Rising Markups and the Role of Consumer Preferences*

Hendrik Döpper
DICE†

Alexander MacKay
Harvard University‡

Nathan H. Miller
Georgetown University§

Joel Stiebale
DICE¶

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Abstract

We characterize the evolution of markups for consumer products in the United States from 2006 to 2019. We use detailed data on prices and quantities for products in more than 100 distinct product categories to estimate demand systems with flexible consumer preferences. We recover markups under an assumption that firms set prices to maximize profit. Within each product category, we recover separate yearly estimates for consumer preferences and marginal costs. We find that markups increase by about 25 percent on average over the sample period. The change is attributable to decreases in marginal costs that are not passed through to consumers in the form of lower prices. Our estimates indicate that consumers have become less price sensitive over time.

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†Düsseldorf Institute for Competition Economics (DICE), Heinrich-Heine University Düsseldorf. Email: doepper@dice.hhu.de.

‡Harvard University, Harvard Business School. Email: amackay@hbs.edu.

§Georgetown University, McDonough School of Business. Email: nathan.miller@georgetown.edu.

¶Düsseldorf Institute for Competition Economics (DICE), Heinrich-Heine University Düsseldorf. Email: stiebale@dice.hhu.de.

1 Introduction

Firms with market power set prices that reflect marginal costs, consumer preferences, and the prices of related products. Economic theory indicates that differences between prices and marginal costs—the markups—have wide-ranging implications for market outcomes. All else equal, an increase in markups transfers wealth from consumers to producers and can cause consumers to change their purchase decisions. These effects lead to less efficient resource allocation and, through reduced production, affect the markets for inputs, such as labor. Changes in markups may also affect the long-run dynamics in an industry by distorting investment and innovation incentives (Aghion et al., 2005). Thus, the growing empirical evidence that markups are rising in the United States and abroad (e.g., De Loecker et al., 2020; Ganapati, 2021a; De Loecker and Eeckhout, 2021) raises important questions for economic policy.

In this paper, we study the markups that arise in the U.S. economy for a vast number of firms and products. Our objective is to understand the supply and demand conditions that influence firms' pricing decisions. Through an analysis of economic mechanisms, we are able to connect markups to other economic outcomes, such as consumer surplus and deadweight loss, and provide context for various policy considerations. For example, with no changes in demand, rising markups may arise from reduced competition (e.g., due to anticompetitive mergers) or from cost-reducing technological progress.[1] Alternatively, rising markups could reflect shifts in consumer preferences, rather than such supply-side changes.

Our approach is to estimate differentiated-products demand systems for more than 100 consumer product categories—such as cereals, bottled water, paper towels, and over-the-counter cold medications—using prices, quantities, and information on consumers' demographics. With demand estimates in hand, we impute the marginal costs and markups that rationalize prices under the assumption of profit maximization. We repeat this procedure separately for each year over 2006–2019, which allows us to compare product categories that differ along important observable dimensions. Our approach is standard in industrial organization (e.g., Berry et al., 1995), although most previous applications focus on a single product category, such as ready-to-eat cereal (Nevo, 2001; Backus et al., 2021) or beer (Miller and Weinberg, 2017). We implement the methodology at scale to obtain markups for hundreds of products.

Using the Lerner index as our measure of markups, we find that average markups increase more than 30 percent between 2006 and 2019, from approximately 0.45 to over 0.60.[2] The aggregate trend is driven by changes within products over time, rather than consumer substitution toward higher markup products. Larger absolute increases obtain for products with higher initial markups; however, in percentage terms, the changes that we estimate are similar for high- and low-markup products. Thus, we interpret our results as indicating that the full

[1]In environments with incomplete pass-through, cost reductions do not yield corresponding declines in price.

[2]The Lerner index is calculated as $\frac{p-c}{p}$, where p and c are price and marginal cost, respectively (Lerner, 1934). As long as marginal cost does not exceed price, it can take values from zero to one.

distribution of markups may be shifting upward over time.

By construction, rising markups must be due to either price increases or marginal cost reductions. We observe that real prices increase during the early years of the sample period and then fall during the later years. Specifically, from 2006 to 2012, real prices increase by seven percent on average but, by 2019, average real prices are only two percent higher than in 2006. Although price increases partially account for rising markups initially, by the latter years of the sample, marginal cost reductions account for nearly all of the aggregate markup trend. We estimate that the average consumer price sensitivity has declined by about 30 percent from 2006 to 2019, which can explain why declines in marginal costs have not led to lower consumer prices. A reduction in consumer price sensitivity reflects an increase in preference for specific brands; in the model, less price sensitive consumers require a greater difference in prices to switch to a less-preferred brand.

We exploit the panel structure of our data to explore potential mechanisms in greater detail. Controlling for product and time fixed effects, we find that products with larger increases in markups tend to have (i) greater reductions in consumer price sensitivity, (ii) greater marginal cost reductions, and (iii) larger increases in market concentration. Although each of these effects are statistically significant, the first two account for substantially more of the variation in markups. In an attempt to explain these changes at a deeper level, we analyze whether changes in price sensitivity are associated with firm-level investments, increased variety or growth in alternative retail channels. For this purpose, we match (for the publicly traded firms) Compustat data on marketing and R&D expenditures. We construct the share of online retail and warehouse clubs for each product category and year from consumer-level data. We find that these factors only account for a small share of the variation in price sensitivity within brands over time. This suggests that lower price sensitivity might be due to exogenous shifts in consumer behavior. Consistent with this hypothesis, we find that the use of coupons (which involves some small efforts by consumers) and coupon redemption rates have fallen by 50 percent and 30 percent over our sample period, respectively.

In our final analyses, we explore consumer surplus and welfare. Our findings indicate that consumer surplus per capita has increased substantially during our sample period despite rising markups. The increase in consumer surplus is likely due to changing preferences, particularly lower price sensitivity. Changes in markups have been costly for consumers despite the increase in consumer surplus. In a counterfactual experiment, we find that consumer surplus would have been 14 percent higher in 2019 had markups been set at 2006 levels.

The changes in consumer surplus vary across the income distribution. While consumers with incomes above the median had substantial gains in surplus during the second half of our sample period, the lowest income quartile experienced substantial losses in some time periods and had approximately the same level of consumer surplus at the end of our sample as they had in 2006. And under the counterfactual of marginal cost pricing, consumer surplus in 2019 increases by about 52 and total welfare increases by 9 percent. Taken together, these analyses suggest an important impact market power on resource allocation, aggregate welfare, and the distribution of income, subjects of longstanding interest (e.g., Harberger, 1954).

Our research contributes to a growing empirical literature on the evolution of markups. A number of studies recover markups from estimates of demand elasticities, as we do, focusing on specific industries over time. Ganapati (2021b) finds that the markups of wholesalers increased over 1992-2012 due to greater scale economies and the expansion of distribution networks, and with consumers benefiting from lower prices and access to higher quality goods. Grieco et al. (2022) find that the markups of automobile manufacturers decreased over 1980-2018 due to greater competition, despite dramatic increases in product quality and reductions in marginal costs. Miller et al. (2022) shows that technology adoption in the cement industry over 1974-2016 reduced marginal costs, but that markups increased only modestly because as cost reductions were mostly passed-through to consumers. Consistent with our results, these studies highlight the role of technological change as a determinant of long run economic outcomes.[3]

Two other articles explore the relationship between changing consumer preferences and markups. Berry and Jia (2010) find that an increase in consumer price sensitivity helps explain a modest decline in the markups of airline carriers over 1999–2006. This result suggests the caveat that the decreases in price sensitivity that we find for consumer products may not extend throughout the economy. As price sensitivity reflects the strength of brand preferences, it may increase in some sectors even as it decreases in others. Finally, Brand (2021) considers the hypothesis that increases in product variety lead to lower price sensitivity. He estimates demand in nine of the consumer product categories that we consider, both in 2006 and 2017, and finds less elastic demand and higher markups in the later year. Key distinguishing factors in our analysis include both the scope our of analysis—we consider a much broader set of product categories in every year—and our use of individual consumer data to link substitution patterns to variation in demographics in the cross section and over time.

The paper proceeds as follows: In Section 2, we discuss our approach for recovering markups and specify the model of demand and supply. We discuss the data set in section 3. In section 4, we describe the estimator and our identification strategy and illustrate our empirical approach using a case study for the ready-to-eat (RTE) cereals industry. Section 5 describes the evolution of markups over time and discusses possible determinants of market power. In section 6, we investigate the role of changes in price sensitivity and its determinants. In Section 7, we calculate consumer surplus and welfare over time for different scenarios. Section 8 concludes.

[3]Also related is Peltzman (2020), which analyzes accounting data on manufacturing firms over 1982-2012 and finds support for rising markups and increasing total factor productivity.

2 Methods

2.1 The Demand Approach to Recovering Markups

We follow the demand approach to recover markups. This approach is often used when data on prices and quantity are available, and it is a staple of the industrial organization literature. The approach invokes the assumption that firms maximize profits and then recovers an estimate for marginal costs that rationalizes the observed prices. Take the case of a single-product firm that sets a price, P, given a residual demand schedule, $Q(P)$, and total costs, $C(Q)$. Differentiating its profit function with respect to price and rearranging yields a first order condition for profit maximization of the form:

$$\frac{P - C'}{P} = -\frac{1}{\varepsilon} \tag{1}$$

where $\varepsilon \equiv \frac{\partial Q(P)}{\partial P}\frac{P}{Q(P)}$ is the price elasticity of demand. The left-hand-side of the equation is the Lerner index, a widely-used measure of markups (Lerner, 1934; Elzinga and Mills, 2011). Knowledge of the demand elasticity identifies the Lerner index. With data on price, one also can recover marginal cost, additive markups (i.e., $P - C'$), and multiplicative markups (i.e., P/C').

The demand approach gained prominence in industrial organization after various methodological advances made it possible to estimate demand systems for markets that contain many differentiated products (e.g., Berry, 1994; Berry et al., 1995). With a demand system in hand, welfare statistics such as consumer surplus can be calculated, and it also becomes possible to conduct counterfactual simulations for policy evaluation or an exploration of causal mechanisms. However, in part due to the computation burden of demand estimation, most applications focus on a single industry or consumer product category. An advance of our paper is that it employs a flexible demand model across many product categories simultaneously.

The main alternative is the so-called *production approach* that was pioneered in Hall (1988) and De Loecker and Warzynski (2012), and is applied to the evolution of markups in De Loecker et al. (2020) and De Loecker and Eeckhout (2021). Under an assumption of cost minimization, the multiplicative markup (i.e., P/C') equals the product of (i) the elasticity of output with respect to a variable input and (ii) the ratio of revenue to expenditures on the variable input. Thus, firm-level markups can be recovered by estimating output elasticities and then scaling with accounting data on revenues and expenditures. As with many research designs, challenges arise in implementation. For example, Raval (2020) finds that using different variable inputs can yield different markups, and Bond et al. (2021) demonstrates that markups may not be identified if revenue is used as a proxy for output.[4] Due to these and other concerns, some scholars have argued that the existing evidence of rising markups is rather suggestive than definitive (e.g., Basu, 2019; Berry et al., 2019; Syverson, 2019).

[4] See also Doraszelski and Jaumandreu (2019) and Suichiro and Tanaka (2021).

Thus, we view large-scale evidence on the evolution of markups obtained with the demand approach as a useful complement to the evidence that has been obtained with the production approach (e.g., De Loecker et al., 2020; De Loecker and Eeckhout, 2021).[5] Implementation of the demand approach comes with its own challenges. As suggested by equation (1), inferences about markups are inextricably linked to the demand elasticities, so an identification strategy is needed to obtain consistent estimates of the demand-side parameters in the presence of price endogeneity. Perhaps more fundamentally, the demand-side approach requires the researcher to specify the structure of the demand system and the nature of competition between firms.

We maintain the assumptions of differentiated-products Bertrand competition and random coefficients logit demand, which have been widely used in the literature to study consumer products. There may be some product categories for which our assumptions are inappropriate, due to collusive pricing (e.g., Miller and Weinberg, 2017; Miller et al., 2021) or inter-temporal price discrimination (Hendel and Nevo, 2006a,b), for example. Our strategy to mitigate any such misspecification bias is to aggregate our results across many product categories. Implemented at scale, this allows us to explore how markups have evolved, the reasons for any such changes, and the consequences for consumers and firms.

2.2 Demand Model

For each product category and each year, we apply the random coefficients logit model of Berry et al. (1995). We work with scanner data that are aggregated to the level of a retail chain, quarter, and geographic region. As in Backus et al. (2021), we assume that each consumer is affiliated with a single retail chain and geographic region, in the sense that they select among the products sold by one chain in their region. Let there be $j = 0, \ldots, J_{cmt}$ products available for purchase in chain c, region r, and quarter t, including an outside good ($j = 0$). Each affiliated consumer chooses among these products. The indirect utility that consumer i receives from a purchase of product $j > 0$ is

$$u_{ijcrt} = \beta_i^* + \alpha_i^* p_{jcrt} + \xi_{jr} + \xi_{cr} + \xi_t + \Delta\xi_{jcrt} + \epsilon_{ijcrt} \tag{2}$$

where p_{jct} is the retail price, the terms $(\xi_{jr}, \xi_{cr}, \xi_t)$ are product×region, chain×region, and quarter fixed effects, respectively, $\Delta\xi_{jcrt}$ is a structural error term, and ϵ_{ijcrt} is a consumer-specific logit error term. A consumer that selects the outside good receives $u_{i0crt} = \epsilon_{i0crt}$.

We assume that the consumer-specific coefficients, β_i^* and α_i^*, depend on a set of observed

[5] One working paper implements both approaches in the context of the U.S. brewing industry, and finds that they deliver similar results (De Loecker and Scott, 2017).

and unobserved demographic variables according to

$$\begin{aligned} \alpha_i^* &= \alpha + \Pi_1 D_i & (3) \\ \beta_i^* &= \beta + \Pi_2 D_i + \sigma v_i & (4) \end{aligned}$$

where D_i contains the observed demographics and $v_i \sim N(0,1)$ contains an unobserved consumer demographic. Allowing β to be absorbed by the product fixed effects, the structural parameters to be estimated are $\theta = (\alpha, \Pi_1, \Pi_2, \sigma)$.

