	0.11	0.15	0.23	0.21	0.09	0.11	0.38	0.24
Soft Drinks - Low Calorie	0.16	0.18	0.21	0.26	0.27	0.35	0.44	0.38
Water-Bottled	0.20	0.25	0.36	0.30	0.25	0.40	0.83	0.58
Cereal - Ready To Eat	0.32	0.37	0.40	0.37	0.30	0.35	0.40	0.36
Light Beer (Low Calorie	0.17	0.17	0.20	0.19	0.14	0.16	0.19	0.16
Toilet Tissue	0.21	0.23	0.29	0.26	0.28	0.39	0.52	0.42
Fruit Drinks-Other Container	0.16	0.22	0.36	0.27	0.14	0.21	0.32	0.28
Dairy-Milk-Refrigerated	0.18	0.25	0.29	0.24	0.21	0.36	0.50	0.36
Yogurt-Refrigerated	0.26	0.29	0.36	0.31	0.22	0.37	0.55	0.42
Median	0.24	0.32	0.41	0.34	0.25	0.38	0.52	0.43

Panel B: Sales-Weighted								
Product Module	Percentiles/Mean in 2006				Percentiles/Mean in 2018			
	25th	50th	75th	Mean	25th	50th	75th	Mean
Soft Drinks - Carbonated	0.12	0.13	0.16	0.15	0.09	0.13	0.40	0.24
Soft Drinks - Low Calorie	0.16	0.20	0.21	0.20	0.30	0.37	0.41	0.38
Water-Bottled	0.21	0.23	0.34	0.30	0.34	0.49	0.83	0.63
Cereal - Ready To Eat	0.33	0.38	0.41	0.37	0.32	0.36	0.42	0.36
Light Beer (Low Calorie	0.17	0.18	0.19	0.18	0.16	0.16	0.18	0.17
Toilet Tissue	0.22	0.24	0.25	0.26	0.29	0.37	0.48	0.41
Fruit Drinks-Other Container	0.19	0.25	0.55	0.34	0.16	0.26	0.41	0.34
Dairy-Milk-Refrigerated	0.13	0.21	0.27	0.21	0.18	0.33	0.46	0.33
Yogurt-Refrigerated	0.26	0.35	0.36	0.32	0.25	0.39	0.59	0.45
Median	0.27	0.34	0.41	0.35	0.31	0.41	0.55	0.45

Notes: For the set of product markets listed in Table 1, we present the 25th, 50th, and 75th percentiles of the distribution of μ_y. The row labeled "Median" refers to the median across all product markets in our sample. Table 12 in Appendix A presents corresponding estimates for all 72 markets for which we compute markups.

Several noteworthy patterns are evident in Table 8. First, comparing the revenue-weighted and unweighted distribution of markups, high-revenue products also tend to have large markups: for the average product market, revenue-weighted markups are 1 to 2 percentage points greater than unweighted markups at the beginning of the sample, and greater than unweighted markups by about 2 to 3 percentage points at the end of the sample.

Second, there is considerable heterogeneity across product markets both in the level of markups and in their change over the sample period. In low-calorie soft drinks, for example, median markups were relatively low—approximately 20 percent at the beginning of the sample—and nearly doubled over the sample period. For light beer, markups were similarly low at the beginning of the sample, but were unchanged through the end of the sample. Finally, compared to both low-calorie soft drinks and light beer, markups were higher for refrigerated yogurt, both at the beginning and at the end of the sample.

Third, there is considerable heterogeneity in markups within product markets, and this heterogeneity increased over time: for the median market, the interquartile range of markups is roughly 14 percentage points at the beginning of the sample and 24 percentage points at the end of over time on a revenue-weighted basis, or 17 and 27 percentage points when UPCs are weighted equally.

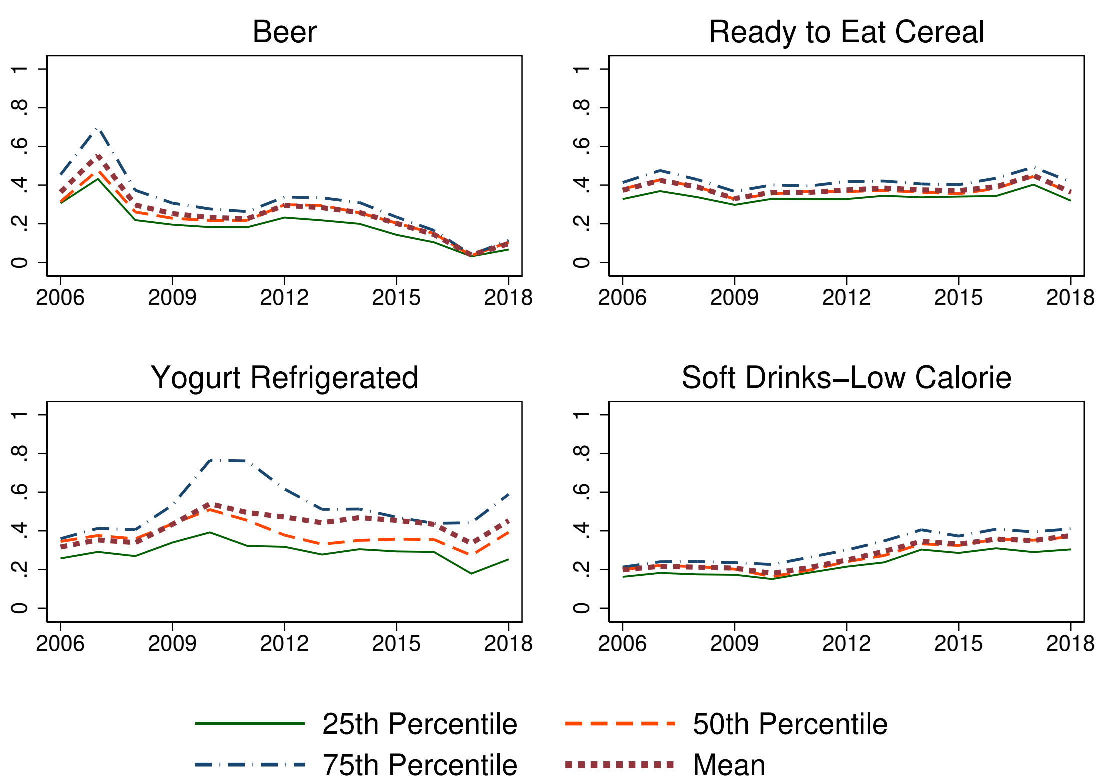
Figure 1: Trends in Markups: Pooled

Notes: For each year, we compute the 25th percentile, median, 75th percentile, and mean of $\tilde{\mu}_{jy}$, pooling across all product markets. In the left panel, we weight products according to their revenue in the year. In the right panel all observations are weighted equally.

In Figure 1, we depict changes in markups throughout our sample period. The median and mean of the pooled markup distribution each increased by approximately 10 percentage points. The 75th percentile markup increased even more sharply, by 17 percentage points. The 25th percentile markup increased more modestly, by only 4 percentage points.

In Figure 2 we show the time trends separately for four of the larger product markets within our sample: beer, refrigerated yogurt, ready-to-eat cereal, and low-calorie soft drinks. There is considerable heterogeneity in the level and trends across these four product markets, with declining markups in beer, increases for low-calorie soft drinks for all quantiles, increases in refrigerated yogurt at the top of the markup distribution, and no discernible trend for ready-to-eat cereal. Weighting products by their revenue, the median markup increased in 51 of the 72 product markets in our sample. Weighting products equally, markups increased in 43 product markets.

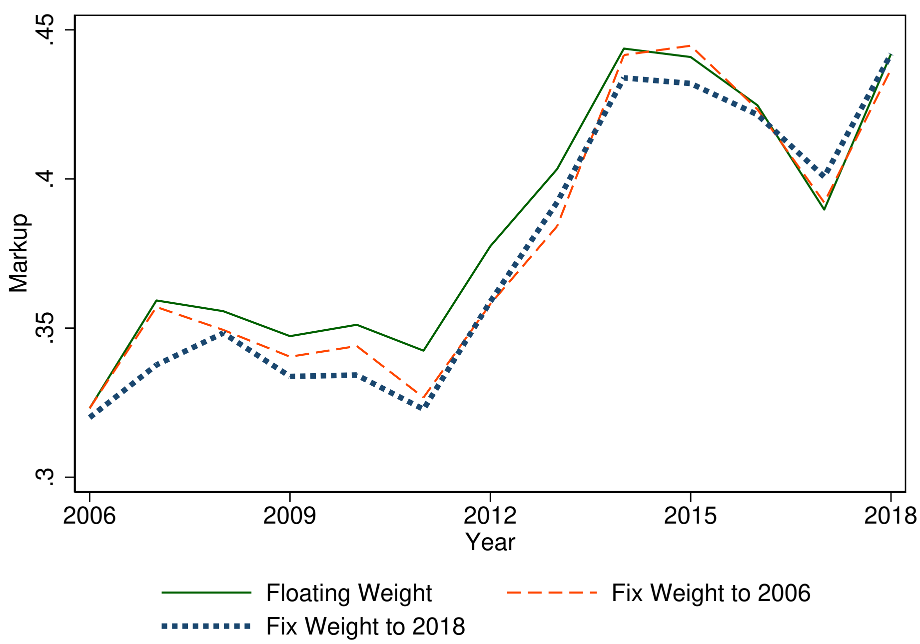
FIGURE 2: Trends in Markups: 4 Product Markets



Notes: For each year and product market we compute the mean of $\tilde{\mu}_{jy}$, both equally weighted across products and revenue-weighted.

