Rising Markups and the Role of Consumer Preferences

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Researcher(s) own analyses is calculated (or derived) based in part 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 researcher(s) 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.
Firms with market power set prices that reflect marginal costs, consumer preferences, and the prices of other goods.

The size of firm *markups*—the wedge between prices and marginal costs—has wide-ranging implications:

- Potential transfer of wealth from consumers to producers
- Leads to allocative inefficiency as consumers shift purchases
- Can reduce production, ergo less demand for inputs (e.g., labor)
- Affects investment and innovation incentives
Research Question

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- Leads to allocative inefficiency as consumers shift purchases
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How and why have markups changed in recent years?
Empirical Setting

We examine a vast number of consumer products sold in grocery stores, drug stores, and mass merchandisers in the U.S.

- Characterize the evolution of markups over 2006-2019
- Consider 133+ distinct product categories (e.g., cereals, yogurt, paper towels, OTC cold medications)
- Exploit panel variation over time and across categories to explore role of mergers, marginal cost changes, shifts in consumer tastes, etc.
- Explore possible mechanisms
- Quantify the short run welfare effects associated with the markup changes—and with market power more generally
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We take the demand approach to recover markups

- Simple case: \( \frac{P - C'}{P} = -\frac{1}{\epsilon} \)
Summary of Results

A rich panel of consumer preferences and marginal costs

- 1,862 sets of category×year BLP-style estimates
- 14.4 million product-retailer-DMA-quarter observations
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Findings:

1. Markups increase by more than 25 percent over 2006–2019

2. These are “within product” changes, and effects are similar for low- and high- markup products

3. Rising markups attributable to marginal cost reductions and less elastic demand over time (which reduces pass-through)

4. Rising markups imply a reduction in consumer surplus by about 12 percent, however... [we’ll come back to this]
Contributions

1. We use models of supply and demand to evaluate changes to markups over time and potential causes, including changes in costs, concentration, and consumer preferences.

2. We identify a secular decline in price sensitivity for consumer products, which is a key driver of increasing markups.

3. We evaluate the implications of changing markups for consumer welfare across the income distribution.
A Growing Literature on Rising Market Power

1. **De Loecker, Eeckhout, & Unger (2020)**. Seminal paper. Infer firm-level markups from data on revenues and costs, under cost minimization.

2. **IO-Style Industry Studies**: Ganapati (2021), Grieco, Murry, & Yurukoglu (2021), Miller, Osborne, Sheu, Sileo (2022). All show technological progress that has benefited consumers.

3. **Preferences and Markups**: Berry and Jia (2010), Brand (2021). Latter looks at nine product categories, 2006 and 2019, asks whether greater product variety leads to less elastic demand.
Plan for the Seminar

1. Models of Demand and Supply
2. Estimation and Identification
3. Data + Validation Checks
4. The Evolution of Markups
5. Mechanisms and Impacts
Rely on the workhorse models of industrial organization:

1. For demand, random coefficients logit (BLP, 1995)
2. For supply, Bertrand competition—prices maximize profits

→ Apply these to every product category

Accept misspecification for some categories

• e.g., due to price coordination (Miller and Weinberg, 2017)
• We aggregate results across many categories to mitigate misspecification bias in any single category
RCL Demand

The indirect utility that consumer $i$ receives from product $j = 1, 2, \ldots$ from retail chain $c$, in region $r$, and in quarter $t$ is

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

- Heterogeneity in consumer-specific coefficients
  - Price ($\alpha_i^*$): depends on income and an indicator for children
  - Intercept ($\beta_i^*$): depends on income, children, and an unobserved $N(0,1)$ “demographic” variable
  - No product characteristics $\rightarrow$ screen out some categories with more differentiation

- Fixed effects for the product\times region, chain\times region, quarter
- We estimate everything separately by category-year
  - Allow for flexible evolution of consumer preferences
Bertrand Equilibrium

We assume that manufacturers set prices to maximize profits, with passive cost-plus pricing on the part of retailers.

The first order conditions for profit maximization can be expressed as

\[
p_{crt} = mc_{crt} + \left( -\Omega_{crt} \circ \left[ \frac{\partial s_{crt}(p_{crt})}{\partial p_{crt}} \right] \right)^{-1} s_{crt}(p_{crt})
\]

- Vectors \( p_{crt}, s_{crt}, \) and \( mc_{crt} \) have prices, market shares, and marginal costs.
- \( \Omega_{crt} \) is an “ownership matrix” that captures multi-product ownership.
- Can recover marginal cost with data on prices and shares, plus demand derivatives obtained from the demand model.
Marginal Cost Specification

