Rising Markups and the Role of Consumer Preferences

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We analyze the evolution of markups for consumer products in the United States from 2006 to 2019. Using detailed data on prices and quantities for products in more than 100 distinct categories, we obtain a panel of markups, marginal costs, and flexible consumer preferences. Our empirical strategy uses separate random coefficients logit models for each category and year and an assumption that firms set prices to maximize profits. We find that markups increased by about 30% on average over the sample period. We attribute this change to decreases in marginal costs and a decline in consumer price sensitivity.

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I. 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—can 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, empirical evidence that markups are rising in the United States and abroad (e.g., De Loecker, Eeckhout, and Unger 2020; De Loecker and Eeckhout 2021; Ganapati 2021) raises important questions for economic policy.

In this paper, we study the markups that arise in the US economy across a large number of firms and products, and examine how supply and demand conditions have influenced firms' pricing decisions over time. Our approach is to estimate models of differentiated-products demand and Nash–Bertrand pricing for more than 100 consumer product categories—such as cereals, shampoo, and over-the-counter cold medications—using data on prices, quantities, and consumer purchasing patterns. The models allow us to recover markups from estimated demand elasticities and first-order conditions for profit maximization. We use the models to consider potential mechanisms that contribute to trends in markups, and to connect markups to other economic outcomes, such as consumer surplus and deadweight loss.

We contribute two main empirical findings to the literature. First, we estimate that average product-level markups increase by about 30% between 2006 and 2019. Second, we show that the increase in markups can be explained by a combination of declining marginal costs and a reduction in consumer price sensitivity. We also find that, despite rising markups, the standard measure of consumer surplus for the products in our sample increases over time, though the change in consumer surplus varies across the income distribution. These findings provide additional context for how to interpret changes in markups in the economy more broadly.

on data from Nielsen Consumer, LLC, and marketing databases provided through the NielsenIQ datasets at the Kilts Center for Marketing data center at the University of Chicago Booth School of Business. The conclusions drawn from the NielsenIQ data are those of the researchers and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein. Computational support and infrastructure were provided by the Centre for Information and Media Technology (ZIM) at Heinrich Heine University Düsseldorf. Hendrik Döpper gratefully acknowledges funding by the Deutsche Forschungsgemeinschaft (DFG) (project 235577387/GRK1974).

Our models feature the random coefficients logit demand system that is standard in industrial organization (e.g., Berry, Levinsohn, and Pakes 1995) and commonly applied in industrial organization to consumer product markets (e.g., Nevo 2001). The demand system can accommodate flexible patterns of consumer substitution at the product level. Given demand parameters and data on prices and quantities, one can recover marginal costs, and thus also markups, from the first-order conditions that govern price-setting behavior. We do so under the assumption of profit maximization by competing firms. This *demand approach* to recovering markups allows us to use counterfactual simulations to evaluate how particular mechanisms affect equilibrium outcomes and welfare.[1]

We estimate the models using detailed sales information from the Kilts NielsenIQ Retail Scanner Data. We aggregate across universal product codes (UPCs) to construct quantities and unitized prices of products (specific brands) for each retail chain, region, and quarter. Data from Capital IQ and Zephyr allow us to identify the parent company of each product in each year, which is important for the supply side of the model. We also use the Kilts NielsenIQ Consumer Panel Data, which contain household-level purchases and demographic information, to help capture differences in product preferences across households and to control for differential selection into the retail chains in our sample by consumers with different demographics.

Most previous applications that employ the random coefficients logit demand model focus on a single product category, such as ready-to-eat cereal (Nevo 2001; Backus, Conlon, and Sinkinson 2021), beer (Miller and Weinberg 2017), or yogurt (Villas-Boas 2007; Hristakeva 2022). We implement the methodology separately for each of 133 categories and across the 14 years in our data. We obtain a panel of preference parameters, marginal costs, and markups for individual products across retailers, geographic regions, and periods from 1,862 estimated models.

Our empirical strategy has two key components to support flexible estimation at this scale. First, we construct "micromoments" from the Consumer Panel Data to identify the parameters that determine variation in preferences across consumers. Second, we apply the covariance restrictions approach of MacKay and Miller (2025) to resolve price endogeneity. Because the covariance restrictions approach requires the joint estimation of supply and demand, the supply-side assumptions can affect the demand estimates. However, these supply-side assumptions are also necessary to recover markups, so we view it as reasonable to employ them in

[1] Our approach is distinct from the production approach (e.g., Hall 1988; De Loecker and Warzynski 2012) that uses a cost-minimization assumption to estimate markups without modeling demand or market competition.

estimation. Further, joint estimation of supply and demand is often used in the literature because it increases efficiency (e.g., Conlon and Gortmaker 2020).

Our results indicate that the average Lerner index, our measure of markups, increases from approximately .45 to .60 from 2006 to 2019.[2] We find that 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, the full distribution of product-level markups shifts upward over time.

Within-product markup changes reflect changes in price or marginal cost. We observe that real prices increase by 7% from 2006 to 2012 but then decrease, such that real prices are only 2% higher in 2019 than in 2006. Thus, marginal cost reductions contribute to rising markups, especially in the later years of the sample. We find that marginal costs decrease at an average annual rate of 2.1%. On the demand side, product-specific demand elasticities decrease by 30% over the sample period. This is primarily driven by a reduction in consumer price sensitivity, which we define as a model primitive that captures the average consumer's responsiveness to price.[3] This demand-side result points to a broad change that affects consumers across the income distribution.

We conduct three analyses that point to reductions in marginal cost and consumer price sensitivity as the primary mechanisms that generate rising markups for consumer products. First, in descriptive regressions that isolate cross-category variation in markup trends, we find that changes in marginal cost and consumer price sensitivity have substantially greater explanatory power than other factors, such as changes in consumer demographics and market concentration. Second, we use a counterfactual simulation to compute equilibrium markups that reflect only changes to marginal costs and consumer price sensitivity, while holding all other factors constant. This yields markup trends that closely track our baseline estimates. Finally, we develop a novel econometric decomposition that isolates the net contribution to markups of all observable factors, including prices, market shares, product ownership, market concentration, and consumer purchasing patterns. Although these observable factors explain most of the cross-category variation in markups, they do not contribute much to aggregate markup trends.

[2] The Lerner index is calculated as $(p - c)/p$, where p and c are price and marginal cost, respectively (Lerner 1934). It typically falls between 0 and 1.

[3] Consumer price sensitivity can reflect both the strength of brand-specific preferences and the perceived value of lower prices; in the model, less price-sensitive consumers require a greater difference in prices to switch to a less-preferred brand.

We take initial steps to explain declining consumer price sensitivity. In descriptive regressions that exploit cross-category variation in trends, we explore whether changes in price sensitivity reflect changes in retail shopping patterns (e.g., involving warehouse clubs, dollar stores, and online shopping) and differences in firm-level marketing and R&D investments. However, these factors do not explain the changes in consumer price sensitivity that we estimate. Lower price sensitivity might arise instead from an increase in consumers' opportunity cost of time. In support of this possibility, we provide data that indicate that the use of coupons, which require a small effort by consumers to obtain lower prices, has been declining since the early 1990s and fell by 50% over our sample period. In addition, data from the American Time Use Survey indicate that the time that consumers spent shopping on consumer products fell by approximately 20% during our sample period.

With declining costs and changing preference parameters, rising markups could coincide with increases or decreases in consumer welfare. In our application, we find that consumer surplus per capita increased despite rising markups. The changes in consumer surplus vary across the income distribution, with more of the gains accruing to higher-income consumers. Even so, rising markups are consequential for consumer surplus. Using a counterfactual simulation, we find that consumer surplus would have been 18% higher in 2019 if markups were scaled down to 2006 levels. We use a standard measure of consumer surplus (Small and Rosen 1981) that applies only to the products in our sample, limiting our ability to address overall consumer welfare. Nonetheless, these analyses indicate that market power can have important impacts on allocations across the income distribution and on aggregate welfare—subjects of long-standing interest (e.g., Harberger 1954).

Our analysis is subject to limitations. Because of the scale of the empirical exercise, our demand specification is simpler than specifications employed by some studies that focus on a single product category. We conduct a series of comparisons with estimates derived from those studies and various validation checks to show that this limitation is unlikely to drive our estimated markup trends. As one example, for coffee, our estimates of marginal costs move one-for-one with the world commodity price index, and, like Nakamura and Zerom (2010), we find that the commodity price is roughly half of total marginal costs. Overall, our approach yields a reasonable distribution of demand elasticities. Another limitation is that we maintain the assumption of Nash–Bertrand competition throughout. Therefore, we do not identify changes in conduct or how they might affect inferences about markups.[4]

[4] Although the Nash-Bertrand assumption is widely maintained in the literature, other forms of conduct may also be relevant in consumer product markets (e.g., Miller and Weinberg 2017).

Our research contributes to a growing empirical literature on the evolution of market power. A seminal contribution is that of De Loecker, Eeckhout, and Unger (2020), which applies the production approach to recover markups of firms that are publicly traded in the United States. A central finding is that average firm-level markups increase significantly from 1980 to 2016, primarily due to a reallocation of revenue toward higher-markup firms. Our research is complementary, as we use a different approach to estimate product-level markups from data on prices and quantities, rather than firm-level markups using data from financial reports. We also find that markups increase, albeit due to within-product changes rather than reallocation.

The papers in the literature that are closest to our own are Brand (2021) and Atalay et al. (2023). Both examine markup trends for consumer products using the demand approach under the assumption of Nash–Bertrand competition, as we do. Brand (2021) considers the hypothesis that increases in product variety lead to lower price sensitivity. He estimates demand in nine consumer product categories for the years 2006 and 2017 and finds less elastic demand and higher markups in the latter year. Key distinguishing factors in our analysis include the scope—we consider a broader set of product categories in every year—and our use of individual consumer data to link substitution patterns to variation in demographics. In addition, we address price endogeneity. Atalay et al. (2023) use a sample of 72 product categories from the NielsenIQ Retail Scanner Data and find similar trends in markups and consumer price sensitivity. They apply a different modeling framework that features nested logit demand, and they use Hausman instruments to address endogeneity in the price and nesting parameters.[5]

Our research also adds to a literature that applies the demand approach to recover markups in specific industries over long time horizons. Ganapati (2025) finds that the markups of wholesalers increased over 1992–2012 due to greater scale economies and the expansion of distribution networks, and that consumers were benefiting from lower prices and access to higher-quality goods. Grieco, Murry, and Yurukoglu (2024) find that the markups of automobile manufacturers decreased over 1980–2018 because of greater competition, despite dramatic increases in product quality and reductions in marginal costs. Miller et al. (2023) show that technology adoption in the cement industry over 1974–2019 increased markups and reduced marginal costs, with price levels changing only modestly. Consistent with our results,

[5] Berry and Jia (2010) also explore the connection between consumer preferences and markups, in the context of commercial airline markets, and find that an increase in consumer price sensitivity helps explain a (modest) decline in the markups 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 can reflect the strength of brand preferences, it may increase in some sectors even as it decreases in others.

these studies highlight the role of cost savings as a determinant of long-run economic outcomes.[6]

The paper proceeds as follows: In section II, we discuss the demand approach for recovering markups and specify the models of demand and supply that we use. Section III describes the data, the estimator, and our identifying assumptions. Section IV summarizes results and explores trends in markups, prices, marginal costs, and consumer price sensitivity over time. It also contains descriptive regressions of markups on possible determinants and catalogs a series of robustness exercises. Section V investigates mechanisms with counterfactual simulations, the econometric decomposition, and possible explanations for changing price sensitivity. The analysis of consumer surplus and welfare is in section VI. Section VII concludes. Appendix A and appendixes B–H (available online) contain robustness analyses and validation exercises.