Quantity demanded is given by $q_{jcrt}(p_{rct};\theta) = s_{jrct}(p_{rct};\theta)M_{rct}$, where $s(\cdot)$ is the market share, p_{rct} is a vector of prices, and M_{rct} is the "market size" of the chain-market-period, a measure of potential demand. We refer readers to (Nevo, 2000) for equations that characterize market shares and the demand elasticities. We use market sizes that scale with the population of the region and the number of stores operated by the retail chain within the region, as we detail in Appendix B. Qualitatively similar results obtain with market sizes that are proportional to the maximum observed sales within a retail chain and region.

Our specification accommodates vertical differentiation among the inside goods because higher quality (more expensive) products may attract relatively price-insensitive consumers. It also incorporates heterogeneity in the utility that consumers receive from the inside goods, which allows the data to determine the extent of substitution between the inside and outside goods.[6] In principle, product characteristics other than price could be incorporated into the demand model. We do not pursue this because it would require matching to auxiliary datasets on characteristics, which would be difficult to implement at scale.[7] As a consequence, the cross-elasticities we obtain are not as flexible as they otherwise could be; this could affect inferences about markup trends if there are changes in multiproduct ownership.

2.3 Supply Model

Consumer products are produced by manufacturers and sold through retail chains. We assume that each manufacturer sets prices to maximize its profit, taking as given the prices of its competitors and passive cost-plus pricing on the part of retailers. Our assumption on retailer behavior is maintained elsewhere in the literature (e.g. Miller and Weinberg, 2017; Backus et al., 2021) and the empirical literature provides support (DellaVigna and Gentzkow, 2019;

[6] An alternative approach that allows data to influence substitution between the inside and outside goods involves specifying a random coefficients nested logit (RCNL) model with the outside good in its own nest (e.g., Grigolon and Verboven, 2014; Miller and Weinberg, 2017). With the RCNL model, the speed of estimation slows dramatically for higher values of the nesting parameter, making the model inappropriate for our application.

[7] Consider the approach that Backus et al. (2021) take to estimate demand for RTE cereals. They obtain auxiliary data from Nutritionix about the nutritional content of the products, such as the grain (e.g., wheat or corn) and the sugar content. These data then are consolidated into a handful of principal components that serve as product characteristics in the demand model. For many of the product categories we consider, and all of the non-food categories, nutritional content either is unavailable or unlikely to drive consumer substitution.

Arcidiacono et al., 2000; Butters et al., 2021). With cost-plus retail pricing, the retail markup becomes part of the marginal cost that the manufacturer must pay to sell their products.[8]

Focusing on the manufacturers' price-setting problem, the first order conditions for profit maximization can be expressed in terms of the additive markup:

$$p_{crt} - c_{crt} = \left(\Omega_{crt} \circ \left[\frac{\partial s_{crt}(p_{crt})}{\partial p_{crt}} \right]' \right)^{-1} s_{crt}(p_{crt}) \tag{5}$$

where the vectors p_{crt}, s_{crt}, and c_{crt} collect the prices, market shares, and marginal costs of products $j = 1, \ldots, J_{crt}$, and Ω_{crt} is an "ownership matrix" in which each j^{th}, k^{th} element equals one if products j and k are produced by the same manufacturer, and zero otherwise.

An implication is that firms find it profitable to adjust their markups with demand conditions, which enter the first order conditions through the market shares. Therefore, we address price endogeneity in estimation.[9] To that end, we decompose marginal cost according to:

$$c_{jcrt} = \eta_{jr} + \eta_{cr} + \eta_t + \Delta\eta_{jcrt} \tag{6}$$

where $(\eta_{jr}, \eta_{cr}, \eta_t)$ are product$\times$region, chain$\times$region, and quarter fixed effects, and $\Delta\eta_{jcrt}$ is a supply-side structural error term. The supply-side structural error term incorporates "cost shifters" that have been used in the literature to estimate demand, including changes in materials costs and distribution costs that affect products and chains differentially.

3 Data

3.1 Data Sources and Estimation Samples

Our primary sources of data are the Retail Scanner Data and Consumer Panel Data of Kilts Nielsen, which span the years 2006–2019. The scanner data contain unit sales and revenue at the level of the universal product code (UPC), store, and week. The consumer panel data contain the purchases of a sample of panelists, again at the UPC code, store, and week level, along with demographic information on the panelists. We employ aggregation and a number of screens to construct samples that are suitable for the model laid out in the previous section.

We take as given the consumer product categories ("modules") that are specified in the data, and that group together UPC codes that consumer might reasonably view as substitutes.

[8]Miller, Sheu, and Weinberg (2020, Appendix E) provides a derivation. Retail cost-plus pricing can arise under nonlinear contracts that specify slotting fees or other fixed transfers between manufacturers and retailers. Indeed, the empirical literature finds evidence of nonlinear contracts in settings similar to ours (e.g., Villas-Boas, 2007; Bonnet and Dubois, 2010; Hristakeva, 2020). See Gandhi and Nevo (2021) for a discussion.

[9]Markup adjustments do not occur in the special case of constant demand elasticities. It may be reasonable to maintain an assumption of exogenous prices if higher frequency weekly data are used in estimation and fixed effects absorb average product quality (e.g., Hendel and Nevo, 2013).

Table 1: Product Categories in the Scanner Data

Rank	Name	Revenue	Brands	Rank	Name	Revenue	Brands
1	Cigarettes	5,375	20	20	Ground And Whole Bean Coffee	1,754	17
2	Soft Drinks - Carbonated	5,275	19	30	Precut Fresh Salad Mix	1,343	18
3	Dairy-Milk-Refrigerated	4,307	18	40	Entrees - Poultry - 1 Food - Frozen	1,139	17
4	Bakery - Bread - Fresh	3,327	19	60	Butter	802	16
5	Cereal - Ready To Eat	3,225	19	80	Creamers-Liquid	636	13
6	Soft Drinks - Low Calorie	3,061	19	100	Baby Accessory	544	18
7	Wine-Domestic Dry Table	2,999	18	120	Snacks - Pretzel	473	16
8	Water-Bottled	2,995	19	140	Fresh Tomatoes	403	15
9	Toilet Tissue	2,880	15	160	Complete Nutritional Products	349	13
10	Light Beer (Low Calorie/Alcohol)	2,558	19	200	Frozen Desserts	275	15

Notes: This table shows a sample of product categories in the data sorted by revenue. *Revenue* is measured in average yearly sales in millions of nominal US $ between 2006 and 2016. *Brands* measures the median of the number of brands within categories excluding fringe brands and private labels.

Within these categories, we define products at the brand level, which consolidates the thousands of UPC codes into a more manageable set. Each UPC code is associated with a "unit" that characterizes its volume (e.g., liters), mass (e.g., ounces), or count (e.g., six-pack). We weight the UPC codes by unit when aggregating to the brand level, and measure price using the ratio of revenue to equivalent unit sales, following standard practice (e.g., Nevo, 2001; Miller and Weinberg, 2017; Backus et al., 2021).[10] We rank products within each category by their total revenue and include up to largest 20 in the estimation sample; typically this includes a private label product. All remaining products are collapsed into a single composite "fringe" product that we assume is priced by an independent firm.

Our baseline sample comprises 133 product categories. We obtain these categories by first identifying categories within the top 200 by revenue, and then applying a screen based on observed price dispersion to avoid categories with highly dissimilar products.[11] Table 1 provides examples of product categories along with their average annual revenue and the number of products that appear in our estimation sample. The largest three categories are cigarettes, carbonated soft drinks, and refrigerated milk, which respectively generate $5.4, $5.3, and $4.3 billion in average annual revenue. The smallest category we consider is frozen desserts, which generates $275 million in average annual revenue.

We use the designated market areas (DMAs) in the Nielsen data as the geographic regions. We restrict attention to the 22 DMAs for which there are at least 500 panelists in every year in the consumer panel data. These DMAs account for about half of the total revenue observed in the scanner data. Within each DMA, we aggregate the store-level data up to the level of the retail chain, as many retail chains set common prices among nearby stores (DellaVigna and Gentzkow, 2019). We include food stores, drug stores, and mass merchandisers. Finally, we aggregate the week-level data up to the level of quarters, following Miller and Weinberg (2017). The average number of retail chains per region is 9.3, and the average number of products per

[10]In a handful of categories, UPC codes differ in terms of whether units are reported in terms of volume, mass, or count. For those categories, we use only those UPC codes associated with the highest-revenue metric.

[11]Our ranking of categories is based on total revenue over 2006–2016. The screen is detailed in Section 3.2.

category, retail chain, and region is 10.3.

To support estimation, we generate consumer-specific demographic draws by sampling 2,000 consumers from the Consumer Panel Data for each region and year.[12] We sample with replacement and using the projection weights provided by Nielsen. Among the available demographics, we select two that we expect should influence demand for many of the consumer products in the data: household income and an indicator for the presence of children in the household. We assume that log of income is what enters demand through equations (3) and (4). We demean the demographics prior to estimation, and also divide the income measure by its standard deviation. The unobserved demographic is drawn from a standard normal distribution that is independent from the observed demographics. We also construct micro-moments from average values of the observed demographics for each product, region, and year, again applying the projection weights.

We account for multi-product ownership using auxiliary data, as ownership information is not provided in the Nielsen databases. We start with a manual search in which we identify the company that owns each product. Because multiple company names could be associated with the same manufacturer when a conglomerate has multiple subsidiary companies, we use data from Capital IQ to obtain the ultimate parent company for each product. This process provides a snapshot of product ownership at the end of our sample period. We backcast ownership for the preceding years using information on mergers and acquisitions (M&A) from the Zephyr database, compiled by Bureau van Dijk. Compared with most other M&A databases, Zephyr has the advantage that there is no minimum deal value for a transaction to be included. We assume that prices are chosen to maximize the profit of the ultimate parent company. Finally, we match our sample with firm-level financial data from Compustat to obtain information on marketing expenditures and R&D. We use these variables to explain variation in price sensitivities across brands and time. This information is available for about half of the observations in our sample because Compustat covers publicly traded firms.

We deflate prices and incomes using the Consumer Price Index such that they are in real dollars as of the first quarter of 2010.[13]

3.2 Selection of Product Categories

Some challenges arise in recovering markups over time using the estimation samples described above. In treating the Nielsen categories as well-defined product markets, we create the potential for model misspecification, due to at least two (related) reasons. The first is that products

[12]By sampling at the region-year level, we implicitly assume that the consumers of retail chains within the same region have the same demographics. We take this approach because we view the consumer panel data as too sparse to reliably sample at the level of a retail chain, region, and year. For a study of consumer demographics and prices as they vary spatially across a city, see Eizenberg et al. (2021).

[13]We deflate using the Consumer Price Index for All Urban Consumers: All Items Less Food and Energy in U.S. City Average. The inflation data are monthly and seasonally adjusted.

in different categories might be substitutes. For instance, one might suspect some amount of consumer substitution between products in the "Light Beer" and "Beer" categories. In principle, these categories could be combined, possibly with richer demand specification that allows for weaker substitution between light beer and beer. However, looking holistically across the Nielsen categories, we are skeptical that cross-category substitution is meaningful for most products. Thus, for our research question, it seems more appropriate to use the Nielsen categories rather than making ad hoc adjustments, and that is the approach we take.

The second reason for concern about Nielsen product categories—which we view as more important for our application—is that some categories, especially non-food categories, include products that might be very weak substitutes (or possibly not substitutes at all). The "Batteries" category, for example, has some products that are probably close substitutes, such as various brands of AAA batteries, along with other products that are functionally quite different, such as D batteries. We use a relatively tractable specification of the random coefficients logit model in order to scale estimation across categories, and do not consider the model to be sufficiently flexible to handle such rich patterns of product differentiation. This can be problematic if the same demand parameters—and especially the price parameter—are inappropriate for different classes of products within the same category.

As a proxy for within-category product heterogeneity, we use the within-category distribution of prices to identify and remove categories for which our model may not be sufficiently flexible. Specifically, we remove categories in which the 99th percentile of prices is greater than five times the median price, and this leaves 133 of the top 200 product categories (by revenue) in our baseline sample. Although we believe this screen focuses attention on product categories for which the model is a relatively better fit, it does not drive results; we obtain similar markup trends more or less stringer screens. In the Appendix, we report our markup trends using all 200 of the product categories (Appendix Figure C.1). The categories in our baseline sample account for 55 percent of revenues in the Retail Scanner Data.[14]

Also worthy of discussion are the compositional changes that occur in the Nielsen data as retail stores enter and exit the sample. Such churn appears to be inconsequential over 2006–2017, but significant changes do occur over 2018–2019. Because we estimate independent models separately in each year, compositional changes do not effect the trends we observe from 2006–2017. We attempt to control for compositional changes by including (yearly) chain$\times$region fixed effects in the demand and marginal cost equations and allowing market sizes to scale separately for each retail chain. Still, compositional changes could affect markups if they change the price sensitivity of the typical consumer represented in the data. Thus, we are most confident in the markup trends we document over 2006–2017 though, for the most part, these trends simply continue through 2018–2019.

[14]The top 200 categories account for 74 percent of revenues.

4 Estimation and Identification

4.1 Objective Function

We estimate the model separately for each category and year using the generalized method of moments (GMM). Thus, we allow the parameters for estimation, $\theta = (\alpha, \Pi_1, \Pi_2, \sigma)$, to vary across categories and years. The GMM estimator for θ is:

$$\hat{\theta} = \arg\min_{\theta} g(\theta)' W g(\theta), \qquad g(\theta) = \begin{bmatrix} g^{MM}(\theta) \\ g^{CR}(\theta) \end{bmatrix} \tag{7}$$

where W is a weighting matrix, $g^{MM}(\theta)$ collects a set of "micro-moments" that summarizes how well the model matches the correlations between demographics and product purchases that we observe in the Nielsen Panelist dataset, and $g^{CR}(\theta)$ implements a covariance restriction between demand-side and cost-side structural error terms. We take a two-step approach to estimation in which we first estimate $\theta_2 = (\Pi_1, \Pi_2, \sigma)$ then estimate the price parameter, α. This reflects that micro-moments identify θ_2 but not α (Berry and Haile, 2020), and that the covariance restriction exactly identifies α conditional on θ_2 (MacKay and Miller, 2022). In Appendix A, we explain why this segmentation has computation advantages in our setting and provide additional details on the estimation procedure.