The increases in markups described in the figures above could be driven by within-product changes in markups over time or by shifts in the composition of products. Figure 3 assesses the relative contribution of these two effects. In the solid (green) line, we plot the revenue-weighted mean markup in each year. (This was also plotted in the left panel of Figure 1.) In addition, we consider two weighted averages, weighting products either according to their revenue in 2006 (assigning zero weight to products that were not sold in 2006) or to their revenue in 2018 (assigning zero weight to products that were not sold in 2018.) These are the orange dash or blue dash-dot lines. Overall, the three lines are close to one another, indicating that changes in composition account for only a small portion of the changes in revenue-weighted average markups.

FIGURE 3: Trends in Markups



Notes: The green solid line plots the revenue-weighted mean markups in each year. The orange dashed line plots the weighted-mean of markups, weighting products according to their revenues in 2006; the blue short-dashed line plots the weighted-mean of markups, weighting products according to their revenues in 2018.

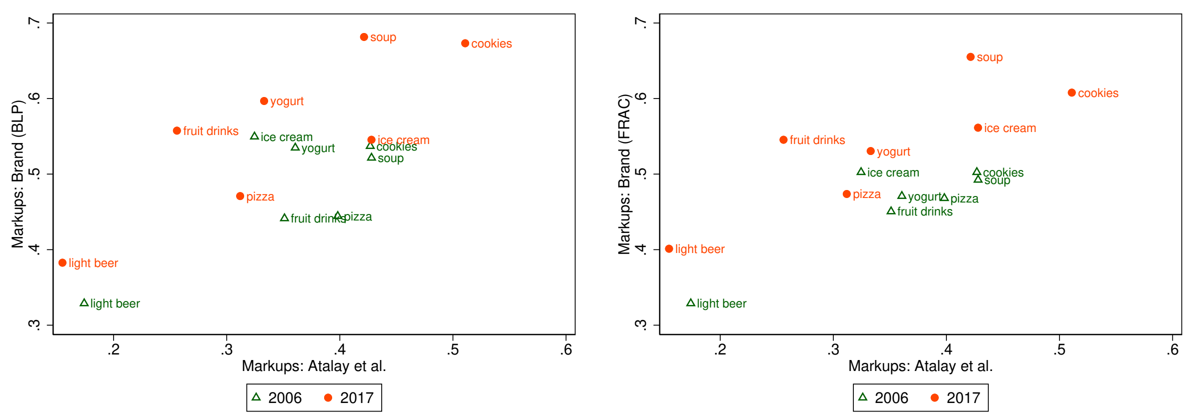
Comparison to other markup estimates

As noted above, two other recent studies have estimated markups using microeconomic methods applied to Nielsen data. Döpper et al. (2022) summarize the trends in their estimated markups by computing medians within product market and then taking the average across product markets. They report average markups of 0.45 in 2006 and 0.60 in 2019. The same calculations in our sample yield somewhat lower overall markups, but with similar estimates for the change over the sample period: we get an average markup of 0.37 in 2006, and 0.50 in 2018.[16]

[16] In addition to the differences in methodologies with which we estimate demand, our papers differ in their sample and unit of observation. The sample in Döpper et al. (2022) includes the top 20 brands in 133 product markets, including private-label brands. The sample in our paper includes 72 markets, products comprising 85 percent of sales in their respective product markets, and excludes private-label products. Furthermore, while Döpper et al. (2022) estimate demand at the brand level, we use products as our unit of observation.

Brand (2020) examines nine product markets, seven of which are included in our sample.[17] Since Brand (2020) reports changes in markups within each individual market, we can directly compare our estimates market by market (as we do in Figure 4). For the 14 observations (seven product markets times two years), there is a strong relationship between the markups we estimate and the markups in Brand (2020).[18] However, while Brand (2020) estimates that markups increased in all seven of those product markets between 2006 and 2017 (by an average of 8 percentage points), we find no discernible trend among this subset of our sample.

FIGURE 4: Comparison with Brand (2020)



Notes: Each panel presents market-year level markups in our paper and in Brand (2020). To compute our market-year markup, we take the revenue-weighted median within each market-year pair.

8 Counterfactual Exercises

Our results indicate that markups have generally trended upward between 2006 and 2018. The increases are mainly due to within-product markup increases, are concentrated in the upper tails of the markup distribution, and display substantial heterogeneity across product markets. In this section, we explore possible mechanisms underlying the upward trend in markups. Three main hypotheses are (1) a decrease in consumer price sensitivity over time, (2) a consolidation of ownership through merger and acquisition, or (3) changes in the marginal costs at which individual products are supplied.[19] Each of these hypotheses can be viewed more precisely through Equation (7) from

[17] The two product markets in Brand (2020)'s dataset not included in ours are "Remaining Fruit" and "Refrigerated Entrees"

[18] Brand (2020) applies two distinct methods to estimate markups: one, called "blp", follows Berry, Levinsohn and Pakes (1995), with one set of parameter estimates for the country; a second, called "frac", allows for parameter estimates to vary by geography. The correlations between our markups and those in Brand (2020) are 0.71 (according to the "blp" measure) or 0.72 (with the "frac" measure). The Spearman rank correlations are 0.44 and 0.54, respectively.

[19] A fourth hypothesis states that changes in the set of products accounts for changes in the markup distribution. At least when observations are revenue-weighted, Figure 3 from the previous section indicates that changes in product composition play a relatively minor role in accounting for shifts in the mean of the markup distribtuion.

Section 5. Decreases in consumer price sensitivity would result from changes in the parameters $\alpha_{y(q)}$ and $\sigma_{y(q)}$. Mergers, acquisitions, and divestitures change the assignment of products to firms, as parameterized by the ownership matrix Ω_t. Changes in marginal costs are reflected in changes in c_t.

Figure 5 presents the main results from our counterfactual exercises. The solid green and the maroon short-dashed lines present the observed distributions—pooling over product markets, weighting product-year observations by units sold—of markups in 2006 and in 2018, respectively. For this figure, we focus only on the products that were present in both years.[20] Consistent with the patterns described above, the distribution of markups shifts to the right, particularly in the upper half of the markup distribution.

In the orange dashed line, we present the distribution of markups that would have been observed in 2018 with preference parameters—the $\alpha_{y(q)}$ and $\sigma_{y(q)}$—kept at their 2006 values. That is, we use the algorithm proposed in Morrow and Skerlos (2011) to solve for the equilibrium prices that would have obtained in 2018 if $\alpha_{y(q)}$ and $\sigma_{y(q)}$ are set equal to their 2006 values and all other fundamentals—the set of available products, marginal costs, the assignments of products to firms—are set to their 2018 values. We then compute the associated counterfactual markups according to Equation (7). The takeaway is that changes in preferences alone explain a substantial portion of the shift in the distribution of markups throughout much of the support (particularly for products above the 50th percentile and below the 90th percentile of the pooled markup distribution). This is consistent with the findings of Döpper et al. (2022), who report that changes in consumers' price sensitivity can explain over half of the changes in markups they measure.