II. Modeling Framework

A. *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 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 $\varepsilon \equiv [\partial Q(P)/\partial P][P/Q(P)]$ is the price elasticity of demand. The left-hand side of the equation is the Lerner index, a measure of markups (Lerner 1934; Elzinga and Mills 2011). Knowledge of the demand elasticity identifies the Lerner index and the price-over-cost markup (i.e., P/C'). With price data, one also can recover marginal cost and the additive markup (i.e., $P - C'$).

The approach can be employed with more general demand systems that allow for multiproduct firms (e.g., Berry 1994; Berry, Levinsohn, and Pakes 1995) and with alternative assumptions about firm behavior, although the most typical equilibrium concepts are Nash–Bertrand and Nash–Cournot

[6] Miller (2025) reviews these industry studies in greater detail. Also related is Peltzman (2022), who analyzes accounting data on manufacturing firms over 1982–2012 and finds support for rising markups and productivity.

competition. The central idea is to use first-order conditions to infer the (unobserved) marginal costs that rationalize observed prices. 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.

The main alternative is the so-called *production approach* that was pioneered in Hall (1986, 1988, 1990) and De Loecker and Warzynski (2012), and is applied to the evolution of markups in De Loecker, Eeckhout, and Unger (2020) and De Loecker and Eeckhout (2021). Under an assumption of static 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 them with accounting data on revenues and expenditures. The production approach does not require prices or marginal costs to be observed.

As the demand approach and the production approach differ in their assumptions and data requirements, they may best be viewed as complements (e.g., De Loecker 2011).[7] In applying the demand approach to consumer products, our research builds on the earlier research of De Loecker, Eeckhout, and Unger (2020) and De Loecker and Eeckhout (2021) in that we construct markups at the (much more narrow) level of a product in a specific market. Our estimates are based on observed prices and quantities at this level, instead of firm-level revenue information that aggregates across many products and markets. Implementation comes with its own challenges and limitations. As inferences about markups are linked to the demand elasticities, an identification strategy is needed to obtain consistent estimates of the demand-side parameters in the presence of price endogeneity. Furthermore, the demand-side approach requires the researcher to specify the structure of the demand system and the nature of competition between firms.

B. Demand Model

For each product category and each year, we apply the random coefficients logit model of Berry, Levinsohn, and Pakes (1995). This demand system incorporates product differentiation and consumer heterogeneity, and it has been widely used in the literature to study consumer products. We work with data that are aggregated to the level of a retail chain, quarter, and geographic region. As in Backus, Conlon, and Sinkinson (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 $j = 0, \ldots, J_{crt}$ products available for purchase in

[7] One working paper implements both approaches in the context of the US brewing industry and finds that they deliver similar results (De Loecker and Scott 2022).

chain c, region r, and quarter t, including an outside good ($j = 0$). Affiliated consumers choose 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_{jcrt} is the retail price, the terms ξ_{jr}, ξ_{cr}, and ξ_t are product $\times$ region, chain $\times$ 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 and unobserved demographic variables according to

$$\alpha_i^* = \alpha + \Pi_1 D_i, \tag{3}$$

$$\beta_i^* = \beta + \Pi_2 D_i + \sigma v_i, \tag{4}$$

where D_i contains the observed demographics and $v_i \sim N(0, 1)$ contains an unobserved consumer demographic. We demean the observed demographics so that α and β characterize average preferences. In doing so, we use a global mean to preserve variation across regions and time. We restrict the unobserved demographics to affect only the constant, rather than also prices, because we find that separately identifying both effects is difficult in practice. Allowing β to be absorbed by the product fixed effects, the structural parameters to be estimated are $\theta = (\alpha, \Pi_1, \Pi_2, \sigma)$.

Because we estimate the model separately for each category-year, all of the structural parameters and fixed effects are allowed to vary freely by product category and year. We omit subscripts for the year and category for notational brevity.

Quantity demanded is given by $q_{jcrt}(\boldsymbol{p}_{crt}; \theta) = s_{jcrt}(\boldsymbol{p}_{crt}; \theta) M_{crt}$, where $s_{jcrt}(\cdot)$ is the market share, $\boldsymbol{p}_{crt}$ is a vector of prices, and M_{crt} is the "market size" of the chain-region-period. Nevo (2000b) provides equations for market shares. We assume that market size—a measure of potential demand—is proportional to the population of the region and the number of stores operated by the chain within the region. Appendix B provides details on this calculation.

Our specification accommodates vertical differentiation among the inside goods because higher-quality (more expensive) products may attract relatively price-insensitive consumers. This can be an important modeling feature in the context of markup trends, especially to the extent that prices or consumer incomes change over time. Relatedly, incorporating heterogeneity in price sensitivity allows the model to more reliably capture the curvature of demand (Miravete, Seim, and Thurk 2022, 2023). Our specification also incorporates heterogeneity in the utility that consumers receive from the inside goods, which allows for flexible substitution patterns between the inside and outside goods. However, we do not incorporate product characteristics other than price and the fixed effects. Including more product characteristics would allow for the inclusion of random coefficients on these characteristics and yield more flexible cross-price elasticities. Doing so would be difficult to implement at scale because it would require category-by-category assessments about which characteristics are appropriate to include and whether or not relevant data are available.

C. 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. Thus, the retail markup becomes part of the marginal cost that the manufacturer must pay to sell its products (Gandhi and Nevo 2021). This assumption is maintained elsewhere (e.g., Miller and Weinberg 2017; Backus, Conlon, and Sinkinson 2021) and is supported by evidence from the empirical literature.[8]

The first-order conditions for profit maximization can be expressed in terms of the additive markup:

$$\boldsymbol{p}_{crt} - \boldsymbol{c}_{crt} = -\left(\Omega_{crt} \circ \left[\frac{\partial \boldsymbol{s}_{crt}(\boldsymbol{p}_{crt})}{\partial \boldsymbol{p}_{crt}}\right]'\right)^{-1} \boldsymbol{s}_{crt}(\boldsymbol{p}_{crt}), \tag{5}$$

where the vectors $\boldsymbol{p}_{crt}$, $\boldsymbol{s}_{crt}$, and $\boldsymbol{c}_{crt}$ collect the prices, market shares, and marginal costs of products $j = 1, \dots, J_{crt}$, and Ω_{crt} is an "ownership matrix" in which each jth and kth element equals 1 if products j and k are produced by the same manufacturer, and 0 otherwise.

We assume that marginal costs are constant in output, following the empirical literature on consumer products (Chevalier, Kashyap, and Rossi 2003; Villas-Boas 2007; Hendel and Nevo 2013; Miller and Weinberg 2017; Backus, Conlon, and Sinkinson 2021). We decompose marginal cost according to

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

where η_{jr}, η_{cr}, and η_t are product × region, chain × region, and quarter fixed effects, and $\Delta\eta_{jcrt}$ is a supply-side structural error term. As in our demand

[8] De Loecker and Scott (2022) find evidence for perfect wholesale-retail pass-through indicating competitive retail markets. There is also evidence that retail prices respond to cost shocks (Butters, Sacks, and Seo 2022) but not shocks to retailer demand (Arcidiacono et al. 2020). Finally, evidence suggests that retail markups have been relatively stable over the period 1980–2014, despite large changes in demand (Anderson, Rebelo, and Wong 2023). Our modeling assumptions are also consistent with nonlinear contracts that specify slotting fees or other fixed transfers.

specification, all fixed effects can vary freely by product category and year because we estimate separate models for each category-year combination. Thus, our model allows for changes in brand-specific technologies over time, and, on an annual frequency, these changes may be correlated with changes in demand (e.g., a plant closure). The supply-side structural error term reflects unobserved shocks to costs, including those due to "cost shifters" that have been used elsewhere in the literature as instruments in demand estimation, such as materials costs and distribution costs that affect products and chains differentially.

Given estimates of demand parameters, knowledge of product ownership, and observed values of prices and shares, we can construct the first-order conditions represented by equation (5) and recover unobserved marginal costs (c_{jcrt}). We use these values to obtain product-level markups, which we calculate as $(p_{jcrt} - c_{jcrt})/p_{jcrt}$ (the Lerner index).

III. Data and Empirical Strategy

A. *Data*

Our primary sources of data are the Retail Scanner Data and Consumer Panel Data of Kilts NielsenIQ, which span the years 2006–19. The scanner data contain unit sales and revenue at the level of the UPC, store, and week from a sample of retail chains. The Consumer Panel Data contain the purchases of a sample of panelists by UPC code, retailer, and day, along with demographic information on the panelists. We use aggregation and a number of screens to construct samples that are suitable for the empirical model.

We take as given that consumers choose between the products that are grouped by NielsenIQ into the same product category (or "module"). The categories contain UPCs that are likely substitutes. Our baseline sample comprises 133 product categories that cover 55% of revenues in the Retail Scanner Data. We obtain these categories by first identifying the top 200 categories by revenue. These categories account for 74% of revenues in the Retail Scanner Data. Within these 200 categories, we apply a screen to select those with relatively modest product differentiation—the ones that the model can reasonably be expected to fit. The screen removes categories for which the 99th percentile of unit prices is greater than five times the median unit price. An example of an omitted category is "batteries," which has some products that are reasonably close substitutes, such as various brands of AAA batteries, along with other products that are functionally quite different, such as D batteries.

Within these categories, we define products at the brand level, which consolidates thousands of UPC codes into a more manageable set. Brands are defined by NielsenIQ and are fairly narrow. For example, in ready-to-eat (RTE) cereals, "Cheerios," "Honey Nut Cheerios," and "Multigrain Cheerios" are three distinct brands. Within a brand, we aggregate sales across UPCs by unit of measurement, which characterizes volume (e.g., liters), mass (e.g., ounces), or count (e.g., six-pack), depending on the category.[9] We measure price using the ratio of revenue to equivalent unit sales, following the standard practice to adjust for differences in package size (e.g., Nevo 2001; Miller and Weinberg 2017; Backus, Conlon, and Sinkinson 2021). Within each category, we treat the top 20 brands by revenue as distinct products, and we collapse the remaining brands into a single composite "fringe" product that we assume is priced by an independent firm. The top 20 brands within each category account for approximately 84% of category revenues and typically include a private label product. The average market share of private label products across categories is about 16% and it has no meaningful trend over time.[10]

We use the designated market areas (DMAs) in the NielsenIQ 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). 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 category, retail chain, and region is 10.3.[11]

Table 1 provides summary statistics for a selection of product categories in the estimation sample sorted by number of observations. We observe more products in the RTE cereals category than in any other product category. Among the chains and DMAs in the baseline sample, the RTE cereals category generated more than $22 billion in revenue over 2006–19. The category for which we observe the fewest products is "fresh mushrooms."