For micro-moments, we use variation in purchase patterns across products and regions to capture heterogeneity in preferences. Each element corresponding to product j and demographic k is given by

$$g_{jk}^{MM}(\theta) = \frac{1}{T_j} \sum_{c,r,t} \left(\frac{\sum_i \omega_i s_{ijcrt}(\theta) D_{ik}}{\sum_i \omega_i s_{jcrt}(\theta)} - \mathcal{M}_{jrk} \right)^2 \tag{8}$$

where T_j is the number of chain-region-quarter combinations in which product j is sold, ω_i is the weight that we place on consumer i, $s_{ijcrt}(\theta)$ is the consumer-specific choice probability implied by the candidate parameter vector, and $\mathcal{M}_{jrk}$ is the mean demographic observed in the data for product and region. That is, we match the implied average demographic of consumers for each product-chain-region-quarter to the average demographic observed in the data for the corresponding product-region (allowing for differences across years and categories).[15] In our baseline specification, we use two observed demographic variables and at most 21 products, so there can be up to 42 micro-moments.

In the second step, we identify the price parameter under the assumption that the demand-side and supply-side structural error terms are uncorrelated in expectation: $\mathbb{E}[\Delta\xi_{jcrt}\Delta\eta_{jcrt}] = 0$.

[15] We allow the average observed demographics to vary by year and category. An alternative approach to the micro-moments would match the implied chain-region demographics to chain-region data, rather than to region-level data. The tradeoff is between the measurement error in the observed component versus the specificity of the moments. However, parameters that fit one set of moments well should also fit the other well.

We construct the empirical analog of the moment condition:

$$g^{CR}(\theta) = \frac{1}{T} \sum_{c,r,t} \Delta\xi_{crt}(\theta)' \Delta\eta_{crt}(\theta) \tag{9}$$

where the $\Delta\xi_{crt}(\theta)$ and $\Delta\eta_{crt}(\theta)$ terms are recovered for each candidate θ using standard techniques, and T is the number of chain-region-quarter combinations for a given year.

4.2 Discussion and Assessment

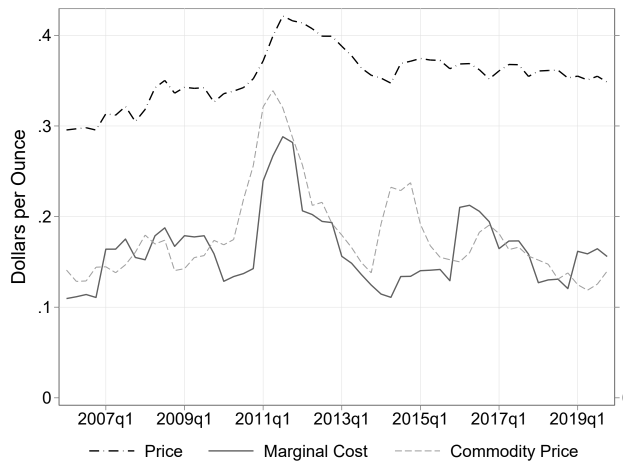
The covariance restriction is appealing in our setting because it can be implemented at scale for different product categories and years. Alternative approaches typically rely on auxiliary data on cost-shifters or product characteristics, which can be difficult and costly to obtain. An additional benefit of the covariance restrictions approach is that—in contrast to an instruments-based approach—there is no "first-stage" relevance condition that must be satisfied (MacKay and Miller, 2022). Even if product characteristics were available for every category and year, there is no guarantee that, for example, markup-shifter instruments that rely on such characteristics (e.g., Berry et al., 1995; Gandhi and Houde, 2020) would meet the relevance condition for every category of interest.

As we have specified the model, the supply-side structural error term incorporates some of the cost-shifter instruments that have been used to estimate demand in the recent literature, including product-specific shipping costs (Miller and Weinberg, 2017) and the prices of product-specific ingredients (Backus et al., 2021). These and other plausibly exogenous cost-shifters may provide much of the variation that we exploit in estimation. Because the marginal cost function includes fixed effects at the product$\times$region, chain$\times$region, and quarter levels, some potentially confounding sources of variation are absorbed, including the possibility that higher quality products are more expensive to produce.[16]

The covariance restrictions approach to estimation differs in some ways from an instrument-based approach (MacKay and Miller, 2022). In particular, the covariance restrictions approach uses all of the endogenous price and quantity data in estimation, rather than only the portions that are attributable to excluded instruments. Although this eliminates the first-stage relevance requirement, it does require the joint estimation of parametric models of supply and demand. Thus, a misspecification of the marginal cost function could affect demand estimates. However, because a fully specified supply-side model is required to recover markups, we view it as

[16]Our supply-side assumption maintains that marginal costs are constant in output. For consumer products, we view this as a reasonable approximation, at least in the range of observed prices, and it is an assumption that often is maintained in the literature (Villas-Boas, 2007; Chevalier et al., 2003; Hendel and Nevo, 2013; Miller and Weinberg, 2017; Backus et al., 2021). However, such a restriction is not universally applicable and, indeed, results in the literature suggest a positive correlation between demand-side and supply-side structural error terms may exist in automobile manufacturing (Berry et al., 1995) and airlines (Ciliberto et al., 2021), two industries for which capacity constraints are relevant.

Figure 1: Prices and Marginal Costs of Coffee Over Time



Notes: This figure plots the time series of quantity-weighted prices and marginal costs (solid line) for ground/whole bean coffee. Prices are observed and marginal costs are recovered from the profit-maximization conditions. Also shown is the commodity price index for coffee (dashed gray line), which is scaled following the right axis.

sensible to also employ the supply model to estimate structural parameters.

We conduct three validation checks to assess the reasonableness of our results. First, we examine one product category—ground/whole bean coffee—to assess the ability of our method to capture marginal costs. Coffee is somewhat unique among our product categories in that a single ingredient (coffee beans) accounts for a substantial portion of marginal costs and commodity prices for this ingredient are well-established. Second, we compare the own-price elasticities of demand that we obtain to those obtained in the literature. Third, we plot the distribution of elasticities that we obtain with our baseline estimates, and also compare this distribution to two alternative approaches that have been used in the literature.

Figure 1 plots the time series of quantity-average weighted prices (dot-dash line) and marginal costs (solid line) for coffee. Prices are observed, and marginal cost are recovered according to equation (5). The gray dashed line plots the commodity price index for coffee, which is scaled separately on the right axis.[17] Overall, our recovered estimates of marginal costs are strongly correlated with the commodity price index. A regression of average marginal costs on the commodity price yields a coefficient of 0.990 ($p < 0.001$), and the correlation between the two time series is 0.62. Our method is able to capture the the large spike in commodity prices in 2011, which is reflected in the spike in marginal costs. We find that, on average, the commodity price is equal to 56 percent of estimated marginal costs. This is consistent with the literature, as Nakamura and Zerom (2010) find that coffee beans account for 45 percent of marginal costs based on data spanning 2001-2004. These results indicate the potential of the

[17]Data on coffee commodity prices were obtained from Macrotrends.net. Available here: `https://www.macrotrends.net/charts/commodities`, last accessed March 1, 2022

Table 2: Average Product-Level Own-Price Elasticities of Demand

Category	Our Estimate	Literature Estimate	Citation
Beer	−4.06	−4.74	Miller and Weinberg (2017)
Ready-to-Eat Cereal	−2.29	−2.42	Backus et al. (2021)
Yogurt	−3.12	−4.05	Hristakeva (2020)

Notes: The Miller and Weinberg (2017) estimate is the median product-level elasticity obtained with the RCNL-1 specification. Our corresponding estimate is the median own-price elasticity across all years, combining "Beer" and "Light Beer," which are not distinguished in Miller and Weinberg (2017). The Backus et al. (2021) estimate is the median product-level elasticity obtained with the "prices only" specification; our corresponding estimate is the median own-price elasticity across all years. Hristakeva (2020) reports a mean product-level elasticity from 2001–2010; to make things more comparable, we report our estimated mean own-price elasticity from 2006–2010.

demand approach to recover reasonable marginal cost estimates.

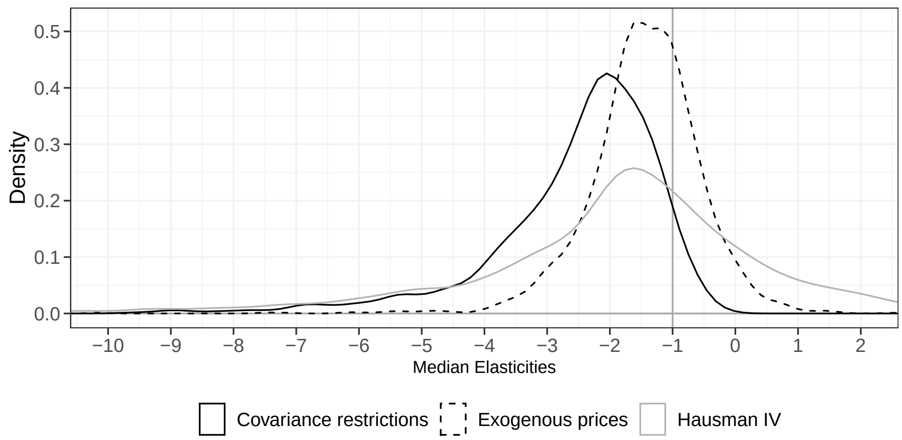
Next, we compare our product-level own-price elasticities of demand to those obtained in the literature using similar data and models. In Table 2, we report estimates for beer, ready-to-eat cereal, and yogurt, for which comparisons are possible. As shown, we obtain average elasticities for beer, ready-to-eat cereal, and yogurt of -4.06, -2.29, and -3.12, respectively. To provide more comparable estimates, we report the median product-level own price elasticities for beer and ready-to-eat cereal, and the mean own-price elasticity from 2006–2010 for yogurt.[18] For beer, we combine beer and light beer categories to match Miller and Weinberg (2017), who do not distinguish between these categories. Miller and Weinberg (2017) report an average elasticity for beer of -4.74, Backus et al. (2021) reports an average elasticity for ready-to-eat cereal of -2.42, and Hristakeva (2020) reports an average elasticity for yogurt of -4.05. Thus, we conclude that our methodology can obtain reasonable results that are consistent with those of studies that make use of specific institutional details to a greater degree.[19]

For the third validation check, we examine the distribution of median own-price elasticities, across all of the 1,862 category-year combinations in our baseline sample. We compare the results we obtain with the covariance restriction to two alternative assumptions that can identify the price parameter and can be applied at scale. First, we consider the assumption that prices are exogenous. For a given model of supply and demand, prices are uncorrelated with demand shocks if both (1) firms do not adjust markups in response to demand shocks and (2) demand shocks are uncorrelated with marginal cost shocks. If demand and cost shocks are correlated, then prices are endogenous even if firms are not responsive to demand. Thus, the covariance restriction we employ is a necessary condition to assuming that prices are exogenous. However, profit maximization generally implies that prices are endogenous, and our

[18]Every paper differs in the exact data sample used. For example, Hristakeva (2020) uses data from 2001–2010. Because we find rising markups over time for yogurt, restricting it to the earlier years of our sample provides a closer comparison.

[19]Appendix Table C.1 provides the demand coefficients that we obtain for ready-to-eat cereals in each year, along with the implied demand elasticities and markups.

Figure 2: Implied Elasticities Under Alternative Identification Restrictions



Notes: This figure plots the density of the median own-price elasticity by category and year under different identification assumptions. The solid line shows the density of implied elasticities using covariance restrictions. The dashed line shows the density of implied elasticities assuming exogenous prices. The dashed line shows the density of implied elasticities using Hausman instruments. The vertical line indicates an elasticity of -1.

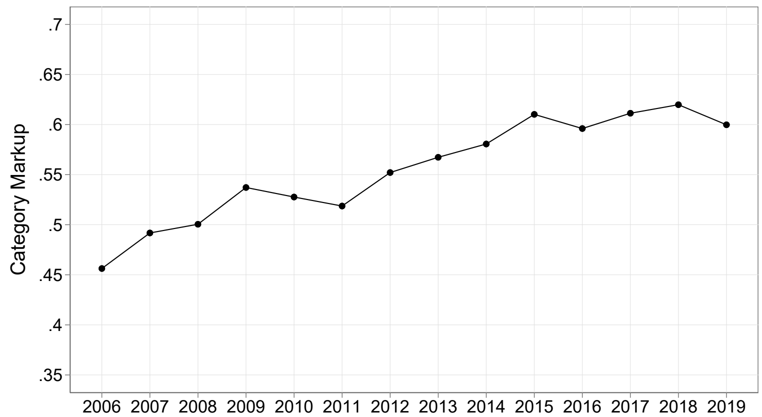
covariance restrictions approach to estimation corrects for price endogeneity.

Second, following Hausman (1996), we use instruments based on the average price of the same product in other regions. This approach is valid if cost shocks are correlated across regions, e.g., due to shared manufacturing or distribution facilities, but demand shocks are uncorrelated across regions. As these conditions may not be satisfied in many empirical settings, the Hausman instruments are best subject to scrutiny when employed (Berry and Haile, 2021; Gandhi and Nevo, 2021).

Figure 2 plots the densities of median own-price elasticities. The solid black line summarizes the results that we obtain with covariance restrictions (our baseline assumption). The dashed line and the solid gray line correspond to exogenous prices and Hausman instruments, respectively. As shown, the peak of the distribution with covariance restrictions occurs an elasticity slightly more negative than -2. Relative to our estimates, the distributions of elasticities with exogenous prices and Hausman instruments are shifted to the right, consistent with price endogeneity arising from firms adjusting prices in response to demand shocks. Though covariance restrictions systematically correct for price endogeneity, Hausman instruments do not, and instead yield more elastic demand than exogenous prices in some cases and more inelastic demand in others.

Using covariance restrictions, demand is never upward-sloping, and only 5 percent of the category-year combinations have inelastic demand (i.e., a median elasticity greater than -1). By contrast, 29 percent of the category-year estimates exhibit inelastic demand with exogenous prices; with Hausman instruments, it is 34 percent. Furthermore, both of those approaches yield several estimates with upward-sloping demand. These results suggest the covariance

Figure 3: Markups Over Time Across Product Categories



Notes: The figure plots the mean of within-category median markups over time. Markups are defined by the Lerner index, $(p - mc)/p$ and are estimated separately by product category and year. When calculating the mean, we winsorize the upper and lower 2.5 percent of observations across all categories and years.

restrictions approach generates reasonable demand elasticities, and that it is a distinctly good way to approach estimation in our context.