The dash-dot blue line considers the impact of changes in marginal costs on the markup distribution. We allow the marginal cost for product j in market t to be a function of quarter fixed effects and store-product fixed effects, or:

$$mc_{jt} = F_q + F_{jr} + \epsilon_{jt}. \tag{8}$$

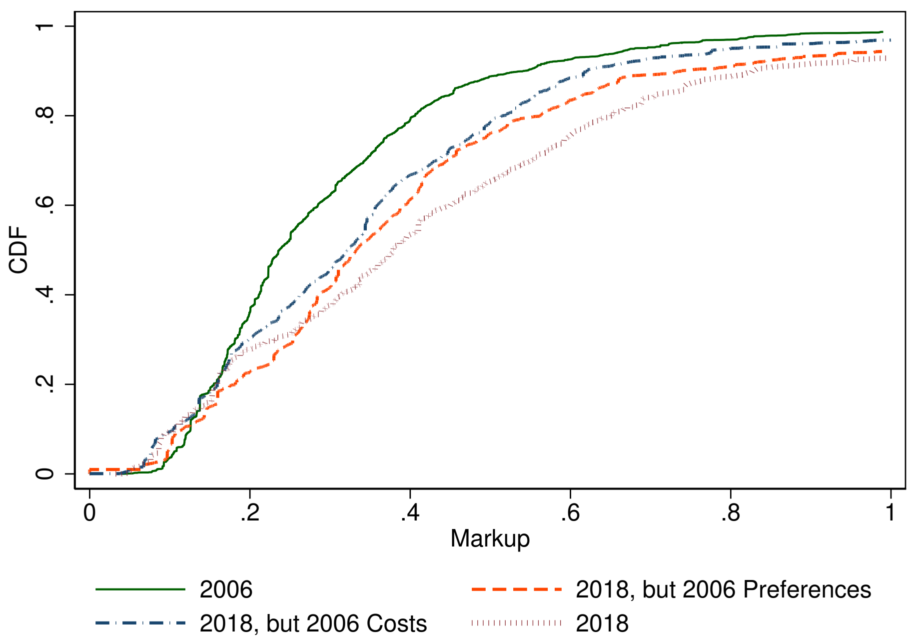
This specification allows for non-parametric time trends in marginal costs along with seasonality. In each product market, we pool across markets the implied marginal costs recovered from Equation (5) and estimate the quarter fixed effects via ordinary least squares. For each product-store combination present in 2018, we remove the time trend to infer its "2006 marginal cost" by replacing the quarter fixed effect in Equation (8) with the estimated value from 2006. We again use the algorithm proposed in Morrow and Skerlos (2011) to solve for the equilibrium prices with these

[20] We assess the sensitivity of our results to restricting to a balanced sample in Figure 8 in Appendix A. Including all products, not only those that are present at both the beginning and end of the sample, the increase in markups is less pronounced than in Figure 5, especially at the top of the distribution. In accounting for the change in markups, with using a balanced panel, changes in preferences account for a decrease in markups at the bottom of the markup distribution (the dashed orange line lies to the right of the short-dash red line below the 25th percentile), but neither accounts for an increase or decrease when all products are considered.

2006 marginal costs holding all other market primitives at their 2018 values. We then compute the associated pooled markup distribution. This distribution essentially mirrors the observed 2018 markup distribution up to the 20th percentile. Beyond this quantile, changes in marginal costs explain a substantial portion (but certaintly not all) of the increases in markups between 2006 and 2018.

We have conducted a third exercise, in which we consider the impact of ownership changes. In this exercise, we compute the counterfactual markup distribution with the assignment of products to firms given by what we observe in 2006 with all other fundamentals—the set of products available, marginal costs, and preference parameters— set to their 2018 values. This distribution lies essentially on top of the observed distribution for 2018 markups, indicating that changes in ownership have not played an important role in markup changes over our sample period.

FIGURE 5: Observed and Counterfactual Markup Distributions



Notes: This figure presents the observed distribution of markups in 2006 and 2018 for the set of products that were sold in both years, as well as the counterfactual markup distributions, as of 2018, either with only preferences given by their 2006 values (orange dashed line) or with marginal costs given by their 2006 values (blue dash-dot lines).

To close, and with the goal of providing additional intuition, we consider the sources of heterogeneity of changes in observable parameters on the markups distribution.

First, with the aim of explaining why ownership changes have such little impact within our counterfactual exercises, we consider changes in concentration that are due to shifts in the assignment of products to firms within our sample period. To begin, for each product market, we compute the Herfindahl-Hirschman Index (HHI) as of 2018. Letting $r_{m,j,2018}$ denote the national revenue share for product j within product market m and $\mathcal{J}_f$ the set of products produced by firm f, we compute

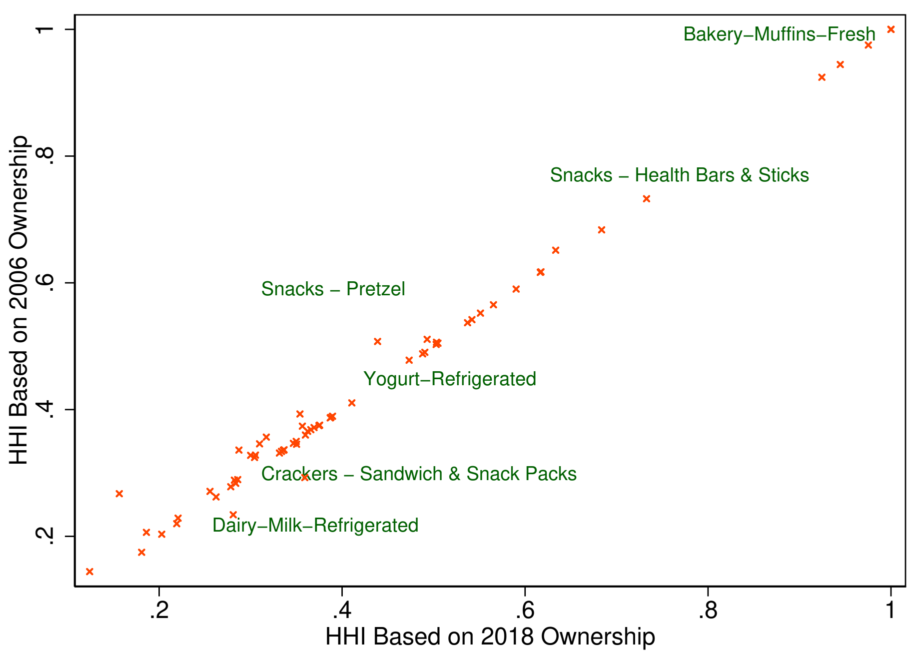
$$HHI_{m,2018} = \sum_f \left(\sum_{j \in \mathcal{J}_f} r_{m,j,2018} \right)^2. \quad (9)$$

We compare this to the HHI which would be observed if we assigned products present in 2018 to their 2006 owners. We compute this statistic as:

$$HHI'_{m,2018} = \sum_f \left(\sum_{j \in \mathcal{J}_{f,2006}} r_{m,j,2018} \right)^2. \quad (10)$$

In contrast to Equation (9), the inner summation within Equation (10) refers to the ownership of products as of 2006, at the beginning of our sample.[21]

FIGURE 6: Changes in Product Assignment



Notes: This figure depicts changes in concentration resulting only from changes in the assignment of products to firms. For each product market, we compare changes in HHI (as computed in Equation (9) to the HHI (as computed in Equation (10) corresponding to the 2006 assignment of products to firms. We list the product market names where it is legible to do so.

Figure 6 compares $HHI_{m,2018}$ to $HHI'_{m,2018}$. With few exceptions, points within this plot fall

[21]For products that were not present in 2006, we assign based on the ownership of other commonly owned products as of the end of the sample. For instance, "Darigold Large Curd Cottage Cheese" (upc 2640017080) was present in 2018 but not 2006. We assign the 2006 parent of this product to that of other Darigold products. Another example, "Go-Gurt Strawberry and Berry Yogurt Tubes 8 ct / 2 oz" (upc 7047013768) was a General Mills product in 2018. GM purchased Yoplait in 2011, so we assign this product as if it were a Yoplait firm in 2006.