We use household demographic data to account for differences in the composition of consumers across markets and changes within markets over time. We generate consumer-specific demographic draws by sampling 5,000 consumers from the Consumer Panel Data for each region and year.[12] We sample with replacement and use the projection weights provided by NielsenIQ. We focus on two demographics that we expect to influence demand for many of the consumer products in the data: household income

[9] In a handful of categories, UPCs differ in terms of whether units are reported in terms of volume, mass, or count. For those, we include only UPCs associated with the type of measurement that accounts for the greatest revenue.

[10] See fig. B1 (figs. B1–H19 are available online) for the distribution of private label market shares across categories and their evolution over time.

[11] For additional details about the data, see app. B.

[12] We do not sample at the chain-region-year level because the decision to purchase from a chain is endogenous in our model. Our approach does not allow for, e.g., within-region geographic patterns that would shift the demographics of potential shoppers for each chain.

TABLE 1
Sample of Product Categories

Rank and Product Category	Observations (1)	Revenue (Million USD) (2)	Retailer-DMA Combinations (3)	Brands per Market (4)	Share Top 20 Brands (5)	Share Private Label (6)
1. Cereal: ready to eat	231,178	22,557	333	19.3	.58	.08
2. Candy: chocolate	229,065	16,162	335	18.9	.54	.03
3. Candy: nonchocolate	225,336	9,420	334	18.6	.61	.14
4. Deodorants: personal	221,618	7,186	333	18.3	.79	.00
5. Soap: specialty	214,153	5,563	355	17.5	.68	.05
6. Tooth cleaners	212,056	7,343	333	17.6	.71	.00
7. Shampoo: liquid/ powder	202,923	7,490	332	16.8	.65	.04
8. Cookies	202,880	17,191	334	16.8	.64	.18
9. Sanitary napkins	201,864	5,128	333	16.7	.79	.18
10. Cold remedies: adult	201,134	9,111	332	16.6	.85	.40
20. Bottled water	160,454	23,333	335	13.2	.90	.38
40. Baby formula	133,082	10,616	323	12.1	.76	.05
60. Nuts: bags	107,314	6,500	334	8.9	.79	.24
80. Fresh muffins	85,228	3,899	332	7.6	.85	.17
100. Tuna: shelf stable	68,711	4,099	332	5.7	.98	.13
120. Cream: refrigerated	52,297	3,402	330	4.6	.70	.30
130. Frozen poultry	33,428	2,145	300	3.9	.86	.27
133. Fresh mushrooms	25,510	2,772	246	3.4	.95	.28
Mean values	108,442	6,766	319	9.8	.84	.16

Note.—This table shows summary statistics for a selection of product categories. The chosen categories are sorted by the number observations in the estimation sample and are indexed by rank. Revenue provides total sales in millions of US dollars (deflated to 2010 Q1) from 2006 to 2019. Statistics are calculated after the data cleaning steps described in the text. Columns 4–6 report raw means across retailer-DMA-year-quarter markets. Shares in this table reflect inside shares (i.e., excluding the outside good).

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 using a global mean, so that variation over time and across markets remains. We 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 use the Consumer Panel Data to construct “micromoments” that identify the demographic parameters. Specifically, we calculate the average values of the observed demographics for consumers that purchase each product in a given region and year, again using the projection weights. In estimation, we search for preference parameters that generate corresponding patterns in the model. Thus, our approach attempts to ensure that, for example, the average income of households that purchased Honey Nut Cheerios in Chicago in 2015 matches the data. When constructing the micromoments, we use only reported purchases from mass merchandisers, grocery stores, and drug stores, and we drop purchases from the largest chains that are not in the Retail Scanner Data. We make these restrictions to match better the distribution of retailers in the Retail Scanner Data, which is disproportionately selected from the aforementioned three channels. Note that we do not restrict our sample of demographic draws based on which retailers the consumers purchase from, so the micromoments allow us to pin down differences in consumer tendencies to purchase from the retailers in our data (captured by β_i^*).

We account for multiproduct ownership using auxiliary data, as ownership information is not provided in the NielsenIQ 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 within each category. 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.[13] As Compustat covers only publicly traded firms, this information is available for about half of the observations in our sample.

We deflate prices and incomes using the Consumer Price Index such that they are in real dollars as of the first quarter of 2010.[14]

B. Estimation and Identification

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

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

[13] The analyses appear in app. sec. G.3.

[14] We deflate using the Consumer Price Index for All Urban Consumers: All Items Less Food and Energy in U.S. City Average. This CPI measure is predominantly constructed from products and services outside the categories in our sample. The inflation data are monthly and seasonally adjusted.

where W is a weighting matrix, $g^{\mathrm{MM}}(\theta)$ collects micromoments that summarize how well the model matches the correlations between demographics and product purchases that we observe in the NielsenIQ panelist dataset, and $g^{\mathrm{CR}}(\theta)$ assesses 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 $\theta_2 = (\Pi_1, \Pi_2, \sigma)$ and then estimate the price parameter, α (see app. C for details on computation and our code, which builds on Brunner et al. 2025). This reflects that micromoments identify θ_2 but not α (Berry, Levinsohn, and Pakes 2004; Berry and Haile 2022), and that the covariance restriction identifies α conditional on θ_2 (MacKay and Miller 2025).

For the micromoments, 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

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

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). In our baseline specification, we use two observed demographic variables and at most 21 products, so there can be up to 42 micromoments.

The covariance restriction is that the demand-side and supply-side structural error terms are uncorrelated in expectation: $\mathbb{E}[\Delta\xi_{jcrt}\Delta\eta_{jcrt}] = 0$. This provides a moment that we use in estimation to identify the price parameter. We construct the empirical analog of the moment as follows:

$$g^{\mathrm{CR}}(\theta) = \frac{1}{T}\sum_{c,r,t}\Delta\boldsymbol{\xi}_{crt}(\theta)'\Delta\boldsymbol{\eta}_{crt}(\theta), \tag{9}$$

where the $\Delta\boldsymbol{\xi}_{crt}(\theta)$ and $\Delta\boldsymbol{\eta}_{crt}(\theta)$ terms are recovered for each candidate θ, and T is the number of chain-region-quarter-product combinations for a given year.

Our identification strategy is well suited for estimation at scale. The primary alternative would be an instrumental variables approach. However, many of the instruments used in the literature require data on nonprice product characteristics to construct markup shifters (e.g., Berry, Levinsohn, and Pakes 1995; Gandhi and Houde 2020) or cost shifters (e.g., Backus, Conlon, and Sinkinson 2021). Furthermore, instruments require a “first stage" relevance condition to be satisfied, and there is no guarantee that the instruments would be relevant for every category. By contrast, the micro-moments and covariance restriction do not require data on nonprice product characteristics, and there is no equivalent relevance condition that must be satisfied.

As we have specified the model, the supply-side structural error term ($\Delta\eta_{jcrt}$) reflects all residual variation in costs, including factors that correspond to observed instruments. For example, variation in $\Delta\eta_{jcrt}$ will capture product-specific shipping costs (Miller and Weinberg 2017) and prices of product-specific ingredients (Backus, Conlon, and Sinkinson 2021), even though these are not observed directly in our approach. When most of the variation in $\Delta\eta_{jcrt}$ is due to such factors, similar economic reasoning can be used to justify the assumption $\mathbb{E}[\Delta\xi_{jcrt}\Delta\eta_{jcrt}] = 0$ as one would use for $\mathbb{E}[\Delta\xi_{jcrt}z_{jcrt}] = 0$, where z_{jcrt} is a vector of cost-shifter instruments.[15]

We absorb potentially confounding sources of variation by incorporating fixed effects at the product × region, chain × region, and quarter levels (all of which are estimated separately by year and category). For example, the fixed effects control for the possibility that higher-quality products are more expensive to produce. Nonetheless, some threats to validity remain. As a leading example, if firms' marginal costs vary with output, then demand shocks will shift marginal costs, and the covariance restriction will be violated. Correlated shifts in quality and marginal cost that occur within a year also could be problematic. Alternatively, if retailers run nonprice promotions when they have excess product inventory, this may boost demand for unobservable reasons, precisely when opportunity costs are low.

We find that our model and identification strategy deliver a reasonable distribution of own-price elasticities, which we report in figure A2. This is an indicator of the potential of our empirical strategy, as demand elasticities are theoretically linked to markups and marginal costs in our model. We also find that our demand estimates are consistent with the literature, for a few categories where comparisons are possible (see app. D).

We consider the robustness of our results to model specification along a few important dimensions. First, we consider the role of the consumer heterogeneity parameters in our model, which are identified by micro-moments constructed from the Consumer Panel Data. In section A1, we estimate an alternative standard logit demand model ($\Pi_1 = 0$, $\Pi_2 = 0$, $\sigma = 0$) for all categories and years. Relative to the logit specification, our baseline estimates obtain more elastic demand estimates and smaller markups.

Next, we consider the omission of product characteristics from the model. First, as noted above, we obtain elasticities and margins that are similar to the literature in other categories. This provides some evidence

[15] See MacKay and Miller (2025) for a more detailed discussion and additional examples.

that product characteristics may not be critical for pinning down markups.[16] A particular example is Backus, Conlon, and Sinkinson (2021), who use similar data and assumptions in their analysis of ready-to-eat cereal but include product characteristics. To address this further, we construct product characteristics for ready-to-eat cereals following the approach of Backus, Conlon, and Sinkinson (2021). We include these characteristics in an alternative set of estimates as a specification check, and we report the results in appendix E. Our estimates for this category are not materially affected by the inclusion of additional characteristics.

Finally, we consider alternative identification strategies for the price parameter. Relative to the covariance restriction approach, using Hausman instruments or assuming that prices are exogenous yields results that are less plausible. With the covariance restriction, demand is always downward sloping, and the median own-price elasticities are larger than 1 in magnitude for 95% of the category-year combinations. Thus, in our baseline model, demand is elastic at most observed prices, consistent with profit maximization by firms with positive marginal costs. By contrast, assuming prices are exogenous or using Hausman instruments produces median own-price elasticities greater than 1 for only 71% and 66% of the category-year combinations, respectively, and demand is upward sloping in several cases (see sec. A2).

IV. The Evolution of Markups in Consumer Products

In this section, we document the evolution of markups over the sample period. We first summarize median category-level markups and the overall distribution of markups. We then disentangle within-product variation from across-product variation, and decompose markup changes into price and marginal cost changes. We also consider how demand for consumer products changes over time, and examine the economic forces that correlate with markup changes.