We decompose marginal cost according to

$$m_{c_{jcr}} = \eta_{jr} + \eta_{cr} + \eta_t + \Delta \eta_{jcr}$$

- Fixed effects for the product×region, chain×region, quarter
- The structural error term $\Delta \eta_{jcr}$ includes variation that is used as an instrument elsewhere:
  - Changes in the prices of product-specific ingredients (Backus, Conlon, and Sinkinson, 2021)
  - Changes in product-specific distribution costs (e.g., Miller and Weinberg, 2017)
  - Exogenous variation in $\Delta \eta_{jcr}$ can identify the price parameter
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Estimation and Identification

Apply the nested fixed point approach of BLP (1995), with updates to the BLPestimatoR package for R (Brunner et al., 2020)

First step:
- Estimate consumer heterogeneity parameters ($\Pi, \Sigma$)
- Use empirical patterns of purchasing habits: micro-moments (Berry and Haile, 2020)

Second step:
- Estimate mean price parameter ($\alpha$)
- Assume (residual) demand and cost shocks are uncorrelated:

$$\mathbb{E} [\Delta \xi_{jcr}(\theta)\Delta \eta_{jcr}(\theta)] = 0$$
Addressing Price Endogeneity

Firms may increase prices in response to higher demand

Can address with instruments or covariance restrictions

- Difficult to find valid instruments for many product categories
  - BLP (1995) and Gandhi and Houde (2020) instruments require non-price product attributes, and relevance might not be satisfied

- With covariance restrictions, directly incorporate how firms adjust markups to demand (MacKay and Miller, 2022)
  - Plausible with fixed effects (e.g., control for quality)
  - Exploits all the endogenous price and quantity variation, so there is no relevance condition

More on covariance restrictions
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Data

1,862 estimation samples (14 years x 133 product categories)

Nielsen Retail Scanner Dataset

- Quantities and prices for the top 20 brands and the “fringe brand” in each category

Nielsen Consumer Panel Dataset

- Purchasing decision of consumers
- Sample demographic draws
- Construct micro-moments

Capital IQ (brand ownership) & Zephyr (merger data) & CPI (price deflator) & Compustat (accounting data)
### Table 1: Sample of Product Categories

<table>
<thead>
<tr>
<th>Rank</th>
<th>Product Category</th>
<th>Observations</th>
<th>Revenue ($ Millions)</th>
<th>Retailer-DMA Combinations</th>
<th>Brands Per Market</th>
<th>Share Top 20 Brands</th>
<th>Share Private Label</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Cereal - Ready To Eat</td>
<td>231,178</td>
<td>22,557</td>
<td>333</td>
<td>19.3</td>
<td>0.58</td>
<td>0.08</td>
</tr>
<tr>
<td>2</td>
<td>Candy - Chocolate</td>
<td>229,065</td>
<td>16,162</td>
<td>335</td>
<td>18.9</td>
<td>0.54</td>
<td>0.03</td>
</tr>
<tr>
<td>3</td>
<td>Candy - Non-Chocolate</td>
<td>225,336</td>
<td>9,420</td>
<td>334</td>
<td>18.6</td>
<td>0.61</td>
<td>0.14</td>
</tr>
<tr>
<td>4</td>
<td>Deodorants - Personal</td>
<td>221,618</td>
<td>7,186</td>
<td>333</td>
<td>18.3</td>
<td>0.79</td>
<td>0.00</td>
</tr>
<tr>
<td>5</td>
<td>Soap - Specialty</td>
<td>214,153</td>
<td>5,563</td>
<td>355</td>
<td>17.5</td>
<td>0.68</td>
<td>0.05</td>
</tr>
<tr>
<td>6</td>
<td>Tooth Cleaners</td>
<td>212,056</td>
<td>7,343</td>
<td>333</td>
<td>17.6</td>
<td>0.71</td>
<td>0.00</td>
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<tr>
<td>7</td>
<td>Shampoo - Liquid/Powder</td>
<td>202,923</td>
<td>7,490</td>
<td>332</td>
<td>16.8</td>
<td>0.65</td>
<td>0.04</td>
</tr>
<tr>
<td>8</td>
<td>Cookies</td>
<td>202,880</td>
<td>17,191</td>
<td>334</td>
<td>16.8</td>
<td>0.71</td>
<td>0.18</td>
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<tr>
<td>9</td>
<td>Sanitary Napkins</td>
<td>201,864</td>
<td>5,128</td>
<td>333</td>
<td>16.7</td>
<td>0.79</td>
<td>0.18</td>
</tr>
<tr>
<td>10</td>
<td>Cold Remedies - Adult</td>
<td>201,134</td>
<td>9,111</td>
<td>332</td>
<td>16.6</td>
<td>0.85</td>
<td>0.40</td>
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<tr>
<td>20</td>
<td>Bottled Water</td>
<td>160,454</td>
<td>23,333</td>
<td>335</td>
<td>13.2</td>
<td>0.90</td>
<td>0.38</td>
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<tr>
<td>40</td>
<td>Baby Formula</td>
<td>133,082</td>
<td>10,616</td>
<td>323</td>
<td>12.1</td>
<td>0.76</td>
<td>0.05</td>
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<tr>
<td>60</td>
<td>Nuts - Bags</td>
<td>107,314</td>
<td>6,500</td>
<td>334</td>
<td>8.9</td>
<td>0.79</td>
<td>0.24</td>
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<tr>
<td>80</td>
<td>Fresh Muffins</td>
<td>85,228</td>
<td>3,899</td>
<td>332</td>
<td>7.6</td>
<td>0.85</td>
<td>0.17</td>
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<tr>
<td>100</td>
<td>Tuna - Shelf Stable</td>
<td>68,711</td>
<td>4,099</td>
<td>332</td>
<td>5.7</td>
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<td>120</td>
<td>Cream - Refrigerated</td>
<td>52,297</td>
<td>3,402</td>
<td>330</td>
<td>4.6</td>
<td>0.70</td>
<td>0.30</td>
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<tr>
<td>130</td>
<td>Frozen Poultry</td>
<td>33,428</td>
<td>2,145</td>
<td>300</td>
<td>3.9</td>
<td>0.86</td>
<td>0.27</td>
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<tr>
<td>133</td>
<td>Fresh Mushrooms</td>
<td>25,510</td>
<td>2,772</td>
<td>246</td>
<td>3.4</td>
<td>0.95</td>
<td>0.28</td>
</tr>
</tbody>
</table>