Of course, our ultimate interest is in the evolution of markups across the many different categories in our estimation sample, and we turn to that exercise next.

5 The Evolution of Markups in Consumer Products

In this section, we document the evolution of markups across consumer products over time. We start by reporting median markups at the product category level before we discuss how the distribution of markups has shifted. We then move the analysis to the product level which allows us to distinguish between variation within and across products and to decompose the evolution of markups into changes in prices and marginal costs.

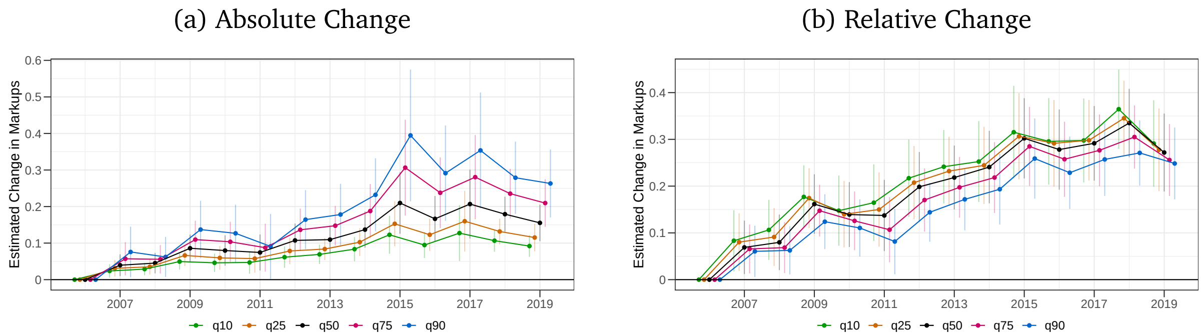
5.1 Aggregate Trends

Our estimation procedure yields a panel of 14.4 million product-level observations across 133 categories and 14 years. To evaluate aggregate trends, we first consider changes in the category-level markups 1,862 category-year combinations in our data. To construct this measure, we take the median markup within each category-year, and we then calculate the mean across categories in each year.[20]

Figure 3 plots the aggregate category-level markups over time. Across categories, we find a substantial increase in the median Lerner index from approximately 0.45 in 2006 to over 0.60

[20]To reduce sensitivity to outliers, we first winsorize the upper and lower 2.5 percent of the observations.

Figure 4: Changes in the Distribution of Markups



Notes: This figure shows coefficients and 95 percent confidence intervals of regressions of percentiles of the markup distribution at the product category level on year dummies using the year 2006 as the base category. In panel (a), outcomes are percentiles of the level of the Lerner index, $(p - c)/p$, in panel (b), outcomes are measured in logarithms.

towards the end of our sample period.[21]

Next, we analyze how the distribution of markups within product categories has shifted over time. For this purpose, we regress different percentiles of the markup distribution on year dummies and document the coefficients and confidence intervals in panel (a) of Figure 4. We use the year 2006, the first year of our estimation sample, as the base category. Hence, the estimated coefficients can be interpreted as the change in markups in each year relative to 2006. The results indicate that, while all quartiles of the distribution have increased over time, the upper part of the markup distribution has changed by a higher amount, especially during the second half of our sample period. In panel (b), we repeat the exercise by using the log of the Lerner index, $\ln(\frac{p-c}{p})$. The results show that the *relative* increase in markups is in fact quite similar across the distribution and even slightly more pronounced for lower quartiles.

Overall, our estimates indicate that the full distribution of markups is shifting upward over time.

5.2 Decomposition of Effects

Aggregate trends in markups may be explained by firms charging higher markups or by consumers shifting to higher-markup products. To evaluate these channels, we analyze the change in markups at the product level, where our unit of observation is a unique product-chain-DMA-quarter-year combination. We regress the log of the Lerner index on quarter, year, and product-chain-DMA fixed effects, using revenues as weights.[22]

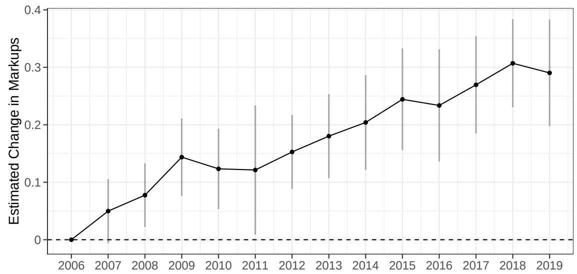
The results of this regression are documented in panel (a) of Figure 5. The figure displays point estimates and 95 percent confidence intervals for the year-specific coefficients. The es-

[21]This corresponds to an average growth rate of 2.3 percent per year.

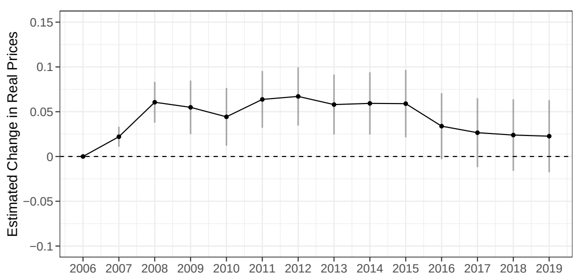
[22]Revenue weights capture an average effect across a quantity-weighted bundle of products when measuring changes to log markups.

Figure 5: Product-Level Changes in Markups, Prices, and Marginal Costs

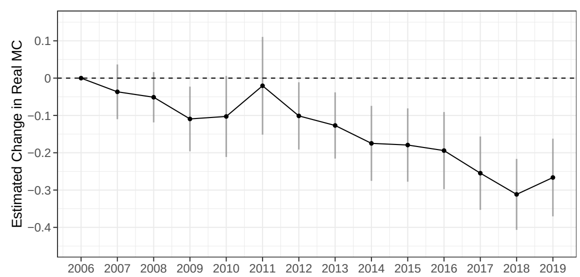
(a) Markups



(b) Prices



(c) Marginal Costs



Notes: This figure shows coefficients and 95 percent confidence intervals of a regressions of the log of the Lerner index, real prices, and real marginal costs at the product-chain-DMA-quarter-year level on year dummies controlling for product-chain-DMA and quarter fixed effects. The year 2006 is the base category.

timates indicate an increase in product-level markups of more than 25 percent between 2006 and 2019. The estimated annual growth rate in product-level markups is 2.2 percent per year. Due to the inclusion of product-chain-DMA fixed effects, year dummies only capture variation within products. Thus, the estimated change over time is not affected by entry and exit or a reallocation of market shares across products. This indicates that, in our sample, aggregate markup trends are mainly driven by changes within products over time. We find similar results if we instead use price-over-cost (p/c) markups, as studied by De Loecker et al. (2020). Figure C.2 in the Appendix shows a plot of the corresponding yearly coefficients.

Table C.2 in the Appendix documents full results of the regression that corresponds to panel (a) of Figure 5 alongside alternative specifications in which we replace year dummies with a linear time trend and consider dropping product-chain-DMA fixed effects or replacing them with category fixed effects. We obtain qualitatively similar results across these specifications, in which we estimate an average yearly increase in average markups between 1.7 and 2.2 percent. We estimate larger changes when controlling for product-level fixed effects, indicating that the within-product changes in markups are greater than the aggregate (revenue-weighted) changes in markups. Though these differences are not significant, this suggests that some of the product-level increase in markups may be offset by the introduction of lower-markup products over time.[23]

Using our detailed data on prices and our demand estimates, we are able to decompose the increase in markups into changes in prices and marginal costs. For this purpose, we regress log prices and log marginal costs on product-DMA-retailer fixed effects and year dummies. Prices and marginal costs are deflated by core CPI and indexed to Q1 of 2010.

The yearly coefficients are documented in panels (b) and (c) of Figure 5. Panel (b) shows that real prices increased at the beginning of our sample period, but declined in later years. From 2006 to 2012, the average real price for products in our sample increased by 7 percent, but by 2019, real prices were only 2 percent higher than in 2006.

Panel (c) of the figure reports the yearly coefficients for log marginal costs. We estimate that marginal costs decline by 1.3 percent per year on average. In 2017–2019, marginal costs are roughly 25 log points lower than in 2006. Thus, though higher real prices account for part of the increase in markups during the first half of our sample, the higher markups we observe at the end of our sample arise from lower real marginal costs, not higher real prices. Overall, our estimates suggest that declines in real marginal costs have not been fully passed on to consumers.[24]

Why might lower costs not lead to lower prices? One potential explanation is that demand is less responsive to prices. To investigate this potential explanation, we evaluate changes in consumer preferences over time. First, we regress the logarithm of the absolute value of own-price elasticities at the product level on the same set of fixed effects used above. We present the results in panel (a) of Figure 6. The displayed coefficients show that price elasticities have declined in magnitude, indicating that demand indeed becomes less responsive to prices over time.

Price elasticities capture several underlying aspects of consumer preferences and may also reflect supply-side factors such as production costs, quality, and competition. To shed additional light on the changes in markups we observe, we isolate two features of consumer preferences and examine trends in these parameters. First, we look at consumer price sensitivity, which reflects the mean price coefficient within a category year. Specifically, we define the price sensitivity as the log absolute value of the mean price coefficient. Thus, a higher value of the price sensitivity parameter indicates that consumers are more sensitive to prices, independent of changes to underlying demographics or other changes in preferences. Second, we examine changes in perceived product quality. We measure quality as the mean value consumers place on products within a category, and we standardize the measure separately within each category.[25]

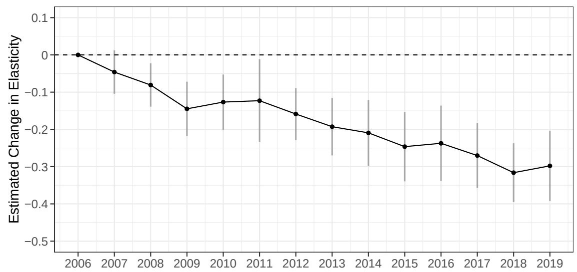
[23] Table C.3 in the Appendix shows results using unweighted regressions. The results are very similar.

[24] Figure C.3 in the Appendix documents results using nominal, i.e., non-deflated, prices and marginal costs and shows that nominal marginal costs are relatively constant over time.

[25] Specifically, we first obtain the product-specific mean utility, and then divide by the absolute value of the mean price coefficient to obtain a value in dollar terms. With demographics normalized to have a mean of zero, the valuation of an average consumer (which we define as $\epsilon_{ij} = 0$ for all j) equals $\overline{V}_{jcrt} = \frac{1}{\alpha}\left(\beta + \xi_{jr} + \xi_{cr} + \xi_t + \Delta\xi_{jcrt}\right)$. We interpret $\overline{V}_{jcrt}$ as a measure of perceived product quality. Within the context of the model, product quality

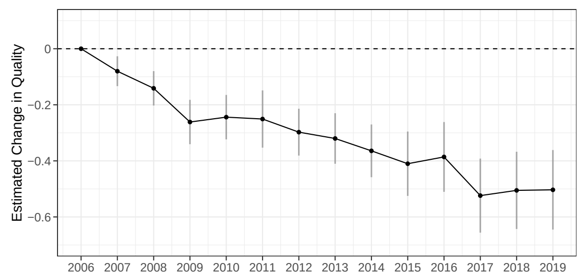
Figure 6: Changes in Elasticity, Price Sensitivity, and Quality

(a) Log Absolute Elasticity



(b) Price Sensitivity

(c) Quality



Notes: This figure shows coefficients and 95 percent confidence intervals of a regression of log absolute elasticity, price sensitivity, and relative quality at the product-chain-DMA-quarter-year level on year dummies controlling for for product-chain-DMA and quarter fixed effects. The year 2006 as the base category.

We repeat the product-level regressions of price sensitivity and quality using the fixed effects as above, and we display the estimated coefficients in panels (b) and (c) of Figure 6. The time trend shows that consumer price sensitivity is decreasing over time, consistent with the declining magnitudes of elasticities. Panel (b) shows that the declines in price sensitivity were large through 2012, corresponding with the increase in real prices we observe over the same period.

On the other hand, we find that perceived quality declined over our sample, as shown in panel (c). In our model, lower quality yields lower shares and more elastic demand. Thus, we find that quality moves in the opposite direction from the estimated trends in elasticities and markups. It is important to emphasize that quality in our model is defined relative to the outside option, i.e., outside of the retailer-DMA-category. The declines in perceived quality that we estimate may be due to increases in perceived utility from substitute retail channels such as online retailers and club stores for example. We explore this matter further in section 6.

To summarize, our decomposition of effects indicates that the increase in markups was driven by lower real marginal costs, without commensurate reductions in real prices. Firms were able to charge higher markups because consumers became less price sensitive over time,

should be interpreted as relative to the outside good. We then standardize this measure using the mean and standard deviation by category across all years.

despite reductions in relative perceived quality.

5.3 Panel Data Analysis

Markups are determined in equilibrium by consumer preferences, production costs, and competition. To evaluate the role of these demand and supply channels, we perform a more detailed analysis that exploits the unique panel structure of our estimates across products and over time. We evaluate how simultaneous changes in preferences, production costs, and competition across product categories correlate with changes in markups. We then examine potential mechanisms that drive these changes.

Specifically, we regress log markups observed for each product-chain-DMA-quarter-year on estimated preference parameters, marginal costs, concentration, and demographics. For preferences, we examine price sensitivity, defined (as above) as the log absolute value of the mean price coefficient. We also relate markups to perceived product quality, based on the mean utility from our demand estimates.[26] We use marginal costs to capture changes in production technology. We standardize marginal costs and quality separately by product category.[27] For concentration, we use the average HHI across DMAs in each year, and we calculate HHI separately for upstream parent companies (brand manufacturers), brands, and downstream retailers. We measure HHI on a 0 to 1 scale. Demographics reflect log income and the presence of young children at home.

Results are displayed in Table 3. Each regression includes fixed effects for each product-market (i.e., brand $\times$ category $\times$ retailer $\times$ DMA) and time period (year-quarter). Thus, the coefficient reflect the correlations of idiosyncratic within-product changes over time. Standard errors are clustered at the product category level.

Column (1) indicates that changes in consumer preferences, measured by price sensitivity, are highly predictive of changes in markups. The price coefficient explains 49 percent of the idiosyncratic within-product changes in markups over time and is is economically significant. A 10 percent decrease in price sensitivity is associated with approximately a 7.5 percent increase in markups.