A. *Aggregate Markup 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 in the 1,862 category-year combinations in our data. We take the median markup within each category-year, and we then calculate the mean across categories in each year. Figure 1 plots this statistic over time. Averaging across categories,

[16] Incorporating product characteristics can allow for richer patterns of horizontal differentiation, which can yield more accurate counterfactual simulations that depend on specific cross-price elasticities, such as merger simulation (e.g., Nevo 2000a) or studies of entry and exit (e.g., Ciliberto, Murry, and Tamer 2021).

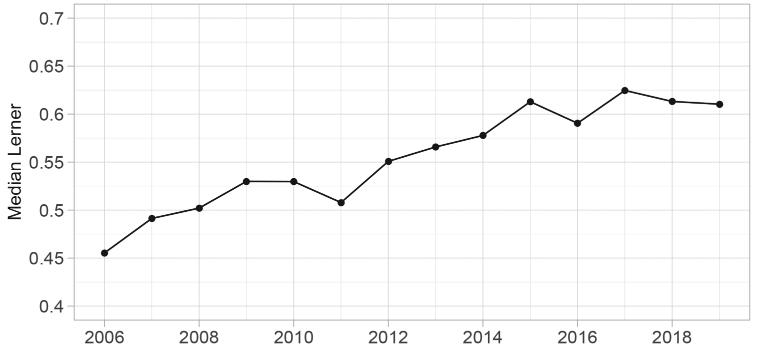

FIG. 1.—Markups over time across product categories. This figure plots the mean of within-category median markups over time. Markups are defined by the Lerner index, $(p - mc)/p$, and are estimated separately by product category and year. When calculating the mean, we winsorize the upper and lower 2.5% of observations across all categories and years.

we find an increase in the median Lerner index from approximately .45 in 2006 to over .60 toward the end of our sample period. This corresponds to an average annual growth rate in markups of 2.3%.

In addition to the median, we find that the full distribution of within-category markups is shifting upward over time. Figure H13 reports the trends for different percentiles of the markup distribution. We regress different percentiles of the within-category markup distribution on year dummies and report the resulting coefficients in panel A. These can be interpreted as changes in markups relative to 2006, the first year of our sample. In panel B, we repeat the exercise with the log of the Lerner index, $\ln[(p - c)/p]$.[17] Panel A shows that the level increase in markups is slightly higher for the upper half of the distribution, while panel B indicates that the relative increase in markups is in fact quite similar across the distribution. These results suggest that the aggregate trends in markups in our sample are not isolated to a subset of products or firms, but rather reflect a broader trend affecting overall categories.

B. *Within-Product Changes in Markups, Prices, and Marginal Costs*

Different economic effects could account for an upward shift in the distribution of markups. Firms could be charging higher markups on existing products, or replacing lower-markup products with newer, higher-markup products. Further, an increasing markup distribution could reflect higher

[17] We find similar changes in the distribution of firm-level markups that we calculate as quantity-weighted averages over brands owned by each parent company.

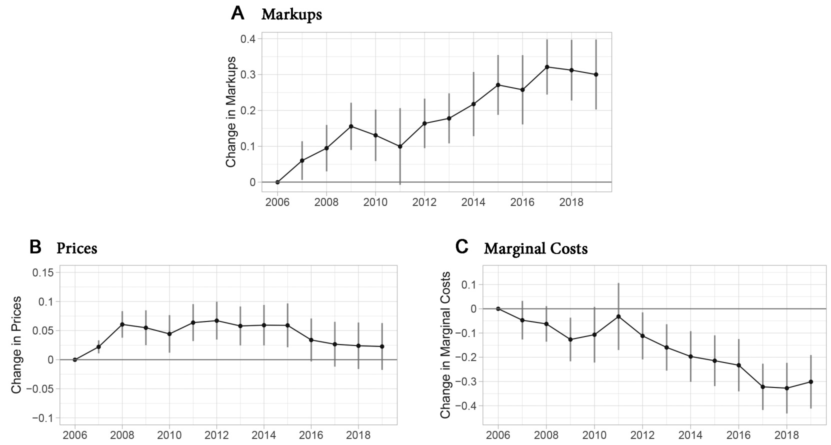

Fig. 2.—Product-level changes in markups, prices, and marginal costs. This figure shows coefficients and 95% confidence intervals from regressions of the log of the Lerner index, real prices, and real marginal costs at the product-chain-DMA-quarter-year level on year dummies while controlling for product-chain-DMA and quarter fixed effects. The year 2006 is the base category.

prices, lower marginal costs, or both, or it could reflect a reallocation of market share from lower-markup products to higher-markup products.

To evaluate these possibilities, we analyze the change in markups, prices, and marginal costs at the product level. For markups, we regress the log of the Lerner index on quarter, year, and product-chain-region fixed effects, using revenues as weights.[18] The unit of observation is a unique product-chain-region-quarter-year combination. The results of this regression are documented in figure 2*A*. The figure displays point estimates and 95% confidence intervals for the year fixed effects. The results indicate a within-product increase in markups of about 30% between 2006 and 2019. The estimated annual growth rate of within-product markups is 2.2% per year. Thus, we find that the shift in the distribution of markups can be explained by changes within products over time.

We find similar results if we use unweighted regressions or if we use a balanced panel of products. Together, these results indicate that the estimated trend is not driven by product entry and exit or a reallocation of market shares across products. We report the full regression results and these alternative specifications in tables H6–H8 (tables D1–H10 are available online). We also consider alternative specifications in which we replace year fixed effects with a linear time trend, drop product-chain-DMA fixed effects, or use category fixed effects. We obtain qualitatively similar results

[18] We weight by revenues instead of quantities to assign higher weights to products with higher initial prices. Revenue-weighted relative changes, which we measure by changes in log markups, are consistent with quantity-weighted absolute changes in a consumption basket.

across these specifications, and estimate average yearly increases in markups between 1.7% and 2.2%. We estimate larger changes when controlling for product-level fixed effects, indicating that within-product changes are greater than the aggregate (revenue weighted) changes in markups. Though these differences are not substantial, they suggest that some of the product-level increase in markups may be offset by the introduction of lower-markup products over time.

Mechanically, within-product markup changes must be driven by price changes, marginal cost changes, or both. To explore, we regress log prices and log marginal costs on product-DMA-retailer, quarter, and year fixed effects. Prices and marginal costs are deflated by core CPI and indexed to Q1 of 2010. The yearly coefficients are documented in figures 2*B* and 2*C*. Figure 2*B* shows that prices increase at the beginning of our sample period, but decline in later years. The average price for products in our sample increases by 7% over 2006–12, but prices are only 2% higher in 2019 than in 2006.

Figure 2*C* of the figure reports the yearly coefficients for log marginal costs. The results indicate a within-product decrease in marginal costs of about 30% between 2006 and 2019. This corresponds to a decline of 2.1% per year on average. Our point estimates suggest that marginal costs increased between 2010 and 2011, though there is some noise and a linear trend cannot be rejected. Thus, higher real prices account for part of the increase in markups during the first half of our sample, while the higher markups we observe at the end of our sample arise primarily from lower real marginal costs. In nominal (i.e., nondeflated) terms, marginal costs are roughly constant over time (see fig. H14).

The extent to which marginal cost reductions lead to higher markups, in a causal sense, depends on equilibrium pass-through relationships and cannot be ascertained solely from the trends shown in figure 2. For example, perhaps prices would have fallen with marginal costs, if not for changes in demand or other factors such as concentration. This motivates a number of empirical exercises later in the paper that investigate causal mechanisms.

However, the marginal cost reductions that we estimate are economically significant on their own. In many markets, costs may decline over time due to innovations in production/distribution technology and operational efficiencies.[19] We observe that, for consumer products, manufacturers sought ways to reduce costs over the sample period. 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. Similarly, Unilever reports realizing €6 billion in cost savings

[19] For one comparison, Grieco, Murry, and Yurukoglu (2024) estimate that marginal costs of automobile manufacturers decrease by 1.4% per year on average over 1980–2018, conditional on vehicle attributes.

over 2017–19.[20] Overall, our finding of declines in marginal costs is consistent with secular increases in productivity across the economy.

C. Changes in Demand

We now examine the changes in demand that are captured by our empirical model. We start with own-price elasticities of demand because these are linked to markups theoretically. We regress the logarithm of the absolute value of own-price elasticity at the product level on quarter, year, and product-chain-region fixed effects, as before. We present the results in figure 3*A*. The coefficients show that price elasticities decline in magnitude, indicating that demand becomes less responsive to prices over time. Price elasticities can be influenced by the level of prices, several underlying aspects of consumer preferences, and supply-side factors such as quality and competition that contribute to the shape of residual demand curves.

We find that the time-series variation in price elasticities is highly correlated with the mean price coefficient, α, which we estimate separately for each category and year. We repeat the regression exercise using price sensitivity, which we define as the log absolute value of the mean price coefficient (i.e., $\log(-\alpha)$) as the dependent variable. Figure 3*B* shows a decline in price sensitivity. The decreases are large through 2012, corresponding with the initial increase in prices that we observe. In the model, changes to α reflect changes that are common to all consumers, as the model controls for factors such as changing consumer demographics and selection by consumers into retailers and products.

While changes in the elasticity may be driven by vertical or horizontal shifts in demand or movement along the demand curve, the changes that are captured by α reflect a rotation in the demand curve. A demand rotation that decreases price sensitivity manifests in the data as a reduced within-market ratio of the variance in quantities over the variance in prices. We observe that this ratio of variances is falling, driven primarily by a decrease in within-market share dispersion (while within-market price dispersion increases slightly). Intuitively, this pattern indicates that demand is becoming less sensitive to price variation. The covariance restriction approach to estimation exploits this empirical pattern to identify changes in price sensitivity. See MacKay and Miller (2025) for additional details.[21]

Our estimates allow us to examine other changes in demand as well. For instance, the fixed effects allow us to characterize changes in perceived product quality over time, relative to that provided by the outside good. We

[20] See the 2019 annual reports of Procter & Gamble Company and Unilever.

[21] This change can also be captured by alternative approaches, even those that are known to deliver biased elasticities. A rotation in demand affects the shape of the price-quantity cloud, which will, e.g., affect even a linear ordinary least squares coefficient. In sec. A3, we examine trends under the alternative identification assumption that prices are exogenous.

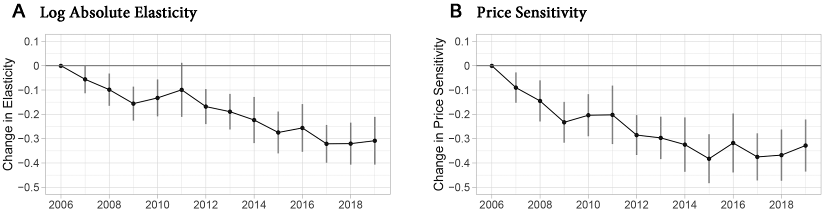

FIG. 3.—Changes in demand. This figure shows coefficients and 95% confidence intervals from regressions of log absolute own-price elasticity and price sensitivity at the product-chain-DMA-quarter-year level on year dummies while controlling for product-chain-DMA and quarter fixed effects. The year 2006 is the base category.

measure product quality as the value that an average consumer obtains from the product (relative to the outside good); to improve comparability across categories we standardize values using the category-level means and standard deviations. Figure H15 shows that perceived product quality declines over the sample period.[22] Improvements in the outside good—which includes shopping through online retailers for example—could contribute to this trend. The same figure plots changes in the coefficients that characterize how observed consumer demographics affect the consumer-specific price coefficient and category-level constant (Π_1, Π_2). Changes in these parameters can also affect substitution to the outside good, relative to substitution among products within a market. In figure H16, we report trends in market elasticities and diversion ratios.