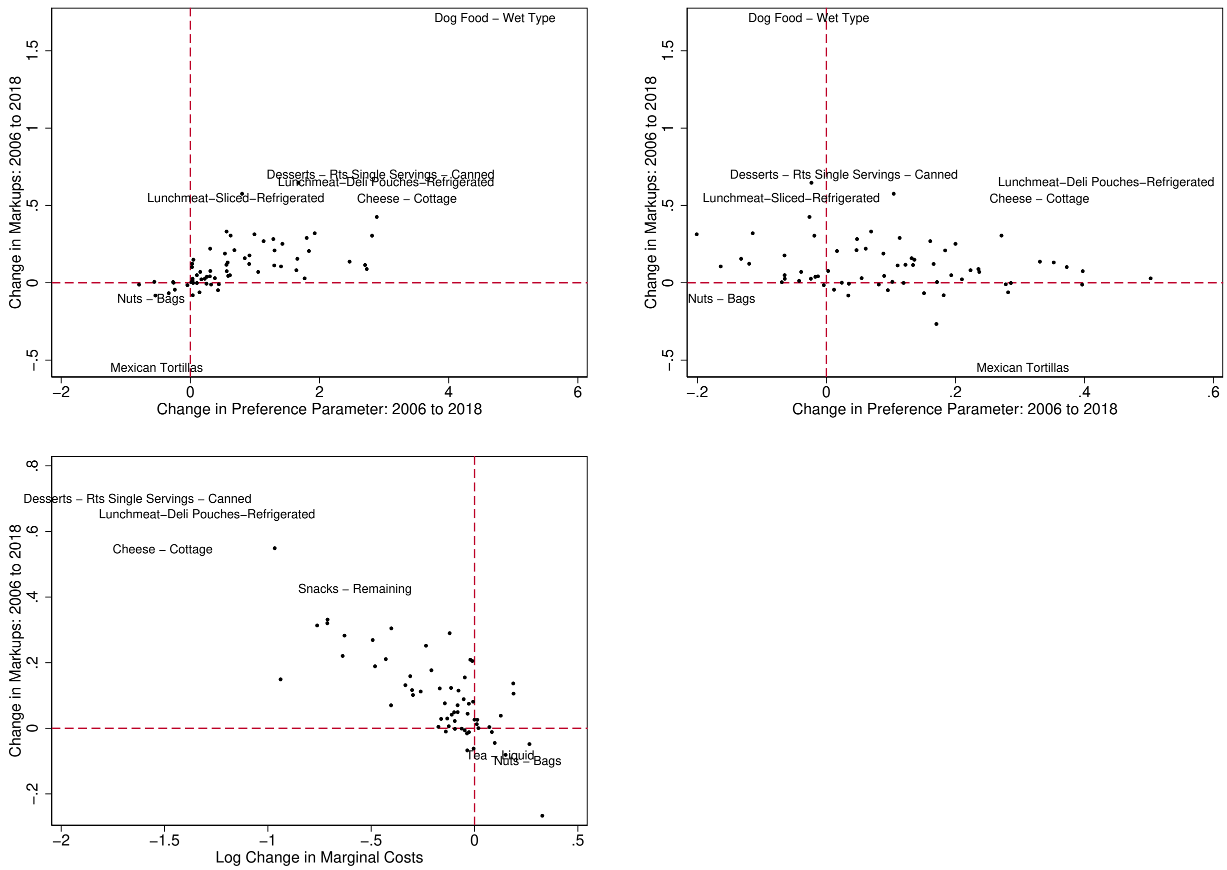
close to the 45-degree line, indicating that changes in the assignment of products to firms correspond to relatively minor changes in HHI. Notable partial exceptions include the market for Pretzels – in which the Bachman Pretzel Company was acquired by Utz Brands – and Dairy Milk – in which Dean Foods spun off WhiteWave Foods.[22] Despite these exceptions, we find that mergers, acquisitions, and divestitures had a minimal impact on national concentration within product markets.

All of this is not to say that HHI was constant within the sample period. Indeed, products have grown or shrunk; and individual products have entered or left the market. But, these margins were inoperative in our "ownership counterfactual" and we purposefully excluded their impact on concentration as depicted in Figure 6.

Second, we link changes in average markups – at the product market level – to changes in our estimates of α and σ for each market; see the top left and top right panels of Figure 7. Consistent with our counterfactual exercises, there is a strong positive relationship between the change in consumers' sensitivity to prices and the change in the market's markups. The Spearman (rank) correlation between the two data series is 0.78. There is a weaker, but still significant relationship between changes in product markets' markups and changes in the correlation of taste shocks within nests. In the bottom left panel of Figure 7, we relate changes in markups and changes in marginal costs (with both averaged across product-store pairs). There is a strong negative correlation between the two. Product markets for which marginal costs have declined also experienced an increase in markups.

[22] In other markets, there was a substantial re-shuffling of products across firms but with no change to HHI. Many of these cases involved one a conglomerate firm purchasing the entire product portfolio of another firm within a specific product market. For instance, the impact of General Mills' purchase of Yoplait had a minimal impact of HHI within the yogurt market, as the former firm had no yogurt brands before its acquisition.

Figure 7: Sources of Product-market-Level Markup Changes



Notes: Each panel presents the difference in (the revenue-weighted mean) markups between 2006 and 2018 by product market. In the top left panel, we relate these markup changes to the product market's change in consumers' sensitivity to prices, between 2006 and 2018. In the top right panel, we relate changes in markups to changes in the correlation of taste shocks within nests. In the bottom left panel, we relate markup changes to changes in the product market's median marginal costs. For ease of readability, in the top left panel we omit the Beer market, for which α fell from -2.71 to -9.21 and for which the average markup decreased by 27 percentage points. In the bottom right panel, we drop five product markets for which median marginal costs are negative either at the beginning or at the end of the sample; for these markets the log change is undefined. Marginal costs, in 2018, were slightly negative for Dairy Milk, Dog Food, Mexican Frozen Food Entrees, and Soup Mixes (Dry and Bases). For these four product markets, markups increased by 65 percentage points, 172 percentage points, 58 percentage points, and 31 percentage points respectively. Marginal costs in 2006 were negative for Mexican Tortillas. For this market, markups fell by 55 percentage points between 2006 and 2018. In the three panels, we spell out the name of product markets where it is readable to do so.

9 Conclusion

This paper examines changes in markups across many different product markets by introducing a new method for scalably estimating demand. In conventional analyses, industrial organization economists thoughtfully specify the product characteristics that households care about. While preferable if the subject is a single product market (or a small number of markets), this approach precludes the analysis of multiple distinct markets. We show that nested logit preferences—where data on within-household substitution patterns are used to automate the assignment of products to nests—offer a viable alternative for researchers seeking to estimate demand across a wide variety of product markets.

We find that markups have generally increased since 2006, with considerable heterogeneity in these increases both within and between product markets. We show that changes in households price sensitivity and products' marginal cost are the main driving force behind the markup increases, with changes in ownership and product assortment having a somewhat surprisingly small impact. Our results thus corroborate previous findings from the macro literature on markups, in the sense that we uncover a significant upward trend in markups overall, but also point to interesting questions about heterogeneity (why markups have increased more in some product markets than others) and about underlying mechanisms (why consumers seem to have become less price sensitive, and why consolidation of ownership explains so little of the changes in markups).

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A Additional Tables and Figures

In Table 1, we provided a description of the 10 largest product markets within our sample. Then, in Tables 6, 7, and 8, we provided estimates of preference parameters, own-price elasticities, and markups for the ten largest markets and for the median among all of the product markets in our dataset. In this appendix, we collect the corresponding estimates for each of the markets in our sample. Table 9 presents the analogue of Table 1; Table 10 presents the analogue of Table 6; Table 11 presents the analogue of Table 7; while Table 12 provides the analogue of Table 8. Finally, while Figure 5 considers counterfactual markup distributions for products that were present at both the beginning and end of the sample, Figure 8 demonstrates that the counterfactual distributions would look similar without restricting to a balanced panel.

Table 9: Sample Description: All 75 Product Markets

Product Market	Stores		UPCs		Revenues		Nests
	2006	2018	2006	2018	2006	2018	
Fruit Drinks & Juices-Cranberry	9157	6945	51	46	123.86	71.43	4
Fruit Drinks-Other Container	15994	16381	277	292	871.41	832.70	4
Fruit Juice-Remaining	6577	6700	115	112	158.25	81.20	4
Soft Drinks - Powdered	9057	5895	55	57	53.78	28.90	3
Tomatoes - Remaining - Canned	6307	6960	66	52	63.58	54.53	10
Mexican Sauce	7358	6637	143	128	140.03	84.16	6
Spaghetti/Marinara Sauce	7012	6520	112	103	174.33	107.58	4
Salad Dressing - Liquid	6799	6680	214	170	92.97	71.51	6
Mexican Tortillas	6236	7301	152	102	276.44	298.61	9
Soup-Canned	13762	11178	200	217	604.86	355.24	2
Soup Mixes - Dry & Bases	13109	10940	46	66	84.47	94.66	3
Cat Food - Wet Type	12974	11477	141	141	162.62	157.49	4
Dog Food - Wet Type	12361	9514	116	158	93.07	48.04	5
Rice - Mixes	6265	6231	74	54	77.71	50.45	2
Snacks - Potato Chips	17587	14923	197	167	672.59	745.47	8
Snacks - Tortilla Chips	14447	15853	54	49	585.43	639.30	4
Snacks - Remaining	13097	13653	133	249	132.66	254.48	7
Snacks - Pretzel	6842	6463	106	108	96.46	113.29	6
Pasta - Macaroni	6103	6713	179	150	77.63	79.96	2
Pasta-Spaghetti	6505	7023	91	65	65.11	64.62	4
Dry Dinners - Pasta	10859	8681	86	87	225.81	205.42	6