Column (3) indicates that lower marginal costs are strongly associated with increased markups. Marginal costs alone can explain 69 percent of the within-product changes in markups. Note that price sensitivity is measured at the category-year level, whereas markups and marginal costs may vary across brands, DMAs, and retailers within each category-year. If we run regressions at the product category level, we find a similar coefficients and a higher R^2 for price sensitivity. We report these results in Table C.4 in the Appendix.

Columns (2), (4), and (5) examine perceived quality, concentration, and consumer demo-

[26]See the previous section for details.

[27]We use standardized marginal costs instead of log marginal costs to include the small fraction of observations where we estimate marginal costs to be negative.

Table 3: Dependent Variable: Log Markup

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Price Sensitivity	-0.745^{***}					-0.423^{***}	-0.430^{***}
	(0.032)					(0.034)	(0.033)
Quality (Standardized)		-0.151^{***}				0.007	0.005
		(0.023)				(0.006)	(0.006)
Marginal Cost (Standardized)			-0.570^{***}			-0.444^{***}	-0.438^{***}
			(0.024)			(0.024)	(0.023)
Income (Log)				0.071^{**}		0.068^{***}	0.080^{***}
				(0.030)		(0.017)	(0.015)
Children at Home				-0.185^{***}		-0.047	-0.026
				(0.065)		(0.048)	(0.050)
Parent HHI					0.525^{**}		0.457^{***}
					(0.241)		(0.105)
Brand HHI					0.162		-0.087
					(0.259)		(0.097)
Retailer HHI					0.009		0.078^{**}
					(0.068)		(0.038)
Brand-Category-DMA-Retailer FEs	X	X	X	X	X	X	X
Time Period FEs	X	X	X	X	X	X	X
Observations	14,403,075	14,403,075	14,403,075	14,403,075	14,403,075	14,403,075	14,403,075
R^2 (Within)	0.486	0.050	0.691	0.000	0.008	0.812	0.815

Notes: This table reports regression results where the dependent variable is log markups. Observations are at the brand-category-DMA-retailer-year-quarter level, and brand-category-DMA-retailer and year-quarter fixed effects are included in each specification. Standard errors are clustered at the category level and are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

graphics. Though we find significant coefficients, each of these measures explains vary little of the variation in log markups, with within R^2 values of 0.05 or less.

In column (6), we combine price sensitivity, quality, and marginal costs with demographic characteristics. The coefficients on price sensitivity and marginal costs decline modestly, but remain large in magnitude and statistically significant. The coefficient on quality becomes effectively zero. Thus, though declines in relative perceived quality are correlated with increasing markups in the time series, products with greater increases in quality do not realize differential changes in markups. Increases in income remain positively associated with greater markups. Changes in price sensitivity, marginal costs, and demographics explain most of the variation in markups over time. The within R^2, which also accounts for time period fixed effects, is 0.81.

In column (7), we add our measures of concentration to the specification. We find that changes in parent-manufacturer concentration remain positively correlated with changes in markups, and the coefficient for retailer concentration increases and becomes statistically significant. The coefficient of 0.457 in column (7) indicates that a 0.02 change in parent company HHI—i.e., a 200-point change on a 0 to 10,000 scale—is associated with a 0.9 percent increase in markups. The relationship between markups and changes in concentration at the retailer level is much weaker and brand-level concentration (which ignores multi-product ownership) remains statistically insignificant. Overall, the inclusion of concentration measures does little to change the explanatory power of the regression, as the R^2 barely changes.

5.4 Discussion

Economic theory provides a tight theoretical connection between changes in marginal costs and markups. In typical models of imperfect competition, a decline in marginal costs will not be fully passed on to consumers (i.e., cost pass-through is less than one). If costs fall faster than prices, then markups increase. Thus, the relationship that we find between markups and marginal costs is a result of imperfectly competitive product markets and declining costs.

This logic applies to other settings: in otherwise stable economic environments, declining costs will yield higher markups due to imperfect competition. In many markets, we expect costs to decline over time due to innovations in production technology and operational efficiencies. Our empirical setting is no exception, as many manufacturers sought ways to reduce costs over this time period. For example, Procter & Gamble, one of the largest companies in our data, began a "productivity and cost savings plan" in 2012 that was estimated to reduce annual costs by $3.6 billion in 2019.[28] Overall, our finding of modest declines in marginal costs is consistent with secular increases in productivity across the economy.

There is also a tight theoretical connection between price sensitivity and markups. Ceteris paribus, firms will charge higher prices to less price sensitive consumers. However, as opposed to our finding of declining marginal costs, it is perhaps more surprising that we find that consumers' price sensitivity declines over time. In the following section, we examine the role of price sensitivity in more detail and discuss potential explanatory factors for the time trend.

6 Price Sensitivity and Markups

6.1 Structural Decomposition

To explore the role of price sensitivity in driving markups, we evaluate the degree to which it influences markups in the cross section and over time. For a broad class of oligopoly models, including our empirical specification, we can write the firm-level price-cost margins as a function of the mean price parameter (α), prices, and inverse supply, λ:

$$p_{jcrt} - c_{jcrt}(\chi_{crt};\theta) = -\frac{1}{\alpha_t}\lambda_{jcrt}(\boldsymbol{q}_{crt}, \boldsymbol{p}_{crt}, D_{crt}, \boldsymbol{\eta}_{crt};\theta), \tag{10}$$

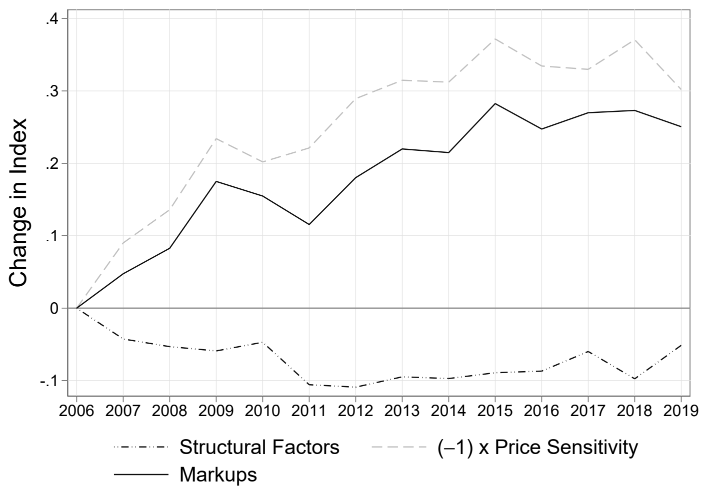
where $\boldsymbol{q}_{crt}$, $\boldsymbol{p}_{crt}$ and $\boldsymbol{\eta}_{crt}$ are the market-level vectors of quantities, prices, and cost shocks, and D_{crt} denotes the $J \times J$ matrix of partial derivatives of inverse demand with respect to prices.[29]

Taking the quantity-weighted average within each category in each year, and dividing by

[28] The Procter & Gamble Company 2019 Annual Report. Available here: https://www.pg.com/annualreport2019/download/PG-2019-Annual-Report.pdf

[29] For example, with single-product Bertrand pricing and logit demand, $\lambda_{jt}(\cdot) = \frac{1}{1-s_{jt}}$. See MacKay and Miller (2022) for the derivation of the general relationship above, in particular equation (4) of that paper.

Figure 7: Decomposition of Markup Trends



Notes: This figure shows the decomposition of changes to the aggregate log Lerner Index into the two components specified by equation (12). The first component, labeled "structural factors," incorporates observable changes in prices and the distribution of market shares. The second component, the negative value of the price sensitivity, reflects mean price parameter across categories. A larger value of this (negative) component means that consumers are less price sensitive.

average price, we obtain an expression for the aggregate Lerner index,

$$\overline{L}_t = \frac{\overline{p}_t - \overline{c}_t}{\overline{p}_t} = -\frac{1}{\alpha_t}\frac{\overline{\lambda}_t}{\overline{p}_t}, \tag{11}$$

for each category. Taking logs, we obtain:

$$\ln \overline{L}_t = \underbrace{\ln\left(\frac{\overline{\lambda}_t}{\overline{p}_t}\right)}_{\text{Structural Factors}} - \underbrace{\ln\left(-\alpha_t\right)}_{\text{Price Sensitivity}}, \tag{12}$$

where we can decompose the (log) category markups into the mean price sensitivity and other structural factors. These structural factors capture marginal costs, demand shocks, and the curvature of demand due to functional form assumptions and nonlinear preference parameters. This term often reflects directly observable data, such as quantities and prices.[30]

Figure 7 presents a decomposition of the aggregate log Lerner index into its constituent parts. For each component, we take the mean across product categories and normalize by subtracting its 2006 value. Consistent with our earlier results, the average log Lerner index increased by 0.25 from 2006 to 2019. Consumer price sensitivity fell by 0.30 over the same period, which is shown in the figure by a 0.30 increase in its negative value (dashed line). This

[30]For example, for a monopolist facing linear demand, $\lambda_t = q_t$. For more flexible demand systems, such as the one we employ here, concentration measures may be correlated with $\frac{\overline{\lambda}_t}{\overline{p}_t}$.

Table 4: Price Sensitivity and Markups Across Product Categories

	(1) 2006 Log Markup	(2) 2006 Log Markup	(3) Δ Log Markup	(4) Δ Log Markup
Price Sensitivity	-0.135^{***}	-0.190^{***}		
	(0.027)	(0.023)		
Δ Price Sensitivity			-0.591^{***}	-0.666^{***}
			(0.012)	(0.009)
Baseline Sample	X		X	
Extended Sample		X		X
Observations	133	200	1,729	2,596
R^2	0.164	0.264	0.579	0.660

Notes: This table reports regression results to examine the cross-sectional and time series relationships of markups and price sensitivity. Columns (1) and (2) capture to cross-sectional variation using the year 2006 for our baseline sample (133 product categories) and the extended sample (200 categories). Columns (3) and (4) capture the time series variation by estimating the model in first differences from 2007 through 2019. The regressions are motivated by the decomposition in equation (12). Standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

decomposition illustrates that the overall change in markups is primarily driven by changes in consumer price sensitivity.

In fact, the structural component of equation (12) decreased from 2006 to 2019 by 0.05. In other words, if the mean price coefficients were held constant over time, the realized changes to other features of the market would have led to a 5 percent decrease in markups. This structural component typical incorporates observable changes in prices and shares, including things such as market concentration. In our empirical model, the structural component can be obtained from the first step in our estimation routine, where we pin down heterogeneity in demand using micro-moments (Berry and Haile, 2020). Consumer price sensitivity is pinned down in the second step by an independent set of moments.[31]

We use equation (12) to motivate a cross-sectional regression to explore the degree to which price sensitivity explains variation in markups across product categories. We regress $\ln \overline{L}_t$ on $\ln(-\alpha_t)$ at the category level in 2006, including a constant. We report the results in Table 4. Variation in price sensitivity explains 16 percent of the cross-sectional variation in category markups for our baseline set of 133 product categories and 26 percent of the variation for the extended sample of 200 categories. This suggests that other structural factors, such as costs and multi-product ownership, are relatively more important in explaining variation in markups across categories.

We next examine how changes in price sensitivity explain changes in markups over time. In specifications (3) and (4), we report results from regressions of changes in log markups ($\ln \overline{L}_t - \ln \overline{L}_{t-1}$) on category-level changes in price sensitivity. Relative to the cross-sectional variation, we find that changes in price sensitivity over time explain substantially more of the

[31]See Appendix A for details.

variation in markups over time: 58 percent for our baseline sample, and 66 percent for the extended sample.

We draw two main insights from this exercise. First, our demand specification is sufficiently rich to attribute much of the variation in markups across categories to structural factors that are uncorrelated with consumer price sensitivity. This need not be the case with less flexible demand systems. For example, with constant elasticity demand, the Lerner index only varies due to differences in price sensitivity (i.e., $\lambda_t = p_t$ and $\ln(\lambda_t/p_t) = 0$).

Second, these results gives us greater confidence that the estimated changes in price sensitivity over time reflect underlying consumer behavior, and not changes in other structural factors. In our econometric approach, we estimate demand separately for each category-year. Hence, there is no systematic relationship that is driven by the assumptions of our model. In other words, variation in markups over time could have yielded a much weaker relationship with price sensitivity.

6.2 Potential Mechanisms

Given the important role of price sensitivity in markups, we next examine potential factors that could explain the change over time. We consider both changes to the composition of retail markets and also firm-level decisions that could affect consumer behavior in the studied markets. A third possibility is that consumers are becoming less price sensitive over time due to other exogenous factors.

Over our sample period, there was substantial growth in alternative retail channels, including warehouse clubs and online retail. The growth in such channels may have shifted some consumers away from the traditional retail channels that we focus on. To the extent that different consumer types were disproportionately drawn to these alternatives, the selection of consumers into traditional retail may have changed over time.

To assess this possibility, we construct the share of revenues by retail channel in each product category and each year, including warehouse clubs and online retail in addition to mass merchandisers, grocery, and drug stores. We use all available data from the Kilts Nielsen consumer panel dataset to construct these measures. We then test whether changes in price sensitivity are correlated with growth in either of these segments, leveraging cross-category idiosyncratic variation over time. Some categories are disproportionately affected by the growth of alternative retail channels. For example, less than one percent of beer was sold online in each year of the sample, whereas the share of online revenues for dry dog food increased from less than 2 percent to over 15 percent over the period.[32] If we see a greater decrease in price sensitivity for categories disproportionately affected by the shift to online, that might suggest that consumer selection may be playing a role.

[32]Across categories and years, the average share from warehouse clubs was 8.8 percent and the average share from online was 2.7 percent.