Mean Values: 108,442, 6,766, 319, 9.8, 0.84, 0.16
Our marginal cost estimates track commodity prices.

Figure 1: Ground and Whole Bean Coffee
Comparisons to the Literature

Table 2: Average Own-Price Elasticities of Demand

<table>
<thead>
<tr>
<th>Category</th>
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<th>Literature Estimate</th>
<th>Citation</th>
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<tr>
<td>Beer</td>
<td>−4.06</td>
<td>−4.74</td>
<td>Miller and Weinberg (2017)</td>
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<tr>
<td>Ready-to-Eat Cereal</td>
<td>−2.29</td>
<td>−2.42</td>
<td>Backus et al. (2021)</td>
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<td>Yogurt</td>
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<td>−4.05</td>
<td>Hristakeva (2020)</td>
</tr>
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Consider Backus et al. (2021):

- Kilts Nielsen scanner data and consumer panel data
- Similar supply model
- Random coefficients logit demand
  - Same demographics
  - Also include product characteristics
- Use instruments instead of covariance restrictions
  → Nearly identical markups
Estimated Demand Elasticities

The graph illustrates the distribution of estimated demand elasticities for different scenarios:

- **Covariance Restrictions** (solid line)
- **Exogenous Prices** (dashed line)
- **Hausman Instruments** (dotted line)

The x-axis represents the median elasticities, while the y-axis shows the density of the estimated values. The graph highlights the concentration of elasticities around certain points, indicating the variability and central tendency of the estimated demand elasticities under different assumptions.
Plan for the Seminar

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**Figure 2: Evolution of Markups Across Product Categories**

Notes: The figure plots the mean of within-category median markups over time. Markups are defined by the Lerner index, \((p - mc)/p\) and are estimated separately by product category and year. When calculating the mean, we winsorize the upper and lower 2.5 percent of observations across all categories and years.
Figure 3: Changes in the Distribution of Markups

Notes: The figure shows coefficients and 95 percent confidence intervals of regressions of percentiles of the markup distribution at the product category level in logs on year dummies using the year 2006 as the base category.

Absolute changes in markup distribution
**Figure 4: Evolution of Markups at the Product Level**

Notes: Regression of log\(((p - c)/p)\) on region $\times$ retailer $\times$ brand FEs, quarter FEs, and year FEs. Figure shows coefficients and standard errors of year FEs. Changes are relative to the base year 2006. Standard errors are clustered at the product category level.
Figure 5: Decomposition into Real Prices and Marginal Costs

Notes: Regressions of log(p) and log(mc) on region × retailer × brand FEs, quarter FEs, and year FEs. Prices and marginal costs are deflated. Figure shows coefficients and standard errors of year FEs. Changes are relative to the base year 2006. Standard errors are clustered at the product category level.
Core Finding #1

Systematic increase in markups at the product level, due to reductions in marginal costs that are not passed on to prices.
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Why might we find falling costs with (modest) price increases?
Core Finding #1

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Why might we find falling costs with (modest) price increases?