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Product Market	Stores		UPCs		Revenues		Nests
	2006	2018	2006	2018	2006	2018	
Crackers - Sandwich & Snack Packs	11138	9344	70	113	66.36	109.94	3
Cereal - Ready To Eat	10089	8293	172	212	1347.69	783.89	6
Crackers - Flavored Snack	7059	7948	59	79	222.66	190.67	4
Cookies	17239	15014	478	463	531.41	467.18	11
Fruit-Dried And Snacks	8210	7284	153	165	76.56	69.63	4
Granola & Yogurt Bars	9087	8417	130	193	185.06	158.87	5
Snacks - Health Bars & Sticks	5292	6621	152	228	59.53	140.88	3
Desserts - Rts Single Servings - Canned	9219	6717	69	102	123.72	77.80	3
Tea - Liquid	15181	17106	135	229	226.57	282.94	4
Ground And Whole Bean Coffee	11550	6968	209	410	47.29	40.61	10
Soft Drinks - Carbonated	22247	21322	155	222	2779.20	2352.27	11
Water-Bottled	20924	19536	185	170	1302.81	1053.79	2
Candy-Chocolate	22048	21022	236	292	535.20	505.85	5
Candy-Non-Chocolate	20373	19775	600	522	168.94	150.48	10
Nuts - Bags	12160	10484	208	228	114.68	126.96	7
Gum-Chewing-Sugarfree	12675	11268	66	88	217.72	138.33	4
Soft Drinks - Low Calorie	21831	16773	111	239	1673.57	1269.90	4
Entrees - Poultry - 1 Food - Frozen	6244	5946	146	156	218.40	146.73	6
Entrees - Italian - 1 Food - Frozen	7245	6809	100	144	231.80	129.09	6
Entrees - Mexican - 1 Food - Frozen	7202	6881	73	108	69.31	63.97	8
Frozen/Refrigerated Breakfasts	5819	6684	80	95	70.48	97.92	4
Pizza-Frozen	6995	9393	163	159	453.65	331.91	6
Vegetables - Potatoes - Frozen/Refrigerated	6785	6733	91	75	169.68	163.45	3
Ice Cream - Bulk	8164	8603	324	343	359.25	253.80	3
Frozen Novelties	7555	7694	256	320	222.27	169.39	9
Cheese - Natural - American Cheddar	6248	6610	77	97	146.22	124.48	5
Fresh Meat	6352	7395	109	164	364.00	515.17	4
Sausage-Dinner	6297	7294	224	251	218.49	333.32	5
Lunchmeat-Sliced-Refrigerated	6659	7866	262	202	325.27	191.09	6
Frankfurters-Refrigerated	6949	9199	83	72	367.36	257.37	5
Bacon-Refrigerated	7001	8350	83	86	424.62	497.68	4
Sausage-Breakfast	7198	6976	113	80	191.51	174.59	3
Spreads-Remaining	2960	6767	64	102	26.93	142.96	6

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Product Market	Stores		UPCs		Revenues		Nests
	2006	2018	2006	2018	2006	2018	
Cheese - Shredded	6649	7037	74	77	230.21	208.76	6
Dairy-Flavored Milk-Refrigerated	9667	7921	143	98	70.75	58.74	8
Yogurt-Refrigerated	7694	7985	159	308	662.48	809.65	3
Cheese - Cottage	5763	5720	112	107	131.75	73.88	5
Lunchmeat-Deli Pouches-Refrigerated	6899	7283	83	91	245.09	229.35	5
Dairy-Milk-Refrigerated	16984	17879	503	209	948.56	678.06	11
Bakery - Bread - Fresh	13844	13907	597	409	418.37	373.03	4
Bakery-Buns-Fresh	7207	8875	152	108	53.32	51.46	2
Bakery-Rolls-Fresh	6512	7453	184	96	48.77	70.68	4
Bakery-Muffins-Fresh	7851	7607	43	41	165.39	210.08	3
Bakery-Cakes-Fresh	11507	10661	198	243	94.32	73.60	3
Bakery-Breakfast Cakes/Sweet Rolls-Fresh	10306	9412	123	67	74.76	55.07	6
Bakery-Doughnuts-Fresh	8325	8149	82	58	38.48	35.86	3
Beer	7480	9607	183	218	768.41	584.61	6
Light Beer (Low Calorie/Alcohol)	7477	9128	61	83	1094.57	751.57	8
Wine-Domestic Dry Table	4572	6520	562	676	286.32	414.63	13
Detergents - Heavy Duty - Liquid	12411	11043	154	250	504.90	267.61	3
Toilet Tissue	19553	15908	57	127	986.27	730.21	6
Disposable Dishes	11773	7502	91	74	147.69	86.66	3
Cigarettes	15647	18559	181	120	1444.62	1491.60	4
Paper Towels	18533	11016	62	98	658.20	472.11	6

Notes: For the two endpoint years within our sample, we count the number of unique stores at which products were sold, the number of unique UPCs, and total revenues (in billions of dollars.). The final column lists the number of nests identified by our Section 4 clustering method.

Table 10: Demand Parameters: All 75 Product Markets

Product Market	α_{2006}	α_{2012}	α_{2018}	σ_{2006}	σ_{2012}	σ_{2018}	$\alpha_{2018} - \alpha_{2006}$
Fruit Drinks & Juices-Cranberry	-3.18	-2.94	-3.15	0.34	0.55	0.71	0.03
Fruit Drinks-Other Container	-1.52	-0.78	-1.27	0.79	0.84	0.82	0.25
Fruit Juice-Remaining	-2.61	-2.60	-2.57	0.35	0.46	0.53	0.04
Soft Drinks - Powdered	-1.51	-2.77	-1.47	0.33	0.90	0.47	0.05
Tomatoes - Remaining - Canned	-3.63	-3.96	-4.19	0.37	0.66	0.47	-0.56

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Product Market	α_{2006}	α_{2012}	α_{2018}	σ_{2006}	σ_{2012}	σ_{2018}	$\alpha_{2018} - \alpha_{2006}$
Mexican Sauce	-2.14	-2.05	-1.60	0.60	0.68	0.69	0.54
Spaghetti/Marinara Sauce	-3.16	-1.43	-1.85	0.31	0.54	0.50	1.30
Salad Dressing - Liquid	-2.88	-2.76	-2.57	0.53	0.56	0.53	0.31
Mexican Tortillas	-0.94	-2.75	-1.46	0.21	0.37	0.51	-0.52
Soup-Canned	-2.50	-2.90	-2.84	0.44	0.52	0.59	-0.34
Soup Mixes - Dry & Bases	-1.06	-0.46	-0.43	0.42	0.61	0.70	0.62
Cat Food - Wet Type	-3.12	-2.45	1.77	0.50	0.63	0.51	4.88
Dog Food - Wet Type	-5.24	-1.55	-0.52	0.58	0.44	0.56	4.72
Rice - Mixes	-2.31	-1.79	-2.01	0.56	0.69	0.62	0.31
Snacks - Potato Chips	-4.95	-2.03	-2.14	0.55	0.48	0.53	2.81
Snacks - Tortilla Chips	-3.13	-1.86	-1.83	0.69	0.72	0.80	1.30
Snacks - Remaining	-4.24	-1.67	-1.35	0.52	0.49	0.49	2.89
Snacks - Pretzel	-3.99	-2.49	-2.16	0.42	0.42	0.44	1.84
Pasta - Macaroni	-1.99	-2.02	-2.23	0.46	0.51	0.47	-0.24
Pasta-Spaghetti	-2.14	-2.39	-2.11	0.47	0.52	0.41	0.03
Dry Dinners - Pasta	-3.25	-2.97	-1.97	0.41	0.58	0.46	1.28
Crackers - Sandwich & Snack Packs	-2.91	-2.60	-2.33	0.51	0.50	0.59	0.59
Cereal - Ready To Eat	-2.59	-1.99	-2.15	0.29	0.54	0.57	0.44
Crackers - Flavored Snack	-2.80	-2.55	-2.70	0.32	0.55	0.60	0.10
Cookies	-2.90	-2.36	-2.73	0.30	0.39	0.51	0.17
Fruit-Dried And Snacks	-2.35	-1.78	-2.31	0.49	0.52	0.60	0.04
Granola & Yogurt Bars	-2.81	-2.23	-2.86	0.52	0.58	0.51	-0.05
Snacks - Health Bars & Sticks	-1.47	-1.99	-1.44	0.66	0.54	0.54	0.03
Desserts - Rts Single Servings - Canned	-3.90	-4.70	-0.95	0.61	0.42	0.64	2.95
Tea - Liquid	-1.38	-2.67	-1.92	0.73	0.57	0.76	-0.54
Ground And Whole Bean Coffee	-5.05	-3.93	-3.28	-0.01	0.43	0.49	1.77
Soft Drinks - Carbonated	-4.37	-2.21	-1.63	0.68	0.85	0.92	2.73
Water-Bottled	-1.35	-1.44	-0.79	0.74	0.77	0.81	0.56
Candy-Chocolate	-2.63	-0.99	-0.83	0.56	0.73	0.67	1.80
Candy-Non-Chocolate	2.79	0.89	-0.27	0.78	0.85	0.93	-3.05
Nuts - Bags	-2.41	-1.73	-3.02	0.61	0.52	0.45	-0.61
Gum-Chewing-Sugarfree	-1.31	-0.92	-1.08	0.83	0.74	0.81	0.22
Soft Drinks - Low Calorie	-3.01	-2.43	-2.09	0.67	0.64	0.60	0.92
Entrees - Poultry - 1 Food - Frozen	-3.24	-2.77	-2.66	0.39	0.55	0.74	0.58