D. *Descriptive Analysis*

Thus far, we have shown that within-product markups increase over the sample period and that, from a mechanical perspective, the change is primarily driven by marginal cost decreases, at least by the end of the sample. We also have shown that consumer price sensitivity and perceived product quality (relative to the outside good) decrease over the sample period. In our model, each of these factors—marginal cost, price sensitivity, and product quality—affect equilibrium markups. Consumer demographics and competitive events, such as mergers and product entry, also matter for equilibrium markups.

In this section, we take initial steps to identify why markups increase, exploiting the unique panel structure of our data. Our approach uses descriptive regressions to identify how changes in different market factors correlate with changes in markups. We use fixed effects to absorb the straightforward

[22] A similar but slightly smaller trend is obtained when we scale quality by the estimated price coefficients.

time-series variation that our figures have highlighted previously.[23] Thus, the question we ask is a relative one: Do products with greater markup increases also have larger marginal cost reductions, bigger decreases in consumer price sensitivity, and so on? One might expect that the factors that explain markup growth may also have important causal effects, although causality cannot be established from descriptive regressions alone. We use the analysis to inform the more formal exploration of mechanisms that we conduct in section V.

Specifically, we regress product-level log markups on marginal costs, consumer preference parameters, consumer demographics, and measures of market concentration. We incorporate fixed effects at the brand-category-DMA-retailer level. We also include year fixed effects, as explained above. Thus, the regression coefficients capture deviations from aggregate trends. Although the regression coefficients are of interest, our main focus is on the ability of the regressors to explain changes in markups, as reflected by their contribution to the R^2.

For the consumer preference parameters, we include price sensitivity and perceived product quality, as defined in section IV.C. We standardize the product qualities and marginal costs, separately for each category, so that they have a variance of 1.[24] For consumer demographics, we use log income and the presence of young children at home. Finally, for market concentration, we examine three constructions of the Herfindahl–Hirschman index (HHI). Parent HHI is calculated for the upstream parent companies of the products (i.e., for the brand manufacturers). Brand HHI is calculated under the counterfactual of single-product firms, and serves to isolate changes in market concentration that are unrelated to product ownership. Finally, retailer HHI is calculated for the retailers, separately for each category and region. We measure the HHIs on a zero-to-one scale.[25]

Table 2 summarizes the results. Column 1 indicates that marginal cost reductions alone can explain 72% of the within-product variation in markups (within $R^2 = 0.715$). The coefficient implies that a 1 standard deviation reduction in marginal costs is associated with a 59% increase in markups. Similarly, column 2 indicates that declines in price sensitivity alone can explain 48% of the within-product variation in markups (within $R^2 = 0.476$).

[23] These figures indicate that, in the time series, rising markups correlate with lower marginal costs, lower consumer price sensitivity, and lower product quality. We do not observe similar correlations between markups, income, and market concentration. In our sample period, real income first decreases, then increases. Similarly, the trends in the concentration measures shown in fig. H17 do not cleanly track the markup trends.

[24] Standardization improves comparability across categories and also eases interpretation of the coefficients. We choose this approach to standardization, rather than logs, to include observations with negative values.

[25] We use the Consumer Panel Data to construct HHI measures. Our results are qualitatively similar if we instead use the Retail Scanner Data.

TABLE 2
FACTORS PREDICTING CROSS-CATEGORY VARIATION IN MARKUP TRENDS

	(1)	(2)	(3)	(4)	(5)	(6)
Marginal cost (standardized)	−.585***					−.461***
	(.020)					(.021)
Price sensitivity		−.728***				−.397***
		(.025)				(.022)
Quality (standardized)			−.137***			.002
			(.021)			(.006)
Income (log)				.101***		.061***
				(.029)		(.013)
Children at home				−.114*		−.017
				(.065)		(.049)
Parent HHI					.323	.221***
					(.206)	(.060)
Brand HHI					−.004	−.102**
					(.186)	(.051)
Retailer HHI					.192***	.069**
					(.068)	(.027)
Brand-category-DMA-retailer fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time period fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,406,731	14,406,731	14,406,731	14,406,731	14,406,674	14,406,674
R^2 (within)	.715	.476	.045	.000	.003	.825

NOTE.—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.
* $p < .10$.
** $p < .05$.
*** $p < .01$.

The coefficient indicates that a 10% decrease in price sensitivity is associated with a 7.3% increase in markups.[26]

Columns 3, 4, and 5 examine perceived quality, consumer demographics, and concentration. Column 4, for example, indicates that markups increase more in regions with more income growth. Although some of the coefficients are statistically significant, these measures explain little of the variation in log markups. The within R^2 values are all less than 0.05.

In column 6, we include all of the regressors. The coefficients on price sensitivity and marginal costs decline modestly, but remain large in magnitude and statistically significant. The coefficient on quality becomes

[26] 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 similar coefficients and a higher within R^2 for price sensitivity. We report these results in table H9.

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. The coefficients on the demographic variables also shrink, though income remains statistically significant.

Turning to concentration, we find that parent HHI and retailer HHI are positively correlated with changes in markups. Yet, these coefficients remain modest. The parent-HHI coefficient of .221 in column 6 indicates that a change in parent company HHI of .02 (i.e., a 200-point change on a 0 to 10,000 scale) is associated with a 0.4% increase in markups. The relationship between markups and changes in concentration at the brand level (which ignores multiproduct ownership) is weaker.

The within R^2 for the multivariate regression is 0.83. Thus, the regressors explain the bulk of within-product markup deviations from the aggregate trends. Among these regressors, the two that contribute the most are marginal costs and price sensitivity; a specification with these two together yields a within R^2 of 0.82. This helps focus our remaining efforts to understand underlying mechanisms, to which we turn in section V.

E. Sensitivity Analyses and Robustness Checks

In this section, we describe several additional robustness checks and alternative specifications to examine the sensitivity of our main results. In each of the analyses, the estimated trends in markups and price sensitivity track our baseline estimates. We provide additional details and present the results in appendix F.

1. Markup measure: Our baseline measure of markups is the Lerner index, $(p - c)/p$. We find very similar results if we instead use price-over-cost markups, p/c, as used by, for example, De Loecker, Eeckhout, and Unger (2020). We report the alternative markup trend in appendix section F.1.
2. Product and retailer composition: To show that our trends are not due to changes in the composition of products and retailers within the sample, we reestimate the model using a balanced panel of brand-chain-DMA combinations. The results are presented in appendix section F.2.
3. Sample of categories: To obtain our baseline estimates, we use a sample of 133 categories that feature modest degrees of price dispersion. We present our estimated markup and price sensitivity trends using a broader sample of the top 200 categories by revenue. The results are in appendix section F.3.
4. Sample of retailers: Our baseline sample is constructed from the Retail Scanner Data, which come from a sample of retail chains. One

possible concern is that consumers select into the chains in our sample and that the selection has changed over time. To address this concern, we construct price and quantity data from the Consumer Panel Data for large retailers that are not included in the Retail Scanner Data, and we estimate the model including these additional retailers. We report the results in appendix section F.4.

5. Sample of geographic markets: Our baseline sample includes the 22 DMAs with at least 500 households in the Consumer Panel Data for each year over 2006–19. We reestimate the model using an expanded sample of 30 DMAs and a restricted sample of the 15 largest DMAs. The set of 30 DMAs includes all DMAs with at least 500 households in the Consumer Panel Data for 2007–19. We present the results in appendix section F.5.
6. Number of brands: Our baseline analysis includes the top 20 brands in each category, and it aggregates the rest to a synthetic “fringe” brand. One question is whether our results depend on the number of brands aggregated into the fringe. As a robustness check, we estimate our model instead using the top 15 brands, and we present the results in appendix section F.6.
7. Time aggregation: Our baseline analysis aggregates the data to the quarterly level. Time aggregation involves a trade-off between the number of observations that are used to identify demand parameters and the sensitivity to short-run fluctuations induced, for instance, by temporary sales. To check the robustness of our results to the level of time aggregation, we include an alternative specification that aggregates to the semiannual level, instead of the quarterly level. We present these results in appendix section F.7.
8. Market definition: We assume that each consumer shops within a retailer-DMA-year-quarter category. Thus, our model does not allow consumers to shop across categories or across retailers within a DMA. Accounting for cross-category substitution by consumers goes beyond the scope of our analysis. As an indicator for the potential impact of cross-retailer substitution on our estimates, we consider an alternative specification in which the market is defined at the level of a DMA-year-quarter category. We estimate this specification by first aggregating the data across retailers within a DMA. We report the resulting estimates in appendix section F.8.
9. Market size: A larger market size implies higher diversion to the outside good and lower diversion among the inside goods. Some demand systems, such as logit, place restrictions on diversion such that the estimates of consumer substitution are sensitive to the assumption on market size. Our random coefficients demand model can flexibly capture substitution between the inside goods and the outside good, so the market size assumption may be less consequential.

Still, we reestimate the model using different assumptions on market size. We present the results of these robustness analyses in appendix section F.9.

V. Mechanisms

Section IV presented our findings of rising markups and provided descriptive analyses that indicate a high degree of correlation between rising markups, marginal cost reductions, and decreasing consumer price sensitivity. Here, we use counterfactual simulations and a novel econometric decomposition to better understand whether these relationships are causal. We also provide additional descriptive evidence about the declines in price sensitivity.

A. Counterfactual Simulations

We use counterfactual simulations to assess the causal effects of aggregate trends in marginal costs and price sensitivity on markups. We start with the estimated model and data from 2006. We then compute equilibrium prices over 2007–19 under simulated changes in marginal costs and price sensitivity, holding fixed product assortments, consumer demographics, and other demand parameters. First, we scale marginal costs uniformly based on the estimated trend from figure 2, holding price sensitivity fixed at 2006 levels. Second, we scale price sensitivity uniformly based on the estimated trend from figure 3, holding marginal costs fixed at 2006 levels. Third, we scale both marginal costs and price sensitivity. We obtain hypothetical time series that inform the extent to which aggregate trends contribute to rising markups.

For reporting purposes, we regress the log of the Lerner index that we obtain under each of these counterfactual scenarios on quarter, year, and product-chain-region fixed effects, weighting by revenue. This follows the approach we use in sections IV.B and IV.C. The year fixed effects then summarize within-product markup changes over time.