Table 5: Potential Mechanisms

	(1) Price Sensitivity	(2) Log Abs. Elasticity	(3) Marginal Cost	(4) Perceived Quality
Log Share Online	-0.117^{**}	-0.086^{*}	-0.202	-0.539^{***}
	(0.049)	(0.047)	(0.136)	(0.140)
Log Share Warehouse Clubs	-0.015	0.022	0.134	-0.112
	(0.063)	(0.063)	(0.191)	(0.158)
Log Marketing Spend	0.011	0.016	0.116^{**}	0.045
	(0.021)	(0.021)	(0.054)	(0.055)
Log R&D	-0.003	-0.004	-0.046	0.021
	(0.023)	(0.020)	(0.056)	(0.069)
Log Num. UPCs	0.102^{*}	0.092^{**}	0.369^{***}	0.474^{***}
	(0.052)	(0.046)	(0.125)	(0.155)
Brand-Category FEs	X	X	X	X
Time Period FEs	X	X	X	X
Observations	1,801	1,801	1,801	1,801
R^2	0.942	0.579	0.115	0.171
R^2 (Within)	0.010	0.007	0.014	0.031

Notes: Standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The next category of mechanisms we investigate addresses whether firm-level investments may yield consumers that are less price sensitive, either through perceived or realized changes to their products. To explore this, we merge our estimates with financial data on marketing and R&D expenses obtained from Compustat. These measures are obtained from annual reports of the parent companies. We also consider whether changes in product variety may account for the changes we observe. We measure product variety as the (log) number of UPCs offered by each brand in each market. We aggregate our data to the category-year level, taking a simple average of each measure. Thus, we seek to evaluate whether categories with disproportional increases in marketing, R&D, or variety, also realized greater declines in price sensitivity.

To explore these relationships, we regress price sensitivity ($\ln(-\alpha_t)$) on the logged values of the above measures. We include category fixed effects and year dummies, so that the coefficients reflect time-series variation within each category that departs from the aggregate trend.

Column (1) of Table 5 reports the results. We find a negative, statistically significant relationship between the share sold online and consumer price sensitivity. We find no relationship between share sold in warehouse clubs, marketing expenditures, or R&D expenditures. We find a marginally significant positive relationship between variety and price sensitivity. We think it is unlikely that firms introduce additional products in order to make consumers more price sensitive, and, since price sensitivity has decreased over time while variety has increased, we think it is likely that this coefficient reflects other factors. Together, all five measures only explain 1 percent of the residual variation in markups, suggesting that neither retail shopping patterns nor firm-level investments are driving the changes in price sensitivity over time.

Our results in column (1) allow for a potential causal link between the growth of online retail and consumer price sensitivity in traditional channels. Though the coefficient is economically meaningful, online sales remained a relatively small share of revenues in 2019—4.4 percent across categories—so we think it is not a plausible explanation for the changes in price sensitivity we estimate in traditional retail channels (87 percent of revenues in 2019). As an additional test, we run a regression using the log absolute elasticity as the dependent variable, instead of the price sensitivity. If online sales were skimming off more price sensitive consumers, we would expect consumers to self select based on demographic characteristics that also affect demand elasticities. Thus, if changes in markups were driven by consumer selection, elasticities should have a stronger relationship with online sales than the (mean) price sensitivity parameter.

Column (2) reports results using price elasticity as the dependent variable. Relative to the estimate for price sensitivity, the coefficient on online sales is smaller by roughly 25 percent and is only marginally significant. Thus, the shift to online sales does not seem to be driven by the tail of the most price-sensitive consumers. The coefficients on the other measures remain similar.

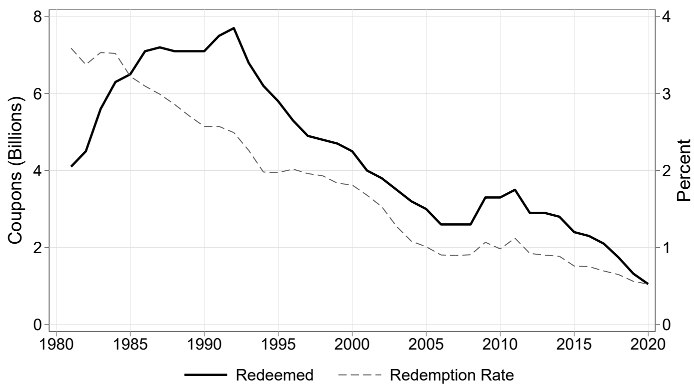
Though we focus on explaining price sensitivity, we also run regressions with marginal costs and perceived quality as the dependent variables. We report results in columns (3) and (4). We find a positive and significant relationship with marginal costs and marketing, suggesting that cost decreases were also correlated with less spending on marketing.

We find a large and highly significant relationship between perceived quality and online sales. As perceived quality captures the value to consumers above and beyond outside options (including online sales), this is consistent with the trends we find in section 5. Online retail became an increasingly popular option over the time period, lowering the (relative) utility of in-store purchases. Conversely, we find no effect of warehouse clubs on perceived quality, though the point estimate is negative.

Finally, we note that product variety is positively correlated with marginal costs and perceived quality. As both marginal costs and quality are falling over time, while variety is rising, this suggests that greater variety may have helped to mitigate the substitution of consumers to other channels (i.e., online), albeit at a higher costs. This is related to the explanation offered by Brand (2021), who suggests that increased variety may lead to less price sensitivity. However, we do not find that changes in quality drive changes in markups. In the time series, quality declines over time, and we estimate a net relationship with markups very close to zero when controlling for other factors (Table 3). Further, increased variety is correlated with higher marginal costs, whereas higher markups are related to lower marginal costs. Thus, product variety does not appear to be driving the trends we observe.

The results in Table 5 suggest that the composition of retail shopping across new channels and firm-level investments cannot account for the stark change in consumer price sensitivity

Figure 8: Coupon Use Over Time



Notes: This figure shows the annual number of coupons redeemed (left axis) and the redemption rate out of all issued coupons (right axis). From 2006 to 2019, coupon redemptions fell from 2.6 billion to 1.3 billion, and the redemption rate fell from 0.90 percent to 0.56 percent. Annual estimates reflect total coupon usage for consumer products in the United States across all channels, including free standing inserts and electronic coupons.

that we document. Another possibility is that the change reflects exogenous shifts in preferences that are not the result of changes to supply. Though it is challenging to directly measure such changes, we are able to pick it up with our econometric methodology.

To corroborate the hypothesis that lower price sensitivity is due to exogenous shifts in consumer behavior, we examine other information about consumer shopping patterns. In particular, we look at the use of coupons for consumer products over time. Coupons typically involve a small amount of effort for the consumer in order to obtain a discount on price. We collect statistics on the number of coupons distributed and redeemed for consumer packaged goods from 1981 through 2020. These statistics reflect industry estimates of coupon use across all channels, including free standing inserts and electronic coupons.[33]

Figure 8 plots the aggregate coupons usage over time. The black line reports the number of coupons redeemed each year (left axis). From 1981 to 1992, the number of coupons redeemed roughly doubled, from 4.1 billion to 7.7 billion. Since that year, there has been a steady decline in the number of coupons redeemed, with the exception of a brief bump due to the recession starting in 2009. Over our sample period, the number of coupons redeemed has fallen in half, from 2.6 billion in 2006 to 1.3 billion in 2019.

This trend reflects a decreasing propensity of consumers to use coupons, rather than coupon availability. To highlight this, the dashed line plots the percent of coupons that are redeemed out of all the coupons that were distributed (right axis). Redemption rates are declining over the entire sample period. From 1981 to 1992, the decline reflects the fact that the growth in the distribution of coupons outpaced the growth in coupon redemption rates. From 1992 to 2015, the annual number of coupons issued remained high while redemption rates fell. In 2015, 316

[33]Industry estimates were obtained from reports by two companies, NCH Marketing from 1981 through 2002, and Inmar Intelligence from 2003 through 2020.

billion coupons were distributed, compared to 309 billion in 1992. From 2016 to 2020, fewer coupons were distributed each year, but redemption fell even faster. The redemption rate fell from 0.90 in 2006 to 0.56 in 2019.

Overall, the declining use of coupons and the declining redemption rates indicate a fundamental shift in consumer shopping behavior. This shift is consistent with lower price sensitivity arising from exogenous factors. Specifically, declining coupon use indicates less willingness to exert small amounts of effort to obtain lower prices. Notably, the shift began in the early 1990s, before the rise of online retail. We view this as additional evidence that declining price sensitivity reflects a longer-run secular trend.

7 Markups, Welfare, and Consumer Surplus

In this section, we analyze how consumer surplus and total welfare for consumer products have changed over time. We also calculate consumer and total welfare for various counterfactual scenarios, to estimate the deadweight loss from (changes in) market power.

The expected value of consumer surplus (CS) in our model is (Small and Rosen, 1981):

$$CS = -\frac{1}{N}\sum_{i}\frac{1}{\alpha_i}\ln\left(\sum_{j}\exp\left(w_{ij}\right)\right) \tag{13}$$

where $w_{ij} = \beta_i^* + \alpha_i^* p_{jcrt} + \xi_{jr} + \xi_{cr} + \xi_t + \Delta\xi_{jcrt}$ and N denotes the number of consumers.[34] Consumer surplus is the additional surplus relative to outside options and can be interpreted as the added value from the presence of the focal products. Producer surplus (PS) reflects profits and is measured as price less marginal costs multiplied with quantities: $PS = (p - c)q$; welfare (W) is the sum of PS and CS.

Table 6 shows the values of consumer and producer surplus per capita for the first and the last year of our sample using observed prices ("Baseline") and prices under different counterfactual scenarios. To compute counterfactual values, we hold fixed estimated preference parameters and marginal costs, and we simulate choices using different prices. First, we scale all prices by the average realized price change for all products in the same category from one year to another (e.g., from 2006 to 2019). Second, we scale all markups by the average realized markup change for all products in that category from one year to another. Because we hold marginal costs fixed, scaling 2006 prices to match 2019 markups results in higher prices than what we observe in the data. Third, we consider a counterfactual where prices equal marginal costs (i.e., no markups). The last two columns in each panel show changes in consumer surplus and welfare relative to the baseline scenario of observed prices, estimated markups, and

[34] In calculating consumer surplus, we use the average price coefficient within each consumer's income decile to avoid dividing by numbers very close to zero. In practice, this matters only for a single category, and we obtain nearly identical results if we use the average price coefficient within income quartiles or across all consumers.

Table 6: Annual Surplus and Welfare Per Capita

(a) 2006 Preferences and Costs

Specification	CS	PS	W	% change CS	% change W
Baseline	610	256	866	0.0	0.0
Prices Scaled to 2019 Levels	586	259	845	-4.0	-2.5
Markups Scaled to 2019 Levels	536	261	797	-12.2	-8.0
Prices Equal to Marginal Costs	930	0	930	52.4	7.4

(b) 2019 Preferences and Costs

Specification	CS	PS	W	% change CS	% change W
Baseline	931	366	1296	0.0	0.0
Prices Scaled to 2006 Levels	963	344	1308	3.5	0.9
Markups Scaled to 2006 Levels	1060	278	1338	13.9	3.2
Prices Equal to Marginal Costs	1412	0	1412	51.7	9.0

Notes: This table reports consumer surplus (CS), producer surplus (PS), and welfare per capita based on estimated demand parameters ("Baseline") and for counterfactual scenarios that hold fixed preferences and marginal costs and vary the price levels.

expected utility in each year.

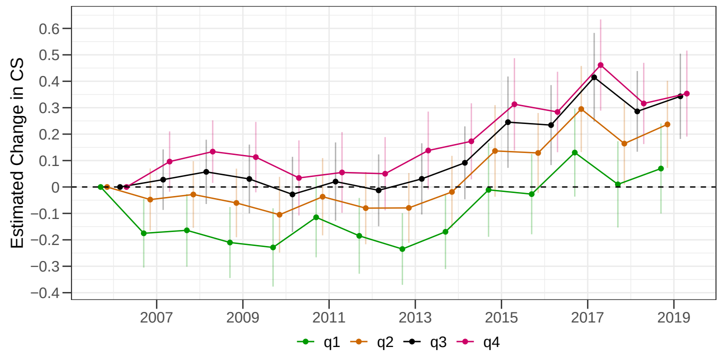
The first row in each panel provides estimates of the realized values of surplus and welfare. Comparing these rows across panels, the results indicate that consumer surplus per capita has increased by about 50 percent between 2006 and 2019, from $610 to $931 per capita. Since average prices have not declined and perceived quality has not increased, the increase in consumer surplus is likely due to lower price sensitivity, i.e., the fact that consumers receive lower disutility from any given price in 2019. Along with higher markups, producer surplus has increased over the period, from $256 to $366 per capita. Overall, we estimate substantial gains in total welfare. Approximately three quarters of the welfare gains have accrued to consumers.

Markups are costly for consumers. If firms would set prices equal to marginal costs, consumer surplus would be substantially higher in both 2006 and 2019, as shown by the final specification in each panel. Our estimates suggest that markups in 2006 produced a modest deadweight loss, reducing aggregate welfare from $930 to $866 per capita (about 7 percent). In 2019, markups resulted in a slightly greater deadweight loss, reducing welfare by about 8 percent.

Despite the overall increase in consumer surplus between 2006 and 2019, consumers suffered from rising markups. Based on 2019 preferences, consumer surplus in 2019 would be almost 14 percent higher if markups were scaled down to match average 2006 levels. If prices were scaled down to match average 2006 levels, consumer surplus in 2019 would be 3.5 percent higher than in the baseline scenario. Counterfactual markup increases are more costly than price increases because marginal costs have been declining over time.

Next, we analyze how the change in consumer surplus over time varies by income class. For this purpose, we calculate the log of consumer surplus per purchasing decision separately by each quartile of the income distribution and for each category-year. We relate these values

Figure 9: Consumer Surplus Over Time By Income Group



Notes: This figure reports coefficients and 95 percent confidence intervals of a regression of the log of consumer surplus by purchase on year dummies, controlling for category fixed effects, separately for different quartiles of the income distribution.

to category and year fixed effects and document the coefficients across years in Figure 9. The results indicate that the overall increase in consumer surplus per capita between 2006 and 2019 is mainly driven by consumers with relatively high income and takes place during the second half of our sample period. In contrast, the lowest quartile of the income distribution suffers from significant losses in consumer welfare until 2014 and reaches a level similar to the initial value in 2006 towards the end of the sample period. In Figure C.4 in the Appendix, we repeat the analysis dividing the sample into deciles. The results confirm that changes in consumer surplus are strongly associated with the income distribution. Consumers in the highest income group gain substantially over time, while losses in consumer welfare are limited to lower income groups. These findings suggest that changes in market power and consumer preferences over time have important distributional consequences.