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Product Market	α_{2006}	α_{2012}	α_{2018}	σ_{2006}	σ_{2012}	σ_{2018}	$\alpha_{2018} - \alpha_{2006}$
Entrees - Italian - 1 Food - Frozen	-2.52	-3.23	-1.67	0.45	0.50	0.58	0.84
Entrees - Mexican - 1 Food - Frozen	-1.65	-1.22	-0.85	0.49	0.51	0.59	0.80
Frozen/Refrigerated Breakfasts	-2.64	-2.52	-1.73	0.40	0.51	0.57	0.91
Pizza-Frozen	-2.16	-2.75	-2.43	0.38	0.33	0.55	-0.27
Vegetables - Potatoes - Frozen/Refrigerated	-2.80	-2.69	-2.42	0.61	0.66	0.67	0.38
Ice Cream - Bulk	-2.48	-2.42	-2.33	0.56	0.50	0.52	0.15
Frozen Novelties	-3.02	-2.95	-2.41	0.38	0.49	0.57	0.61
Cheese - Natural - American Cheddar	-3.63	-3.20	-3.31	0.34	0.40	0.42	0.32
Fresh Meat	-1.89	-1.84	-1.88	0.47	0.34	0.40	0.02
Sausage-Dinner	-2.41	-1.09	-2.11	0.53	0.71	0.52	0.30
Lunchmeat-Sliced-Refrigerated	-1.58	-1.36	-0.88	0.54	0.65	0.49	0.71
Frankfurters-Refrigerated	-2.63	-2.19	-2.06	0.13	0.37	0.53	0.56
Bacon-Refrigerated	-3.91	-2.75	-2.27	0.20	0.39	0.42	1.64
Sausage-Breakfast	-2.87	-2.58	-2.84	0.51	0.58	0.46	0.03
Spreads-Remaining	-3.70	-2.70	-1.77	0.64	0.42	0.53	1.93
Cheese - Shredded	-3.00	-3.93	-2.86	0.39	0.45	0.67	0.14
Dairy-Flavored Milk-Refrigerated	-2.58	-3.29	-0.90	0.67	0.84	0.65	1.67
Yogurt-Refrigerated	-4.04	-1.84	-1.58	0.24	0.46	0.57	2.47
Cheese - Cottage	-4.73	-2.36	-1.38	0.26	0.53	0.59	3.35
Lunchmeat-Deli Pouches-Refrigerated	-4.03	-3.71	-1.00	0.34	0.45	0.77	3.03
Dairy-Milk-Refrigerated	-6.73	-5.32	-4.02	0.29	0.33	0.42	2.71
Bakery - Bread - Fresh	-1.97	-1.36	-0.84	0.57	0.65	0.73	1.13
Bakery-Buns-Fresh	-3.61	-2.99	-3.87	0.70	0.68	0.72	-0.26
Bakery-Rolls-Fresh	-3.00	-2.71	-2.90	0.50	0.43	0.43	0.10
Bakery-Muffins-Fresh	-3.25	-2.44	-2.25	0.27	0.30	0.07	0.99
Bakery-Cakes-Fresh	-2.91	-3.38	-1.86	0.47	0.63	0.71	1.05
Bakery-Breakfast Cakes/Sweet Rolls-Fresh	-1.76	-1.52	-1.20	0.68	0.73	0.80	0.56
Bakery-Doughnuts-Fresh	-2.48	-3.76	-1.80	0.48	0.37	0.53	0.68
Beer	-2.71	-3.04	-9.21	0.38	0.45	0.55	-6.50
Light Beer (Low Calorie/Alcohol)	-6.52	-7.93	-7.31	0.13	0.34	0.53	-0.79
Wine-Domestic Dry Table	-2.60	-1.50	-1.18	0.51	0.56	0.71	1.43
Detergents - Heavy Duty - Liquid	-3.86	-2.74	-2.46	0.71	0.59	0.55	1.40
Toilet Tissue	-4.17	-4.12	-2.52	0.45	0.32	0.32	1.66
Disposable Dishes	-2.31	-2.27	-1.89	0.35	0.47	0.45	0.43

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Product Market	α_{2006}	α_{2012}	α_{2018}	σ_{2006}	σ_{2012}	σ_{2018}	$\alpha_{2018} - \alpha_{2006}$
Cigarettes	3.90	9.10	6.65	0.52	0.21	0.42	2.75
Paper Towels	-3.71	-3.73	-3.45	0.43	0.33	0.41	0.25

Notes: We present estimates of α_y and σ_y for $y \in \{2006, 2012, 2018\}$. The final column presents $\alpha_{2018} - \alpha_{2006}$.

Table 11: Own-Price Elasticity: All 75 Product Markets

Product Market	Unweighted				Revenue-Weighted			
	2006	2010	2014	2018	2006	2010	2014	2018
Fruit Drinks & Juices-Cranberry	-4.21	-5.40	-7.67	-7.78	-3.93	-4.46	-6.42	-6.05
Fruit Drinks-Other Container	-7.93	-9.25	-2.23	-7.61	-7.40	-8.50	-1.95	-6.87
Fruit Juice-Remaining	-4.08	-3.88	-5.19	-5.28	-3.88	-3.64	-5.11	-5.07
Soft Drinks - Powdered	-3.66	-9.38	-8.30	-3.15	-2.92	-5.51	-5.69	-2.56
Tomatoes - Remaining - Canned	-4.72	-6.38	-5.87	-6.16	-4.47	-6.02	-5.64	-5.29
Mexican Sauce	-4.61	-5.01	-5.77	-3.95	-4.84	-5.76	-6.00	-3.98
Spaghetti/Marinara Sauce	-5.17	-3.51	-3.86	-4.24	-4.98	-3.31	-3.57	-4.06
Salad Dressing - Liquid	-5.59	-5.68	-5.73	-4.76	-4.77	-4.93	-4.79	-3.87
Mexican Tortillas	-1.04	-2.87	-2.93	-2.68	-1.26	-3.22	-3.09	-2.68
Soup-Canned	-4.62	-3.86	-5.18	-6.26	-4.23	-3.60	-4.82	-5.82
Soup Mixes - Dry & Bases	-2.36	-2.80	-2.37	-2.33	-3.13	-3.07	-2.24	-2.28
Dog Food - Wet Type	-11.29	-7.47	-6.90	-1.85	-10.86	-6.76	-6.41	-1.58
Rice - Mixes	-5.46	-6.89	-5.14	-4.54	-5.48	-6.38	-4.64	-4.05
Snacks - Potato Chips	-9.72	-5.27	-3.54	-4.12	-8.30	-4.71	-3.15	-3.94
Snacks - Tortilla Chips	-9.25	-9.18	-7.75	-7.71	-8.24	-7.91	-6.80	-7.07
Snacks - Remaining	-8.29	-4.79	-2.90	-2.77	-7.01	-4.55	-2.74	-2.51
Snacks - Pretzel	-5.73	-4.85	-3.65	-3.62	-5.51	-4.78	-3.50	-3.68
Pasta - Macaroni	-3.49	-3.71	-3.81	-4.35	-3.04	-3.55	-3.18	-3.52
Pasta-Spaghetti	-3.20	-3.22	-3.60	-2.95	-2.94	-3.16	-3.04	-2.78
Dry Dinners - Pasta	-5.54	-5.68	-3.27	-3.16	-4.91	-4.95	-3.09	-2.90
Crackers - Sandwich & Snack Packs	-4.52	-6.32	-5.55	-5.49	-4.81	-5.75	-5.51	-4.57
Cereal - Ready To Eat	-3.47	-3.72	-3.74	-4.00	-3.40	-3.66	-3.67	-3.87
Crackers - Flavored Snack	-3.85	-4.43	-4.26	-5.71	-3.82	-4.18	-3.78	-4.54
Cookies	-4.21	-4.77	-3.99	-5.45	-3.90	-4.19	-3.64	-4.77
Fruit-Dried And Snacks	-4.35	-3.41	-4.03	-5.46	-4.09	-3.35	-4.09	-4.77