Figure 4 depicts the results. The dash-dotted line plots changes in markups under the assumption that marginal costs track the aggregate trend but that demand and other factors are fixed. We find that marginal cost reductions alone yield an increase in markups of about 13% over the sample period. The dashed line plots changes in markups under the assumption that price sensitivity tracks the aggregate trend but that other factors are fixed. Declines in price sensitivity alone yield in an increase in markups by about 15%. The solid black line plots markup changes when both marginal costs and price sensitivity track aggregate trends, while everything is held fixed. In that scenario, markups increase by about 29% (roughly

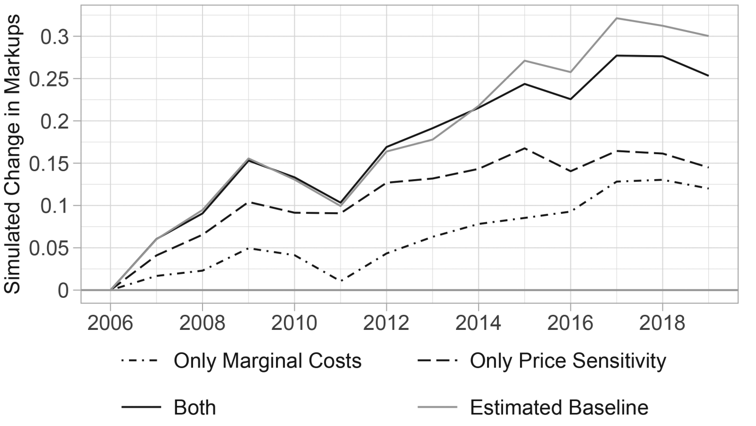

Fig. 4.—Simulated markup changes. This figure plots counterfactual log changes in markups from simulations that scale marginal costs (dash-dotted line), price sensitivities (dashed line), or both (solid line) according to the average realized changes that are reported in figures 2 and 3. Markups are defined by the Lerner index, $(p - mc)/p$, and changes are reported relative to 2006. Product assortments, consumer demographics, and other demand parameters are held fixed at 2006 values in each simulated year. The solid gray line plots the estimated change in log markups in the realized data for comparison.

0.25 log points), and the overall trend is similar to the estimated changes in markups reported in figure 2, which we plot here with the solid gray line.

These counterfactual simulations indicate that aggregate changes in marginal costs and price sensitivity can account for the vast majority of the time-series variation in markups. Marginal cost reductions lead to higher markups because, in our estimated model, there is incomplete pass-through of costs to equilibrium prices. A reduction in price sensitivity leads to firms choosing higher prices and markups, all else equal. These factors have different relative impacts over time. For the first half of our sample, increases in markups can be mainly attributed to changes in price sensitivity, while falling marginal costs are the primary driver of rising markups in the second half. Together, the two trends explain approximately 85% of the aggregate increase in markups by 2019.

The black line in figure 4 nearly overlaps the estimated markup trend from 2006 through 2014. From 2014 to 2019, both the counterfactual and the estimated markups continue to increase, but the lines diverge slightly. Several factors could explain these differences, including factors we hold fixed (e.g., product assortment, demographics), as well as the fact that changes in marginal costs and price sensitivity were not uniform across products. A counterfactual that instead imposes category-level mean changes in marginal costs and price sensitivity yields larger changes in markups that can fully explain the estimated change by 2019.

B. Econometric Decomposition

We now develop a novel econometric decomposition that provides an alternative approach to assessing the impact of price sensitivity. The thought experiment involves holding fixed the data, and considering the implications of trends in the data for trends in markups, when interpreted through the lens of the model. Thus, it is conceptually distinct from the counterfactual simulations of section V.A, which take as primitives the demand and cost parameters.

Our starting point is the result of MacKay and Miller (2025) that product-level additive markups can be expressed in terms of the mean price parameter α and a known function of data, $\lambda(\cdot)$, for a broad class of oligopoly models. With random coefficients logit demand and Bertrand pricing, this takes the form

$$p_{jcrt} - c_{jcrt} = -\frac{1}{\alpha}\lambda_{jcrt}(\boldsymbol{s}_{crt}, \boldsymbol{p}_{crt}, \boldsymbol{x}_{crt}, \boldsymbol{D}_{rt}, \boldsymbol{\nu}_{rt}, \boldsymbol{\Omega}_{rt}; \Pi_1, \Pi_2, \sigma). \tag{10}$$

The arguments in $\lambda(\cdot)$ include vectors of market shares and prices ($\boldsymbol{s}_{crt}$ and $\boldsymbol{p}_{crt}$). They also include a matrix, $\boldsymbol{x}_{crt}$, of nonprice data that is interacted with the parameters Π_1, Π_2, and σ; in our implementation, $\boldsymbol{x}_{crt}$ is a vector of ones. Finally, $\boldsymbol{D}_{rt}$ and $\boldsymbol{\nu}_{rt}$ contain consumer demographics, and $\boldsymbol{\Omega}_{rt}$ summarizes product ownership. Though $\lambda(\cdot)$ depends on the parameters Π_1, Π_2, and σ, we identify these parameters by matching micromoments and therefore treat them as data for this exercise. Importantly, α has no effect on $\lambda(\cdot)$ conditional on the data.

Taking the quantity-weighted average within each category and year and dividing by average price, we obtain an expression for the aggregate Lerner index,

$$\bar{L} = \frac{\bar{p} - \bar{c}}{\bar{p}} = -\frac{1}{\alpha}\frac{\bar{\lambda}}{\bar{p}}. \tag{11}$$

In logs, we obtain

$$\ln \bar{L} = \underbrace{-\ln(-\alpha)}_{-1\times\text{Price Sensitivity}} + \underbrace{\ln\left(\frac{\bar{\lambda}}{\bar{p}}\right)}_{\text{Observable Factors}}. \tag{12}$$

This decomposes (log) category markups into price sensitivity (i.e., $\ln(-\alpha)$) and a term that captures the net effect of observable factors: prices and market shares, product characteristics, consumer demographics, consumer purchasing patterns, and the ownership of products (e.g., market concentration). By contrast, α is not observed and requires an additional identifying assumption. Thus, the econometric decomposition allows us to assess the role of α in determining markups, holding fixed the model specification and the observable factors in the data.

Figure 5 plots changes in the aggregate log Lerner index ($\ln \bar{L}$) and the contribution of observable factors ($\ln(\bar{\lambda}/\bar{p})$) over the sample period, relative to 2006. Consistent with our earlier findings, the average log Lerner index increases by 0.25 from 2006 to 2019. However, the structural component decreases from 2006 to 2011 and remains below 2006 levels thereafter. In 2019, it is 5% lower than in 2006. Thus, without a change in price sensitivity, the trends in the data are consistent with a modest decline in markups. If we were to estimate a restricted model in which α were held fixed over time, then we would estimate that the log Lerner index exactly tracks the contribution of the observable factors.

Thus, to understand rising markups among the consumer products that we examine, it is necessary to have an understanding of consumer price sensitivity and how it has changed over time. An econometrician with data on product ownership, market shares, prices, and consumer purchasing patterns—which are sufficient to recover $\lambda(\cdot)$ within a specific modeling context—could make incorrect inferences about markup trends unless the model also allows for changes in price sensitivity. This points to a strength of our modeling approach: As we estimate demand separately for each category and each year, our estimates of price sensitivity can adjust flexibility over time with the shifts in the empirical variation in the data.

We also explore the cross-category variation in the components of equation (12). Within individual years, we find that variation in price sensitivity explains a modest fraction of the cross-sectional variation in markups: 16% in 2006 and 10% in 2019. Thus, it must be that other features, such as consumer purchasing patterns and multiproduct ownership, explain

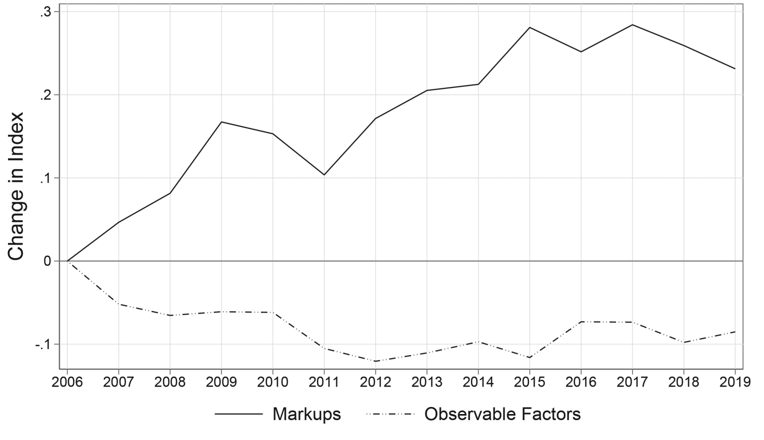

FIG. 5.—Econometric decomposition of markup trends. This figure shows the changes to the aggregate log Lerner index (black line) and the observable factors (dash-dotted line) specified by equation (12). The difference between the lines is due to changes in price sensitivity.

most of the variation in markups across categories. As these features are included in the observable factors component of the econometric decomposition, observable factors are informative of cross-sectional variation in markups even without identification of α.

We also consider a panel regression with observations at the category × year level in which the dependent variable is the year-over-year change in the (log) aggregate Lerner Index and the independent variable is the year-over-year change in price sensitivity. We find that changes in price sensitivity within categories over time explain 59% of the within-category variation in markups over time. Though changes in price sensitivity explain the majority of the changes in markups at the category level, a meaningful portion of the category-level variation over time is explained by observable factors. We report these results via regression in table H10.

This finding, combined with the cross-sectional results, points to the flexibility of our model to incorporate observable factors that are important for determining markups. Further, this highlights that our demand specification is sufficiently rich to attribute much of the variation in markups across categories to observable factors that are uncorrelated with mean price sensitivity. This need not be the case with less flexible demand systems. For example, with constant elasticity demand, the Lerner index only varies because of differences in price sensitivity (i.e., $\lambda_t = p_t$ and $\ln(\lambda_t/p_t) = 0$).

C. *Explanations for the Decline in Price Sensitivity*

Why does consumer price sensitivity decline? We consider three sets of possible explanations. First, we consider whether our results might reflect an increasing selection by price-sensitive consumers away from the retailers in our sample. Second, we consider whether the change may reflect investments by firms to reduce price sensitivity directly, for example, through marketing expenditures. Third, we consider whether there is corroborating evidence for broad secular changes in price sensitivity. We add the caveat that our analyses below are suggestive and may be better addressed in future research.

To address selection, we analyze how aggregate consumer spending patterns change over time, and we consider how our estimates change with an extended sample of retailers. In appendix G, we document that revenue shares for the main retail channels in which our products are purchased—mass merchandisers, grocery stores, drug stores, warehouse clubs, and dollar stores—are stable over our sample period.[27] We validate this within the NielsenIQ data and using auxiliary revenue data from large retailers.

[27] Consistent with Caoui, Hollenbeck, and Osborne (2023), we find that dollar store sales increase over our sample, but they remain a small share of revenues across retail channels.