8 Conclusion

This paper analyzes the evolution of market power in consumer products in the US between 2006 and 2019. For this purpose, we combine retail scanner data on quantities and prices with consumer level data across more than 100 product categories. This approach allows us to estimate demand with flexible consumer preferences and recover time-varying markups for individual products under the assumption of profit maximization. Our results indicate that markups increase by more than 25 percent during our sample period. In contrast to previous research on the evolution of market power, we estimate similar changes across different quartiles of the markup distribution. In addition, we find similar increases in markups within product categories over time which implies that the results are not driven by a reallocation of market shares towards products with higher markups. We decompose changes in markups into changes in prices and changes in marginal costs. Overall, the nominal prices of products rise at a similar rate as inflation during our sample period. Thus, real prices remain almost constant, and the increase in markups we estimate is primarily due to falling (real) marginal costs. Our results suggest that prices do not decrease along with marginal costs because of changes in consumer preferences. Our estimates suggest that consumers became about 25 percent less price sensitive over the sample period. Due to decreased price sensitivity, consumer surplus increased during our sample period despite rising markups. The increase in consumer surplus is, however, concentrated among consumers with relatively high income.

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Appendix

A Details on Estimation

This appendix provides details on the estimation procedure. We estimate the parameters in two steps, which is possible because the mean price parameter and the other ("nonlinear") structural parameters are identified by two independent sets of moments. The parameters for estimation are $\theta = (\alpha, \Pi, \Sigma)$. We first estimate $\theta_2 = (\Pi, \Sigma)$ and then estimate α, the mean price parameter, in the second step. Our micro-moments identify θ_2 but not α (Berry and Haile, 2020), and the covariance restriction exactly identifies α given θ_2 (MacKay and Miller, 2022). In principle, a single search could be used to estimate the parameters jointly, as is standard practice for applications that rely on instruments for identification (e.g. Berry et al., 1995; Nevo, 2001; Miller and Weinberg, 2017; Backus et al., 2021). However, our approach has substantial computational benefits, as we explain below.

A.1 First Step

In the first estimation step, we use the micro-moments to pin down the "nonlinear" parameters, i.e., $\theta_2 = (\Pi, \Sigma)$. To implement this, we estimate GMM while holding fixed the price parameter at a given value. Because the parameters are identified separately, the specific value chosen for the price parameter has no impact on the micro-moment contributions to the objective function.[35]

For any candidate θ_2, there is a unique vector of the mean product valuations that align the predicted and observed shares (δ). For example, in the special case of $\theta_2 = \overrightarrow{0}$ the mean valuations have a closed-form solution:

$$\delta_{jcrt}\left(\theta_2^{(0)}\right) \equiv \log(s_{jcrt}) - \log(s_{0crt}) \tag{A.1}$$

We proceed to estimate θ_2 based on equation (7) while holding fixed the price parameter. For each candidate θ_2, we recover the mean valuations $\{\delta_{jcrt}(\theta_2)\}$ using the contraction mapping of Berry et al. (1995) with a numerical tolerance of 1e-9. We then calculate the micro-moments with $\{\delta_{jcrt}(\theta_2)\}$ and $\tilde{\alpha}$. We choose the parameters $\{\delta_{jcrt}(\theta_2)\}$ that minimize the micro-moment contributions to the objective function. We apply equal weights to each micro-moment in estimation.

A.2 Second Step

In the second step, we hold fixed the estimated nonlinear parameters and choose the price parameter that minimizes the objective based on the covariance restriction moment. In other

[35] We initialize this step with a price parameter such that the average elasticity when $\theta_2 = \overrightarrow{0}$ is equal to -1.

words, we estimate α taking as given the estimates of θ_2 obtained in the first step. This is possible because micro-moments do not identify the mean price parameter (Berry and Haile, 2020). To do so, we recover $\Delta\xi_{jcrt}(\theta_2)$ as the residual from the OLS regression of $(\delta_{jcrt}(\theta_2) - \alpha p_{jcrt})$ on the fixed effects for each candidate α. We also obtain marginal costs from using equation (5), looping over the chain-region-quarter combinations, and then recover $\Delta\eta_{jcrt}(\theta_2)$ as the residual from the OLS regression of marginal costs on the fixed effects. We are then able to calculate the loss function, update the candidate α, and repeat to convergence. We constrain the search to negative values of α. The constraint imposes downward-sloping demand for a consumer with the mean income level.

A complication is that there may be two values for α that satisfy the covariance restriction, with the smaller (more negative) value being the true price parameter under sensible conditions (MacKay and Miller, 2022). Care must then be taken to ensure that the estimator converges to the smaller value. Figure C.5 illustrates this in the context of RTE cereals. Each panel traces out the contribution of the covariance restriction to the objective function for different values of α. In 2006 and 2018, a unique negative α satisfies the covariance restriction, and the constraint we place on the parameter space ($\alpha < 0$) is sufficient to recover the correct estimate. In other years, both possible solutions are negative, and thus could be obtained from estimation, even though the larger (less negative) value is implausibly close to zero.[36]

We proceed by selecting starting values of $\alpha^{(0)} = \phi\tilde{\alpha}$ where $\tilde{\alpha}$ is as defined for the first step of estimation and delivers an average elasticity of -1 when $\theta_2 = \overrightarrow{0}$, and $\phi = (2, 4, 6, 8, 10, 12)$. Thus, for each year-category, we estimate with six different starting values. As these starting values are quite negative, the estimator tends to converge on the more negative value of the price parameter that satisfies the covariance restrictions. In the category-years for which the estimator finds both solutions, we select the more negative solution as our estimate of α. This appears to be a robust solution given the θ_2 we estimate.

The two-step approach allows us to more readily evaluate the possibility of multiple solutions for the covariance restriction. In addition, the objective function contribution of the covariance restriction moment can be poorly behavior for unreasonable candidate θ_2 parameters that would be considered if estimation of both θ_2 and α were performed simultaneously. Thus, our two-step approach to estimation conveys both speed and numerical stability, both of which are important given the scale of the empirical exercise.

[36]The larger values imply that firms are pricing in the inelastic portion of their residual demand curves. A related complication is that the numerical stability of the moment tends to deteriorate as the candidate α approaches the higher solution, which can lead to convergence issues if the estimator considers parameters near the higher solution.

A.3 Computation Notes

Our code builds on the BLPestimatoR package for R (Brunner et al., 2020).[37] The package has a slim R skeleton and fast C++ routines for computationally intensive tasks. As micro-moments and covariance restrictions are missing from the package, we added code to cover that part of estimation. All time-critical parts are in C++. In early experiments, we replicated our results for some categories using the PyBLP package for Python (Conlon and Gortmaker, 2020).[38] We ultimately selected the augmented R package because it allowed us to calculate the micro-moments more quickly; our understanding is that the speed of PyBLP has improved substantially during the course of our research.

In estimation, we use BFGS with a numerical gradient. When searching for θ_2 in the first step of estimation, there are a handful of categories for which BFGS fails to converge, and for those categories we use Nelder-Mead instead. We estimate each category-year combination in parallel using the HILBERT computational cluster at the University of Düsseldorf. There are 2800 estimation routines (200 categories and 14 years). Each routine requires one CPU core and up to 12GB of memory. The longest runs take slightly more than 72 hours and most finish in less than 24 hours. The entire estimation procedure takes around one week.

B Data Details

B.1 Market Size

Recall from Section 2.2 that the quantity demanded in our model is given by $q_{jcrt}(p_{rct};\theta) = s_{jrct}(p_{rct};\theta)M_{rct}$, where $s(\cdot)$ is the market share, p_{rct} is a vector of prices, and M_{rct} is the market size, a measure of potential demand. As is standard in applications involving random coefficients logit demand, an assumption on market size is needed in order to convert observed quantities into market shares and then estimate the model. Our approach is to use market sizes that scale with the population of the region and the number of stores operated by the retail chain within the region. We apply the following steps for each product category:

1. Obtain a "base" value by multiplying the population (at the region-year level) with the number of stores (at the retail chain-region-quarter-year level). This obtains $BASE_{crqy} \equiv POP_{ry} \times NS_{crqy}$ where POP_{ry} is the population in region r and year y and NS_{crqy} is the number of stores operated by retail chain c in region r, quarter q, and year y.

2. Obtain the total quantity of the inside products: $Q_{crqy} = \sum_j q_{jcrqy}$.

3. Calculate $\gamma_{cr} = mean_{q,y}\left(\frac{Q_{crqy}}{BASE_{crqy}}\right)$ as the average quantity-to-base ratio among the periods observed for each retail chain and region. This can be used to convert the base value

[37] https://github.com/cran/BLPestimatoR, last accessed March 26, 2021

[38] https://github.com/jeffgortmaker/pyblp, last accessed March 26, 2021.

into units that are meaningful in terms of total quantity-sold. In the calculation of γ_{cr}, we exclude a handful of quantity-to-base ratios that are less than 5 percent of the mean ratio, which helps avoid extraordinary small inside good market shares.

4. We obtain the market size by scaling the base value according to

$$M_{crqy} = \frac{1}{0.45} \gamma_{cr} BASE_{crqy}$$

which generates markets sizes for each retail chain, region, quarter, and year, such that the combined share of the inside goods is around 0.45, on average.

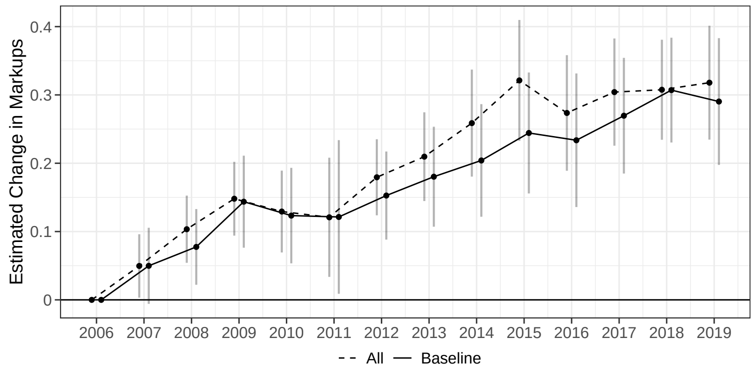
5. For a small minority of cases (<5 percent of categories), this procedure generates a combined share of the inside goods that exceeds 0.90 in some period, which is high enough that we encounter numerical problems in estimation. For any category in which this occurs, we repeat the steps above using the alternative conversion factor $\gamma_{cr} = max_{q,y} \left(\frac{Q_{crqy}}{BASE_{crqy}} \right)$, which leads to market sizes that are more workable in practice.

B.2 Other Details

We make a number of adjustments to the Nielsen data as we construct the estimation samples. First, we drop two large chains from the Consumer Panel Data that do not appear in the Retail Scanner Data. Second, we impute household income using the midpoint of the bins provided in the Consumer Panel Data data. It is possible to obtain a comparable income measure for the highest-income bin because addition high-income bins are provided from 2006 to 2009; we estimate a midpoint of $137,500. Third, we observe that many fewer consumers are in the top income bin in 2006 than in 2007 and subsequent years. To produce a more consistent demographic representation of consumers, we rescale the Nielsen projection weights in 2006 so that the top bin occurs with the same frequency as it does in 2007. We scale down the projection weights for the other bins in 2006 proportionately. Fourth, in an attempt to reduce measurement error, we drop products that are extreme outliers in terms of their price—which we implement by dropping observations with a price below the 0.5 percentile or above the 99.5 percentile. We implement this screen before culling restricting attention to the 22 DMAs. Fifth, we exclude four categories from the ranking that, for some years, exist in the scanner data but not the consumer panel data: prerecorded videos, magazines, cookware, and sunscreens. Finally, we note that we define food categories as belonging to the product departments "Dry Grocery," "Frozen Foods," "Dairy," "Deli," "Packaged Meat," "Fresh Produce," and "Alcoholic Beverages." Non-food categories belong to the product departments "Health and Beauty Care," "Non-food Grocery," and "General Merchandise."

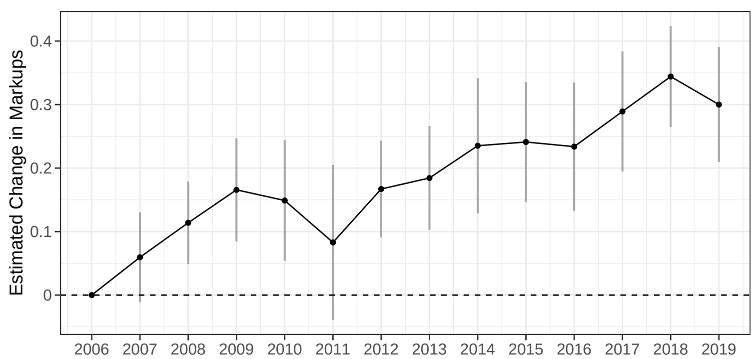
C Appendix Figures and Tables

Figure C.1: Markups Over Time: Alternative Samples



Notes: This figure displays the changes in product-level markups over time for our baseline sample (133 product categories, solid line) and the extended sample (200 product categories, dashed line). The 133 product categories in the baseline sample are selected based on a proxy for within-category product heterogeneity. Point estimates and 95 percent confidence intervals are obtained from regressions of the log of the Lerner index $(p - c)/p$ on year dummies controlling for product-chain-DMA and quarter fixed effects. Observations are at the product-chain-DMA-quarter-year level. The year 2006 is the base category.

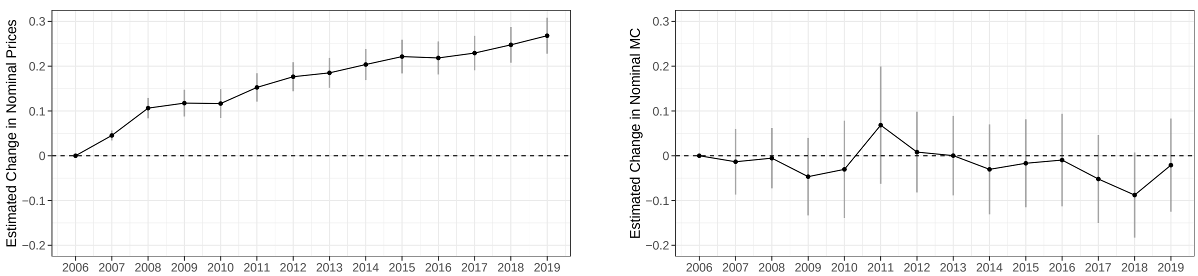
Figure C.2: Markups Over Time: Price-Over-Cost Markups



Notes: This figure shows coefficients and 95 percent confidence intervals from a regression of log markups at the product-chain-DMA-quarter-year level on year dummies controlling for product-chain-DMA and quarter fixed effects. The year 2006 is the base category. Markups are defined as price over marginal cost (p/c) as in De Loecker et al. (2020).