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Product Market	Unweighted				Revenue-Weighted			
	2006	2010	2014	2018	2006	2010	2014	2018
Granola & Yogurt Bars	-5.37	-6.01	-5.82	-5.73	-5.17	-5.73	-5.74	-5.08
Snacks - Health Bars & Sticks	-4.57	-6.20	-3.78	-3.29	-4.32	-5.65	-3.55	-3.21
Desserts - Rts Single Servings - Canned	-8.32	-8.50	-4.69	-2.48	-8.76	-8.48	-4.07	-2.10
Tea - Liquid	-5.58	-7.71	-6.20	-9.23	-4.74	-6.59	-5.42	-7.33
Ground And Whole Bean Coffee	-6.11	-6.04	-6.72	-5.80	-5.45	-6.11	-6.33	-5.50
Soft Drinks - Carbonated	-10.40	-14.32	-5.67	-16.62	-10.49	-13.51	-5.37	-14.72
Water-Bottled	-5.79	-6.54	-3.54	-4.21	-5.67	-6.13	-3.14	-3.61
Candy-Chocolate	-5.00	-4.57	-6.25	-2.78	-4.39	-4.16	-5.72	-2.48
Nuts - Bags	-7.04	-4.62	-3.63	-6.40	-4.86	-3.05	-3.25	-5.61
Gum-Chewing-Sugarfree	-6.62	-4.19	-1.98	-5.27	-6.43	-4.11	-1.91	-4.80
Soft Drinks - Low Calorie	-7.22	-9.46	-4.20	-4.71	-7.33	-8.86	-4.17	-4.57
Entrees - Poultry - 1 Food - Frozen	-4.84	-5.79	-4.65	-8.64	-5.12	-5.72	-4.58	-7.80
Entrees - Italian - 1 Food - Frozen	-4.72	-5.37	-4.26	-4.05	-4.48	-5.00	-3.67	-3.49
Entrees - Mexican - 1 Food - Frozen	-3.06	-5.80	-3.42	-2.59	-2.69	-4.42	-2.60	-1.89
Frozen/Refrigerated Breakfasts	-4.05	-4.38	-3.08	-3.83	-3.64	-4.01	-2.74	-3.30
Pizza-Frozen	-4.24	-4.89	-4.50	-6.23	-3.73	-4.12	-3.55	-4.70
Vegetables - Potatoes - Frozen/Refrigerated	-6.12	-7.77	-5.53	-6.31	-5.86	-7.05	-4.93	-5.48
Ice Cream - Bulk	-5.15	-4.98	-4.00	-4.22	-4.97	-4.81	-4.05	-4.14
Frozen Novelties	-5.07	-4.95	-5.79	-5.64	-5.08	-4.89	-5.69	-5.33
Cheese - Natural - American Cheddar	-4.57	-4.69	-4.73	-5.09	-4.27	-4.25	-4.20	-4.54
Fresh Meat	-3.16	-2.70	-2.44	-3.20	-3.32	-2.84	-2.46	-3.16
Sausage-Dinner	-4.63	-4.53	-3.74	-4.07	-4.57	-4.40	-3.57	-3.84
Lunchmeat-Sliced-Refrigerated	-3.46	-3.68	-2.65	-1.79	-3.58	-3.86	-2.60	-1.76
Frankfurters-Refrigerated	-2.77	-2.95	-3.37	-3.94	-3.12	-3.25	-3.49	-3.99
Bacon-Refrigerated	-3.81	-3.23	-3.42	-3.55	-4.22	-3.46	-3.76	-3.70
Sausage-Breakfast	-5.11	-4.76	-7.12	-5.21	-4.94	-4.63	-6.56	-4.59
Spreads-Remaining	-8.95	-5.39	-3.11	-3.13	-7.59	-5.50	-3.27	-3.01
Cheese - Shredded	-4.24	-6.16	-8.09	-6.31	-4.17	-5.85	-7.85	-6.20
Dairy-Flavored Milk-Refrigerated	-5.22	-6.65	-1.81	-1.87	-5.72	-6.84	-1.65	-1.72
Yogurt-Refrigerated	-4.46	-3.40	-3.42	-4.38	-4.45	-3.45	-3.50	-4.20
Cheese - Cottage	-5.76	-4.81	-4.06	-2.58	-5.66	-4.70	-3.87	-2.44
Lunchmeat-Deli Pouches-Refrigerated	-5.29	-4.64	-4.67	-3.71	-5.96	-4.72	-4.70	-3.21
Dairy-Milk-Refrigerated	-7.46	-4.02	-6.17	-5.77	-8.52	-4.44	-6.62	-6.38

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Product Market	Unweighted				Revenue-Weighted			
	2006	2010	2014	2018	2006	2010	2014	2018
Bakery - Bread - Fresh	-4.29	-3.20	-2.61	-3.04	-4.23	-3.06	-2.51	-2.88
Bakery-Buns-Fresh	-10.39	-6.01	-11.46	-12.76	-10.19	-5.93	-10.77	-11.79
Bakery-Rolls-Fresh	-5.37	-5.08	-4.07	-4.50	-5.26	-5.19	-3.98	-4.42
Bakery-Muffins-Fresh	-3.80	-2.91	-2.72	-2.11	-3.91	-2.81	-2.45	-1.96
Bakery-Cakes-Fresh	-5.57	-4.95	-4.39	-6.53	-7.01	-4.64	-4.14	-6.10
Bakery-Breakfast Cakes/Sweet Rolls-Fresh	-5.88	-5.94	-6.43	-5.31	-4.45	-4.22	-4.53	-3.87
Bakery-Doughnuts-Fresh	-3.90	-3.66	-2.87	-3.16	-4.45	-3.67	-2.92	-3.13
Beer	-3.75	-5.79	-5.62	-17.31	-3.74	-5.60	-5.50	-17.78
Light Beer (Low Calorie/Alcohol)	-6.84	-8.66	-8.90	-11.96	-6.86	-8.49	-8.05	-10.06
Wine-Domestic Dry Table	-5.27	-4.21	-4.66	-3.82	-6.01	-4.67	-5.09	-4.32
Detergents - Heavy Duty - Liquid	-10.62	-6.76	-7.56	-6.23	-12.33	-8.01	-8.31	-6.52
Toilet Tissue	-6.45	-5.66	-3.86	-3.58	-6.25	-5.69	-3.84	-3.58
Disposable Dishes	-3.52	-4.50	-5.36	-3.60	-3.50	-5.36	-6.26	-3.97
Paper Towels	-5.18	-4.82	-4.50	-4.94	-5.10	-4.89	-5.08	-5.63

Notes: This table presents the revenue weighted and unweighted average own-price elasticity for each market-year pair for 2006, 2010, 2014, and 2018.

Table 12: Markups: All 72 Product Markets

Product Market	2006				2018			
	Median		Mean		Median		Mean	
	UW	W	UW	W	UW	W	UW	W
Fruit Drinks & Juices-Cranberry	0.35	0.36	0.35	0.35	0.44	0.46	0.44	0.45
Fruit Drinks-Other Container	0.22	0.25	0.27	0.34	0.21	0.26	0.28	0.34
Fruit Juice-Remaining	0.35	0.42	0.40	0.42	0.28	0.31	0.34	0.33
Soft Drinks - Powdered	0.84	0.83	0.74	0.73	0.83	0.85	0.75	0.88
Tomatoes - Remaining - Canned	0.30	0.29	0.30	0.30	0.31	0.31	0.28	0.31
Mexican Sauce	0.38	0.42	0.37	0.42	0.56	0.58	0.55	0.61
Spaghetti/Marinara Sauce	0.24	0.28	0.31	0.31	0.37	0.49	0.42	0.52
Salad Dressing - Liquid	0.32	0.29	0.31	0.34	0.43	0.38	0.40	0.41
Mexican Tortillas	1.37	1.32	1.52	1.42	0.71	0.84	0.81	0.88
Soup-Canned	0.40	0.42	0.41	0.47	0.35	0.37	0.35	0.41