These data indicate that there are no broad shifts in consumer spending among these channels. In appendix section F.4, we address selection across retailers within these channels by providing estimates from an extended sample that incorporates additional large retailers that are observed in the Consumer Panel Data, but not the Retail Scanner Data. Our estimated markup and price sensitivity trends are very similar to our baseline estimates. These analyses mitigate concerns that shifts across channels by price-sensitive consumers might be driving our results.

The second set of possibilities is that firms make investment decisions that lower consumer price sensitivity. Such decisions might be reflected in marketing expenditures, R&D expenditures, or the variety of products that they offer for a particular brand. In appendix section G.3, we also show that changes in these variables do not explain changes in price sensitivity. Therefore, we do not find support for the hypotheses that declining price sensitivity is due to firm-level investment decisions.

Finally, we consider whether changes in price sensitivity may reflect exogenous shifts in preferences that are not the result of changes to supply. To explore this possibility, we examine other information about consumer shopping patterns. In particular, we look at the use of coupons and estimates of time spent shopping for consumer products. Coupon redemptions are a plausible proxy for price sensitivity because they typically involve a small amount of effort in order to obtain a discount on price. To evaluate coupon use, 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 freestanding inserts and electronic coupons.[28]

Figure 6 plots the aggregate coupon 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

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

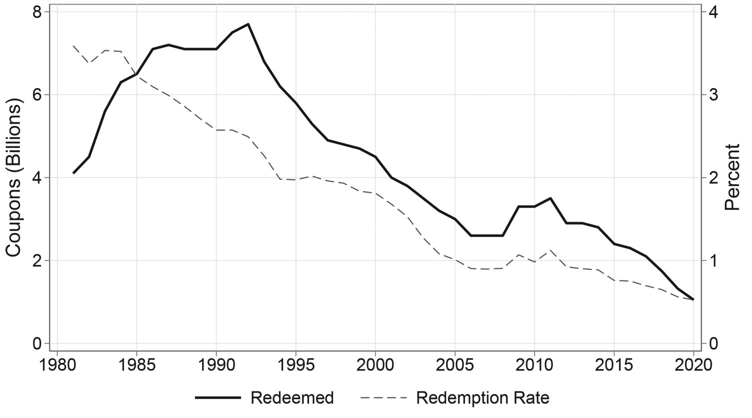

Fig. 6.—Coupon use over time. This figure shows the annual number of coupons redeemed (left axis) and the redemption rate out of all issued coupons (right axis). From 2006 to 2019, coupon redemptions fell from 2.6 billion to 1.3 billion, and the redemption rate fell from 0.90% to 0.56%. Annual estimates reflect total coupon usage for consumer products in the United States across all channels, including freestanding inserts and electronic coupons.

high while redemption rates fell. In 2015, 316 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.

Concurrently, adults in the United States spent less time shopping for consumer products. Data from the American Time Use Survey indicate that both the frequency and duration of shopping trips declined over our sample period. For adults between the ages of 25 and 54, time spent on consumer goods purchases fell by 21%, from 3.01 to 2.38 hours per week.[29] We also find that, in the Consumer Panel Data, households visit approximately 10% fewer unique retailers each week on average in 2019 compared to 2006. This seems to reflect a long-run trend. Aguiar and Hurst (2007b) and Aguiar, Hurst, and Karabarbounis (2013) provide evidence for reduced time spent shopping between the 1960s and 2003 and between 2003 and 2010, respectively.

Overall, the declining use of coupons and the reduced time spent purchasing consumer goods suggest a fundamental shift in consumer shopping behavior that is consistent with lower price sensitivity arising from exogenous factors. Both trends indicate that consumers are less willing to exert effort to obtain lower prices. For instance, Aguiar and Hurst (2007a) provide

[29] The American Time Use Survey reports both the frequency of adults participating in an activity in a given day, which declined by 5%, and the daily time spent conditional on participation, which declined by 16%.

evidence that shopping intensity is negatively correlated with consumer prices. Notably, the decline in coupon use 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. A potential explanation for this trend is an increase in the opportunity costs of time spent shopping, possibly due to changes in preferences for leisure, or changes to labor supply and the within-household distribution of wages. Consistent with the latter, Griffith, Jin, and Lechene (2022) provide evidence that the opportunity cost of time for households in the United Kingdom has increased since the 1980s, and that this change is correlated with an increase in labor force participation and earnings among secondary earners.[30]

VI. Markups, Welfare, and Consumer Surplus

In this section, we analyze how consumer surplus, producer surplus, and total welfare for consumer products have changed over time. We also examine various counterfactual scenarios in order to estimate the deadweight loss from (changes in) market power and to explore the consequences of rising markups for consumers and firms.

We follow Small and Rosen (1981) and calculate consumer surplus in dollar terms.[31] This yields the additional consumer surplus provided by the products in our sample, relative to a counterfactual in which only the outside option is available to consumers. Thus, it can be interpreted as the equivalent variation that would compensate consumers for the loss of the product-retailer combinations in our data.[32] Our measure of producer surplus reflects variable profits and is measured as price less marginal costs multiplied with quantities: $\mathrm{PS} = \Sigma_{j>0}(p_j - c_j)q_j$. Our measure of producer surplus does not reflect fixed costs; thus this analysis does not inform whether brand manufacturers earn economic profit. We measure welfare (W) as the sum of producer and consumer surplus. The deadweight loss that exists in an observed equilibrium can be calculated by comparing the welfare that obtains with the equilibrium to the welfare that obtains under a counterfactual with prices set equal to marginal costs.

[30] An alternative potential explanation, following results in the marketing literature, is that consumers are responding to broad shifts in the pricing behavior of firms. For example, Mela, Gupta, and Lehmann (1997) argue that price-oriented promotions increase consumer price sensitivity in the long run. Therefore, a decline in price sensitivity could potentially be a response to a large-scale decline in price-oriented promotional activity.

[31] With the observed set of products, consumer surplus is given by $\mathrm{CS} = -(1/N)\Sigma_i(1/\alpha_i)\ln(\Sigma_j \exp(w_{ij}))$, where $w_{ij} = \beta_i^* + \alpha_i^* p_{jcrt} + \xi_{jr} + \xi_{cr} + \xi_t + \Delta\xi_{jcrt}$ for the inside products $(j > 0)$, $w_{0j} = 0$ for the outside good $(j = 0)$, and N denotes the number of consumers.

[32] The model assumes complete information, while, in reality, consumers may face search costs or other frictions that are not explicitly captured by this representation. Consumers may engage in search both across and within retailers. If search costs are increasing over time, that may be reflected in our estimates as a reduction in price sensitivity.

These exercises have an important limitation when considering overall welfare. We do not take a stance on utility received outside of the products in our sample, and our consumer surplus calculations are relative to the outside utility value. Thus, overall consumer welfare may decline even if we find increasing consumer surplus for the products in our sample. For example, if housing became more expensive, consumers would perhaps get greater relative utility from consumer products but be worse off. For these reasons, we focus on exploring the relationship between markups and welfare within the products and markets of our sample.

Table 3 shows per capita consumer surplus, producer surplus, and welfare for 2006 and 2019 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 consumer choices using different prices. We consider three counterfactual scenarios. 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 in which prices equal marginal costs (i.e., no markups). The last

TABLE 3
ANNUAL SURPLUS AND WELFARE PER CAPITA

Specification	Consumer Surplus	Producer Surplus	Welfare	Percent Change Consumer Surplus	Percent Change Welfare
	A. 2006 Preferences and Costs				
Baseline	678	264	942		
Prices scaled to 2019 price levels	653	268	920	−3.7	−2.3
Markups scaled to 2019 markup levels	600	293	893	−11.5	−5.2
Prices equal to marginal costs	999	0	999	47.3	6.0
	B. 2019 Preferences and Costs				
Baseline	942	369	1,311		
Prices scaled to 2006 price levels	975	348	1,323	3.5	.9
Markups scaled to 2006 markup levels	1,111	236	1,347	17.9	2.7
Prices equal to marginal costs	1,379	0	1,379	46.4	5.2

NOTE.—This table reports consumer surplus, producer surplus, 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.

two columns in each panel show changes in consumer surplus and welfare relative to the baseline scenario.[33]

Comparing the baseline scenarios, the results indicate that per capita consumer surplus increased by about 39% (i.e., about 2.6% annually) between 2006 and 2019, from $678 to $942. As average prices did not decline and perceived relative quality did not increase, the increase in consumer surplus is likely due to lower price sensitivity, that is, that consumers receive lower disutility from any given price in 2019. Along with higher markups, producer surplus increased over the period, from $264 to $369 per capita. Thus, approximately 70% of the increase in welfare has accrued to consumers.

Markups are costly for consumers. With marginal cost pricing, 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 reduced per capita welfare from $999 to $942 (6%). In 2019, markups reduced welfare by about 5%.

The changes in markups over this period are economically meaningful. Holding fixed the 2006 preferences, marginal costs, and product assortments, increasing markups to 2019 levels would reduce consumer surplus by 11.5%. However, markup trends do not occur in isolation. Changes in markups are often concurrent with and in response to other factors. For example, declining marginal costs mitigate the impact of rising markups on prices and consumer welfare. When scaling up prices—which are the relevant demand variables—to match 2019 levels, the decrease in consumer surplus is much smaller (3.7%). Analogous results obtain if 2019 markups and prices are scaled down to 2006 levels.

Thus, to interpret the impacts of changing markups on welfare, it is necessary to take a stand on what other factors are changing at the same time. Markups are equilibrium objects that are determined by supply and demand. If marginal costs and price sensitivity had not changed, the aggregate trends in markups would have likely looked quite different. This is an important consideration for potential policy responses to markup trends.

In our final analysis, we analyze how the change in consumer surplus varies by income. 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 to category and year fixed effects and document the coefficients across years in figure 7. The results indicate that the increase in per capita consumer surplus between 2006 and 2019 is mainly driven by consumers with relatively high income and takes place during the second half of the sample period. In contrast, the lowest quartile of the income distribution has lower consumer surplus

[33] To mitigate the potential impact of outliers, we winsorize the consumer surplus estimates at the 1st and 99th percentiles from the pooled set of 133 categories across 14 years and six scenarios: baseline, scaling prices or markups to 2006 levels, scaling prices or markups to 2019 levels, and prices equal to marginal costs (across 11,172 observations).