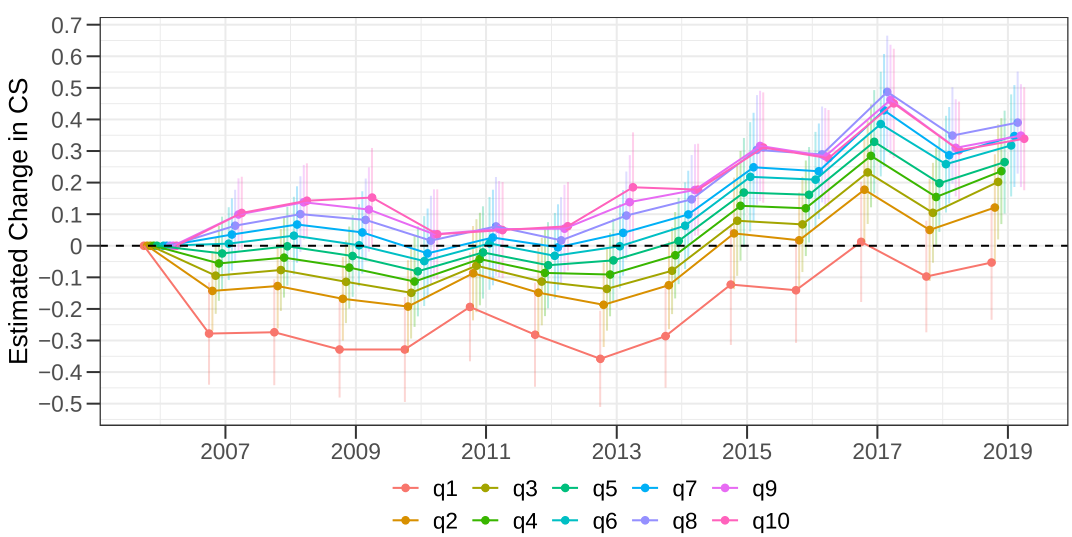
Figure C.3: Product-Level Changes in Nominal Prices and Marginal Costs

(a) Prices | (b) Marginal Costs



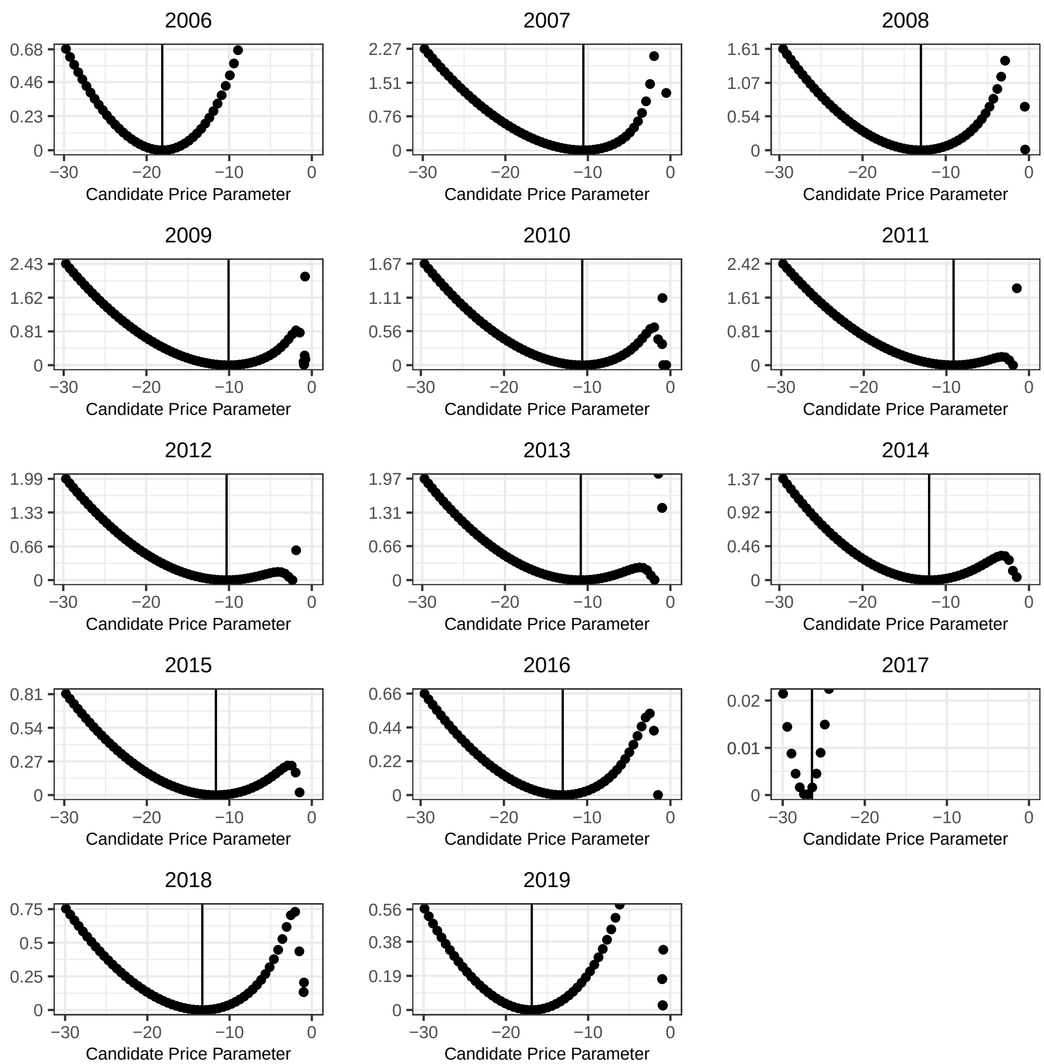
Notes: This figure shows coefficients and 95 percent confidence intervals of regressions of the log of nominal prices and marginal costs at the product-chain-DMA-quarter-year level on year dummies controlling for for product-chain-DMA and quarter fixed effects. The year 2006 is the base category.

Figure C.4: Consumer Surplus Over Time By Income Group, Deciles



Notes: This figure reports coefficients and 95 percent confidence intervals of a regression of the log of consumer surplus by purchase on year dummies, controlling for category fixed effects, separately for different deciles of the income distribution.

Figure C.5: Contribution of Covariance Restriction to Objective Function With RTE Cereals



Notes: This figure plots the contribution of the covariance restriction to the objective function, scaled by ten thousand, for different candidate price parameters over the range $[-30, 0]$. Other parameters are held fixed at the levels obtained in the first step of estimation.

Table C.1: Estimation Results for RTE Cereals

Panel A: Point Estimates and Standard Errors

	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Price	-18.111	-10.547	-12.987	-10.070	-10.599	-9.128	-10.289	-10.834	-11.999	-11.627	-12.933	-26.440	-13.316	-16.857
	(0.016)	(0.013)	(0.012)	(0.012)	(0.008)	(0.005)	(0.006)	(0.005)	(0.006)	(0.011)	(0.018)	(0.003)	(0.010)	(0.019)
Demographic Interactions														
Income×Price	0.678	1.328	1.157	0.589	0.315	0.729	0.797	1.250	0.852	0.639	0.679	0.898	0.502	0.313
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.010)	(0.001)	(0.001)
Income×Constant	0.150	0.218	0.420	0.215	0.294	-0.006	-0.073	-0.106	-0.050	-0.032	0.026	0.611	0.196	0.314
	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.005)	(0.001)	(0.002)
Children×Price	-0.437	-1.432	-0.744	1.141	1.650	2.836	3.321	2.389	2.327	2.405	2.937	2.675	2.454	2.204
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.008)	(0.002)	(0.002)
Children×Constant	7.095	4.727	5.764	2.207	3.579	0.869	0.567	0.681	0.528	0.801	2.288	8.394	4.346	5.172
	(0.021)	(0.022)	(0.016)	(0.013)	(0.014)	(0.003)	(0.000)	(0.001)	(0.001)	(0.008)	(0.024)	(0.014)	(0.010)	(0.023)
Random Coefficient														
N(0,1)×Constant	5.649	3.840	5.226	2.261	4.452	0.689	0.003	0.240	0.243	1.412	4.758	17.462	8.510	10.220
	(0.019)	(0.023)	(0.016)	(0.019)	(0.019)	(0.009)	(0.010)	(0.009)	(0.010)	(0.019)	(0.047)	(0.030)	(0.019)	(0.044)

Panel B: Other Statistics

	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Observations	15,441	16,336	16,604	16,791	17,241	17,329	16,444	16,213	16,443	15,829	15,487	14,365	18,850	17,805
Median Own Elasticity	3.353	1.996	2.573	2.016	2.029	1.744	2.067	2.151	2.349	2.196	2.374	4.732	2.308	2.957
Median Lerner	0.345	0.578	0.454	0.562	0.578	0.627	0.522	0.498	0.455	0.500	0.490	0.253	0.504	0.397

Notes: This table summarizes the results of estimation for the RTE Cereals category for each year in the sample. Panel A provides the parameters and the standard errors, which are clustered at the region level. Panel B provides the number of product-chain-region-quarter observations, the revenue-weighted median own price elasticity of demand, and the revenue-weighted median Lerner index.

Table C.2: Product-Level Markups Over Time, Sales-Weighted Regressions

	(1) Log Markup	(2) Log Markup	(3) Log Markup	(4) Log Markup	(5) Log Markup	(6) Log Markup
Trend	0.018***		0.017***		0.022***	
	(0.003)		(0.003)		(0.003)	
Year=2007		0.048*		0.048*		0.050*
		(0.028)		(0.028)		(0.028)
Year=2008		0.078***		0.078***		0.078***
		(0.028)		(0.028)		(0.028)
Year=2009		0.151***		0.148***		0.144***
		(0.033)		(0.034)		(0.034)
Year=2010		0.131***		0.127***		0.123***
		(0.035)		(0.035)		(0.035)
Year=2011		0.124**		0.120**		0.121**
		(0.056)		(0.056)		(0.057)
Year=2012		0.156***		0.147***		0.153***
		(0.033)		(0.033)		(0.033)
Year=2013		0.184***		0.173***		0.180***
		(0.037)		(0.038)		(0.037)
Year=2014		0.201***		0.189***		0.204***
		(0.042)		(0.043)		(0.042)
Year=2015		0.229***		0.216***		0.244***
		(0.046)		(0.045)		(0.045)
Year=2016		0.209***		0.194***		0.234***
		(0.051)		(0.050)		(0.049)
Year=2017		0.239***		0.224***		0.270***
		(0.044)		(0.042)		(0.043)
Year=2018		0.264***		0.261***		0.307***
		(0.042)		(0.040)		(0.039)
Year=2019		0.241***		0.239***		0.290***
		(0.051)		(0.047)		(0.047)
Quarter FEs	X	X	X	X	X	X
Category, Retailer & DMA FEs			X	X		
Brand-Category-DMA-Retailer FEs					X	X
Observations	14,403,075	14,403,075	14,403,075	14,403,075	14,403,075	14,403,075
R^2	0.012	0.013	0.352	0.353	0.770	0.771

Notes: Dependent variable is the log of the Lerner index. Standard errors are reported in parentheses. $^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

Table C.3: Product-Level Markups Over Time, Unweighted Regressions

	(1) Log Markup	(2) Log Markup	(3) Log Markup	(4) Log Markup	(5) Log Markup	(6) Log Markup
Trend	0.018***		0.020***		0.023***	
	(0.003)		(0.003)		(0.003)	
Year=2007		0.075***		0.072**		0.080***
		(0.028)		(0.028)		(0.028)
Year=2008		0.093***		0.089***		0.105***
		(0.029)		(0.029)		(0.030)
Year=2009		0.153***		0.148***		0.170***
		(0.035)		(0.035)		(0.036)
Year=2010		0.141***		0.137***		0.159***
		(0.038)		(0.037)		(0.038)
Year=2011		0.117***		0.112**		0.138***
		(0.043)		(0.043)		(0.043)
Year=2012		0.172***		0.167***		0.197***
		(0.037)		(0.037)		(0.037)
Year=2013		0.195***		0.190***		0.218***
		(0.034)		(0.033)		(0.034)
Year=2014		0.223***		0.218***		0.250***
		(0.042)		(0.040)		(0.041)
Year=2015		0.302***		0.304***		0.340***
		(0.052)		(0.050)		(0.053)
Year=2016		0.254***		0.256***		0.292***
		(0.047)		(0.045)		(0.048)
Year=2017		0.274***		0.282***		0.320***
		(0.049)		(0.046)		(0.049)
Year=2018		0.265***		0.281***		0.318***
		(0.039)		(0.038)		(0.040)
Year=2019		0.223***		0.241***		0.277***
		(0.041)		(0.041)		(0.042)
Quarter FEs	X	X	X	X	X	X
Category, Retailer & DMA FEs			X	X		
Brand-Category-DMA-Retailer FEs					X	X
Observations	14,403,075	14,403,075	14,403,075	14,403,075	14,403,075	14,403,075
R^2	0.011	0.014	0.349	0.351	0.753	0.756

Notes: Dependent variable is the log of the Lerner index. Standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.4: Dependent Variable: Log Category Markup

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Price Sensitivity	-0.672^{***}					-0.400^{***}	-0.410^{***}
	(0.027)					(0.037)	(0.037)
Quality (Standardized)		-0.208^{***}				-0.002	-0.001
		(0.011)				(0.008)	(0.008)
Marginal Cost (Standardized)			-0.243^{***}			-0.141^{***}	-0.138^{***}
			(0.010)			(0.010)	(0.010)
Income (Log)				-1.927		-0.346	0.157
				(2.253)		(0.769)	(0.768)
Children at Home				-5.576		-2.049	-2.761
				(6.934)		(2.822)	(2.700)
Parent HHI					0.811^{**}		0.524^{***}
					(0.337)		(0.144)
Brand HHI					-0.366		-0.067
					(0.289)		(0.122)
Retailer HHI					0.226		0.263
					(0.548)		(0.259)
Category FEs	X	X	X	X	X	X	X
Year FEs	X	X	X	X	X	X	X
Observations	1,862	1,862	1,862	1,862	1,862	1,862	1,862
R^2 (Within)	0.720	0.502	0.712	0.001	0.008	0.846	0.850

Notes: Dependent variable is the log of the mean Lerner index within a category-year. Standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.