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Product Market	2006				2018			
	Median		Mean		Median		Mean	
	UW	W	UW	W	UW	W	UW	W
Soup Mixes - Dry & Bases	1.73	1.22	1.69	1.44	1.13	2.09	1.54	1.75
Dog Food - Wet Type	0.18	0.19	0.18	0.19	1.78	1.90	1.67	1.91
Rice - Mixes	0.41	0.43	0.37	0.37	0.59	0.65	0.50	0.59
Snacks - Potato Chips	0.19	0.30	0.21	0.26	0.55	0.58	0.50	0.56
Snacks - Tortilla Chips	0.38	0.42	0.38	0.42	0.49	0.56	0.49	0.53
Snacks - Remaining	0.19	0.24	0.23	0.27	0.60	0.66	0.64	0.69
Snacks - Pretzel	0.26	0.27	0.29	0.26	0.49	0.47	0.52	0.47
Pasta - Macaroni	0.54	0.64	0.53	0.59	0.51	0.59	0.45	0.54
Pasta-Spaghetti	0.54	0.55	0.55	0.57	0.59	0.60	0.56	0.59
Dry Dinners - Pasta	0.30	0.33	0.32	0.39	0.63	0.69	0.61	0.67
Crackers - Sandwich & Snack Packs	0.38	0.32	0.41	0.34	0.34	0.39	0.37	0.38
Cereal - Ready To Eat	0.37	0.38	0.37	0.37	0.35	0.36	0.36	0.36
Crackers - Flavored Snack	0.41	0.43	0.39	0.42	0.34	0.40	0.36	0.42
Cookies	0.33	0.40	0.38	0.40	0.35	0.46	0.36	0.42
Fruit-Dried And Snacks	0.33	0.33	0.36	0.38	0.30	0.35	0.34	0.37
Granola & Yogurt Bars	0.32	0.35	0.32	0.33	0.25	0.34	0.28	0.31
Snacks - Health Bars & Sticks	0.32	0.39	0.37	0.44	0.41	0.46	0.49	0.57
Desserts - Rts Single Servings - Canned	0.21	0.20	0.23	0.21	0.76	0.80	1.01	0.91
Tea - Liquid	0.39	0.39	0.46	0.45	0.22	0.26	0.31	0.36
Ground And Whole Bean Coffee	0.21	0.27	0.23	0.24	0.24	0.25	0.27	0.27
Soft Drinks - Carbonated	0.15	0.13	0.21	0.15	0.11	0.13	0.24	0.24
Water-Bottled	0.25	0.23	0.30	0.30	0.40	0.49	0.58	0.63
Candy-Chocolate	0.31	0.34	0.32	0.35	0.59	0.63	0.59	0.64
Nuts - Bags	0.25	0.36	0.33	0.39	0.26	0.32	0.28	0.29
Gum-Chewing-Sugarfree	0.52	0.64	0.52	0.61	0.31	0.45	0.47	0.63
Soft Drinks - Low Calorie	0.18	0.20	0.26	0.20	0.35	0.37	0.38	0.38
Entrees - Poultry - 1 Food - Frozen	0.29	0.31	0.31	0.32	0.34	0.44	0.35	0.45
Entrees - Italian - 1 Food - Frozen	0.30	0.30	0.37	0.36	0.40	0.49	0.45	0.52
Entrees - Mexican - 1 Food - Frozen	0.77	0.85	0.79	0.79	0.62	0.89	0.92	1.36
Frozen/Refrigerated Breakfasts	0.35	0.39	0.34	0.38	0.41	0.47	0.43	0.50
Pizza-Frozen	0.38	0.40	0.38	0.42	0.28	0.39	0.33	0.43
Vegetables - Potatoes - Frozen/Refrigerated	0.32	0.41	0.34	0.37	0.27	0.28	0.32	0.40

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Product Market	2006				2018			
	Median		Mean		Median		Mean	
	UW	W	UW	W	UW	W	UW	W
Ice Cream - Bulk	0.32	0.32	0.34	0.37	0.40	0.41	0.43	0.44
Frozen Novelties	0.30	0.30	0.33	0.32	0.29	0.36	0.34	0.37
Cheese - Natural - American Cheddar	0.32	0.34	0.32	0.35	0.31	0.34	0.31	0.34
Fresh Meat	0.42	0.40	0.48	0.46	0.40	0.40	0.43	0.46
Sausage-Dinner	0.30	0.33	0.34	0.34	0.33	0.36	0.36	0.38
Lunchmeat-Sliced-Refrigerated	0.42	0.48	0.54	0.54	0.82	0.81	1.17	1.08
Frankfurters-Refrigerated	0.46	0.37	0.50	0.43	0.42	0.32	0.50	0.51
Bacon-Refrigerated	0.33	0.28	0.33	0.29	0.38	0.36	0.40	0.37
Sausage-Breakfast	0.29	0.28	0.31	0.31	0.29	0.31	0.30	0.32
Spreads-Remaining	0.28	0.28	0.28	0.28	0.41	0.62	0.48	0.60
Cheese - Shredded	0.40	0.44	0.38	0.40	0.36	0.37	0.32	0.34
Dairy-Flavored Milk-Refrigerated	0.49	0.43	0.46	0.44	1.36	0.92	1.26	1.08
Yogurt-Refrigerated	0.29	0.35	0.31	0.32	0.37	0.39	0.42	0.45
Cheese - Cottage	0.27	0.28	0.26	0.28	0.85	0.89	0.78	0.83
Lunchmeat-Deli Pouches-Refrigerated	0.26	0.23	0.26	0.23	0.65	0.91	0.82	0.89
Dairy-Milk-Refrigerated	0.25	0.21	0.24	0.21	0.36	0.33	0.36	0.33
Bakery - Bread - Fresh	0.32	0.35	0.34	0.35	0.52	0.55	0.58	0.62
Bakery-Buns-Fresh	0.15	0.15	0.16	0.17	0.13	0.17	0.17	0.17
Bakery-Rolls-Fresh	0.22	0.24	0.25	0.27	0.29	0.31	0.29	0.32
Bakery-Muffins-Fresh	0.36	0.36	0.38	0.35	0.65	0.71	0.64	0.67
Bakery-Cakes-Fresh	0.30	0.21	0.37	0.29	0.33	0.32	0.35	0.36
Bakery-Breakfast Cakes/Sweet Rolls-Fresh	0.32	0.41	0.37	0.45	0.37	0.62	0.45	0.56
Bakery-Doughnuts-Fresh	0.41	0.35	0.45	0.37	0.59	0.59	0.60	0.58
Beer	0.34	0.31	0.36	0.36	0.09	0.10	0.09	0.10
Light Beer (Low Calorie/Alcohol)	0.17	0.18	0.19	0.18	0.16	0.16	0.16	0.17
Wine-Domestic Dry Table	0.26	0.18	0.34	0.26	0.42	0.29	0.64	0.51
Detergents - Heavy Duty - Liquid	0.16	0.15	0.22	0.18	0.26	0.21	0.36	0.29
Toilet Tissue	0.23	0.24	0.26	0.26	0.39	0.37	0.42	0.41
Disposable Dishes	0.41	0.45	0.46	0.53	0.53	0.42	0.55	0.49
Paper Towels	0.25	0.25	0.28	0.28	0.32	0.30	0.36	0.32

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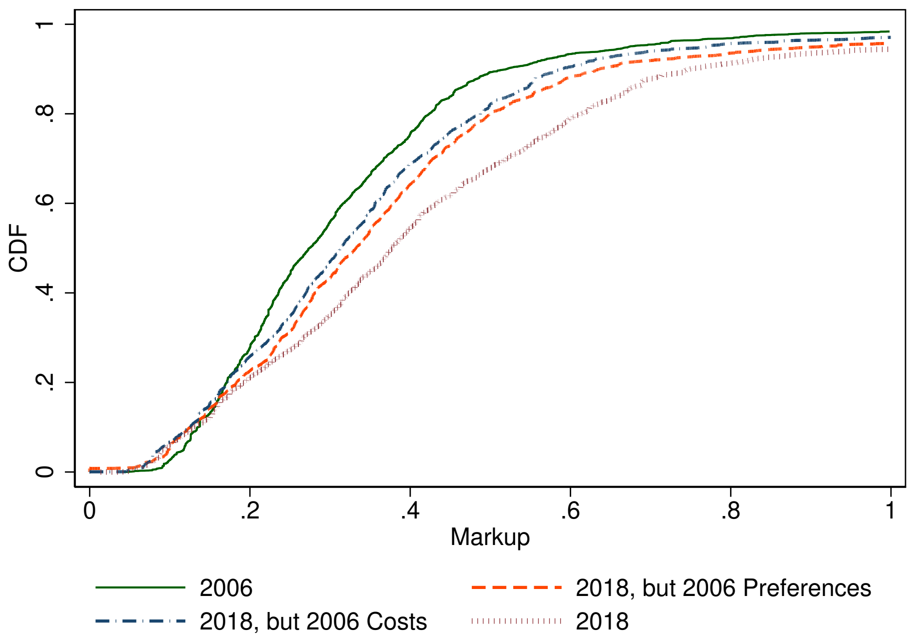
Product Market	2006				2018			
	Median		Mean		Median		Mean	
	UW	W	UW	W	UW	W	UW	W

Notes: This table provides estimates of the mean and median markups within each of the product markets of our sample in 2006 and 2018. Compared to Table 10, we omit three product markets: Cat Food - Wet Type, Candy-Non Chocolate, and Cigarettes. These three product markets have positive estimates of α for at least one year in our sample. Columns labeled "UW" weight each product equally, while those labeled "W" weight products according to their revenues in the year.

FIGURE 8: Observed and Counterfactual Markup Distributions



Notes: See the notes for Figure 5. In contrast to that figure, the sample includes all products, not only those which were present in both 2006 and 2018.