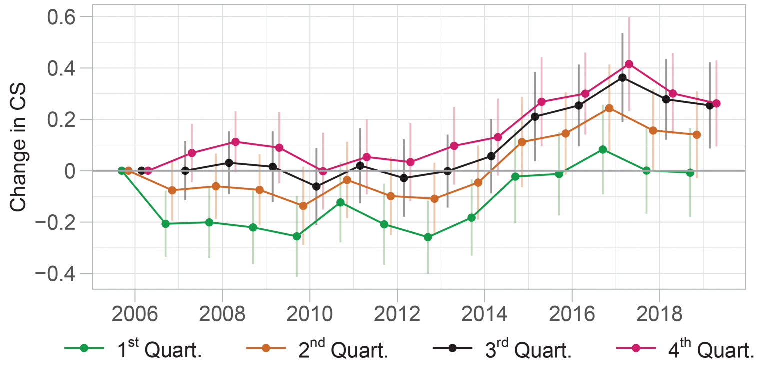

FIG. 7.—Consumer surplus over time by income group. This figure reports coefficients and 95% confidence intervals from regressions of the log consumer surplus per purchase on year dummies while controlling for category fixed effects, separately for different quartiles of the income distribution.

through 2016. The reduction in consumer surplus for the lowest-income households coincides with the increase in real prices in the first half of our sample. After this point, real prices fall and consumer surplus for this quartile increases, recovering to 2006 levels at the end of the sample period. In figure H18, 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 see increases in consumer surplus over time, while lower income households have, on average, lower consumer surplus over our sample period. These findings suggest that changes in market power and consumer preferences over time have important distributional consequences.

VII. Conclusion

This paper analyzes the evolution of markups in consumer products in the United States between 2006 and 2019. We 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 increased by about 30% during our sample period. This reflects within-product changes and is primarily due to reductions in marginal costs, rather than increases in (real) prices. Changes in marginal costs, along with declining consumer price sensitivity, account for the vast majority of the time-series variation in aggregate markup changes between 2006 and 2019.

Our model indicates that consumer surplus has increased despite rising markups, though the increases are concentrated among higher-income consumers. The standard welfare measure in our analysis does not account for changes to outside options or why price sensitivity has declined, and it imposes simplifying assumptions, such as full information. We welcome future work that explores welfare impacts in greater detail while addressing some of these limitations.

Data Availability

Code and information about the data to replicate the tables and figures in this article can be found in Döpper et al. (2024) in the Harvard Dataverse, https://doi.org/10.7910/DVN/STTTNP.

Appendix

A. Alternative Model Specifications

A1. Random Coefficients Logit versus Logit Demand

We examine whether the consumer heterogeneity parameters we include in our baseline specification materially change the estimated elasticities and implied markups. For a comparison, we estimate a standard logit demand model ($\Pi_1 = 0$, $\Pi_2 = 0$, $\sigma = 0$) for all categories and years. Figure A1 plots the density of median elasticities in our baseline model (black line) against those in the logit specification (dashed line).

Relative to the logit specification, our baseline estimates obtain more elastic demand estimates and smaller markups. The mean across the category-year median elasticity estimates is -2.60 in our baseline specification and -1.96 in the logit specification. More than twice as many estimates have a median elasticity greater than -1 (inelastic demand) with the logit specification. Median category-year markups are 0.120 higher in the logit specification (0.686 vs. 0.566). These differences are all statistically significant (p-value $< .001$). We obtain an increasing trend in markups with the logit specification, but the trend is steeper, rising from 0.54 to 0.78.

A2. Alternative Identification Strategies

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 to those obtained under two alternative assumptions that can identify the price parameter and be applied at scale. The first alternative assumption is that prices are exogenous.

The second alternative approach to estimation uses instruments based on the average price of the same product in other regions (Hausman 1996). This approach is valid if cost shocks are correlated across regions due to shared manufacturing or distribution facilities, for example, but demand shocks are uncorrelated across regions. These conditions may not be satisfied in many empirical settings. For example, validity can be threatened if firms employ region-wide or national advertising campaigns. Thus, Hausman instruments are at best subject to scrutiny when employed (Berry and Haile 2021; Gandhi and Nevo 2021).

Figure A2 plots the densities of median own-price elasticities. The solid black line summarizes the results that we obtain with covariance restrictions (our baseline assumption). As shown, the peak of the distribution with covariance restrictions occurs at an elasticity slightly more negative than -2. Relative to our estimates, the distributions of elasticities with exogenous prices (the dashed line) and Hausman instruments (the solid gray line) are shifted to the right, yielding more inelastic demand overall.

Using covariance restrictions, demand is never upward-sloping, and only 5.5% of the category-year combinations have inelastic demand (i.e., a median elasticity greater than -1). By contrast, 28.8% of the category-year estimates exhibit inelastic demand with exogenous prices; with Hausman instruments, it is 34.1%. Furthermore, both of those approaches yield several estimates with upward-sloping demand. These results suggest the covariance restrictions approach generates reasonable demand elasticities, and that it is a distinctly good way to approach estimation in our context.

The differences in the distributions are consistent with price endogeneity arising from firms adjusting prices in response to demand shocks. Typically, firms will charge higher prices for larger demand shocks. This will show up as a bias term and lead to less elastic or even upward-sloping demand under the (misspecified) assumption of exogenous prices. Covariance restrictions systematically correct for this form of price endogeneity, yielding more elastic demand relative to those obtained under the assumption of exogenous prices. By contrast, Hausman instruments yield more elastic demand than exogenous prices in some cases and more inelastic demand in others.

A3. Trends with Exogenous Prices (No Supply Model)

We examine whether the estimated trends in demand, in terms of more inelastic demand and reduced price sensitivity, are robust to the supply model and the covariance restrictions that we invoke to identify the mean price parameter. As described in the text, the other demand-side parameters are identified by micromoments. Thus, here we focus on the mean price parameter, which also has implications for the implied elasticities.

We show that a similar trend is obtained when we estimate demand using the assumption that prices are exogenous, which does not invoke the supply model to pin down the demand parameters. Though elasticity estimates under this approach are often unreasonable in terms of levels (see sec. A2), a change in the estimated parameters would be consistent with a rotation of the demand curve.

Figure A3 shows that we find similar trends in elasticities (fig. A3*A*) and the mean price parameter (fig. A3*B*) under the assumption that prices are exogenous. This finding indicates that the reduced-form relationship between prices and quantities is becoming more "vertical" (on a price-quantity graph) over time, consistent with a rotation in the demand curve. The covariance restriction approach finds a similar trend while correcting for price endogeneity. The fact that the trends are similar suggests that our finding of reduced price sensitivity is not sensitive to the particular supply-side assumptions we invoke in estimation.[34]

[34] Of course, as indicated in the main text, a model of firm behavior is required to calculate markups and evaluate whether they are increasing. Regardless of whether firms actually exert market power, a finding of less elastic demand points to a increase in market power potential. We thank Chad Syverson for offering this interpretation.

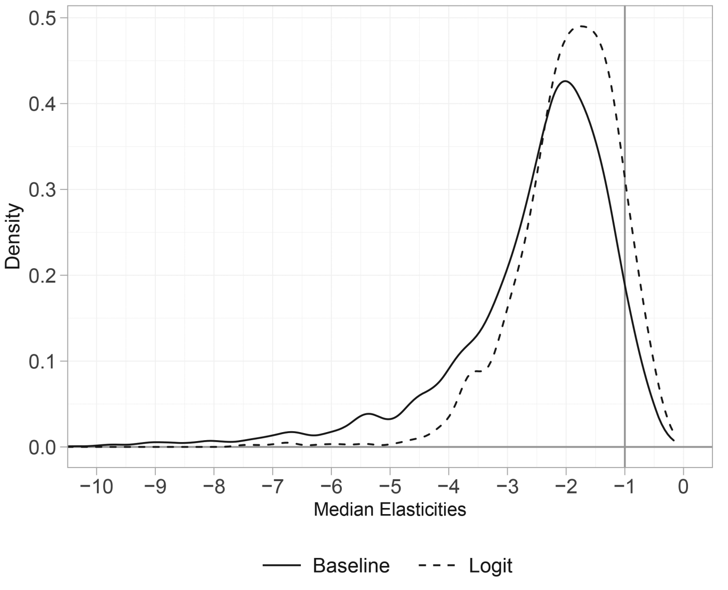

FIG. A1.—Implied elasticities for baseline and logit estimates. This figure plots the density of the median own-price elasticity by category and year. The solid black line shows the density of median elasticities using our baseline specification. The dashed line shows the density of median elasticities from a logit specification without random coefficients. Random coefficients allow for richer consumer heterogeneity.

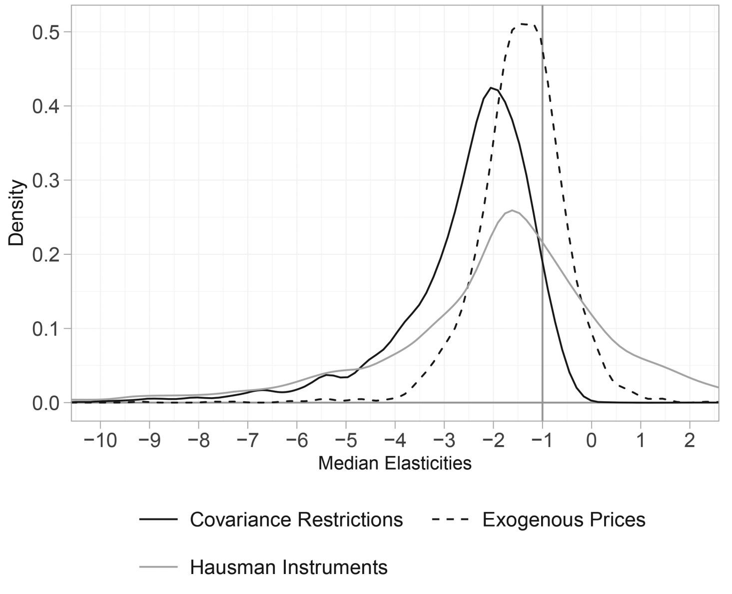

FIG. A2.—Implied elasticities under alternative identification restrictions. This figure plots the density of the median own-price elasticity by category and year under different identification assumptions. The solid black line shows the density of implied elasticities using covariance restrictions. The dashed line shows the density of implied elasticities assuming exogenous prices. The solid gray line shows the density of implied elasticities using Hausman instruments. The vertical line indicates an elasticity of -1.

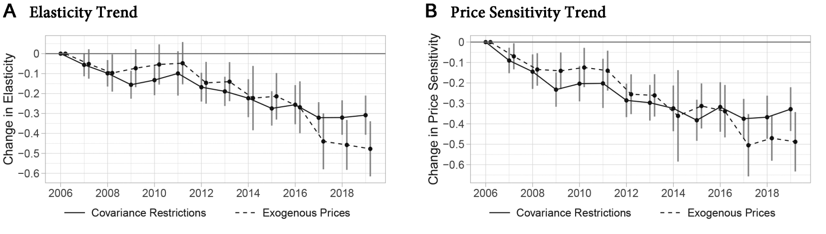

FIG. A3.—Changes in demand over time. This figure shows coefficients and 95% confidence intervals from regressions of the log absolute value of the own-price elasticity (A) and price sensitivity (B) at the product-chain-DMA-quarter-year level on year dummies while controlling for product-chain-DMA and quarter fixed effects. The year 2006 is the base category. The baseline estimates are plotted with a black line and employ covariance restrictions to estimate mean price parameters. The dashed line corresponds to estimates that instead employ an assumption that prices are exogenous.

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