- Imperfect competition generates incomplete pass-through
- Mergers and acquisitions
- Demographic trends
- Perceived product quality
- Consumer preferences, including price sensitivity
**Figure 6: Changes in Own-Price Elasticity**

Notes: Regressions of log absolute elasticity on region × retailer × brand FEs, quarter FEs, and year FEs. Figure shows coefficients and standard errors of year FEs. Changes are relative to the base year 2006. Standard errors are clustered at the product category level.
Figure 7: Changes in Price Sensitivity

Notes: Regressions of price sensitivity on region × retailer × brand FE, quarter FE, and year FE. Figure shows coefficients and standard errors of year FE. Changes are relative to the base year 2006. Standard errors are clustered at the product category level.
### Table 3: Determinants of Markups Changes at the Product Level

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
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</thead>
<tbody>
<tr>
<td>Marginal Cost (Standardized)</td>
<td>$-0.564^{**}$</td>
<td>$-0.450^{**}$</td>
<td>$-0.449^{**}$</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>(0.024)</td>
<td>(0.023)</td>
<td>(0.023)</td>
<td></td>
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<tr>
<td>Price Sensitivity</td>
<td>$-0.721^{***}$</td>
<td></td>
<td></td>
<td>$-0.392^{***}$</td>
<td>$-0.393^{***}$</td>
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<tr>
<td></td>
<td>(0.030)</td>
<td></td>
<td></td>
<td>(0.022)</td>
<td>(0.022)</td>
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<tr>
<td>Quality (Standardized)</td>
<td>$-0.142^{***}$</td>
<td></td>
<td></td>
<td>0.006</td>
<td>0.007</td>
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<tr>
<td></td>
<td>(0.022)</td>
<td></td>
<td></td>
<td>(0.006)</td>
<td>(0.006)</td>
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<td></td>
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<tr>
<td>Income (Log)</td>
<td></td>
<td></td>
<td></td>
<td>0.052^{**}</td>
<td>0.059^{***}</td>
<td>0.058^{***}</td>
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<td></td>
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<td></td>
<td>(0.025)</td>
<td>(0.013)</td>
<td>(0.013)</td>
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<td>Children at Home</td>
<td></td>
<td></td>
<td></td>
<td>$-0.175^{***}$</td>
<td>$-0.076^{***}$</td>
<td>$-0.083^{***}$</td>
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<td></td>
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<td></td>
<td></td>
<td>(0.064)</td>
<td>(0.026)</td>
<td>(0.027)</td>
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<tr>
<td>Parent HHI</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.236</td>
<td>0.236^{***}</td>
<td></td>
</tr>
<tr>
<td></td>
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<td></td>
<td></td>
<td></td>
<td>(0.186)</td>
<td>(0.046)</td>
<td></td>
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<tr>
<td>Brand HHI</td>
<td></td>
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<td></td>
<td></td>
<td>0.091</td>
<td>$-0.097^{**}$</td>
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<td></td>
<td>(0.178)</td>
<td>(0.048)</td>
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<td>Retailer HHI</td>
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<td>0.203^{***}</td>
<td>0.074^{***}</td>
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<td></td>
<td>(0.077)</td>
<td>(0.025)</td>
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<td>Brand-Category-DMA-Retailer FEs</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
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<tr>
<td>Time Period FEs</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
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<tr>
<td>$R^2$ (Within)</td>
<td>0.719</td>
<td>0.468</td>
<td>0.047</td>
<td>0.000</td>
<td>0.003</td>
<td>0.826</td>
<td>0.827</td>
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</tbody>
</table>

Structural decomposition

DMMS

Rising Markups

29
Core Finding #1

Systematic increase in markups at the product level, due to reductions in marginal costs that are not passed on to prices

Why might we find falling costs with (modest) price increases?

• Imperfect competition generates incomplete pass-through
• Mergers and acquisitions
• Demographic trends
• Perceived product quality
• Consumer preferences, including price sensitivity
Figure 8: Simulated Markup Changes

- Only Marginal Costs
- Only Price Sensitivity
- Both
- Estimated Baseline
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Exploring Potential Mechanisms

Falling marginal costs from 2006 to 2019 → higher markups

Why might marginal costs be falling?

- Innovation in production technology and operational efficiencies
- Example: Procter & Gamble implemented a “productivity and cost savings plan” in 2012 that was estimated to reduce annual costs by $3.6 billion in 2019
- Magnitudes may seem plausible—our estimates correspond to 2.1 percent reductions annually (e.g., nominal costs are flat)
Exploring Potential Mechanisms

Declining price sensitivity from 2006 to 2019 → higher markups

What might cause consumers to become less price sensitive?

1. Changing retail patterns (online, warehouse clubs)
2. Firm-level investments in marketing, R&D, or new products
3. Secular/exogenous changes to consumer preferences
Table 4: Share of Revenue by Retail Channel

<table>
<thead>
<tr>
<th></th>
<th>2007</th>
<th>2019</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Focal Channels</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mass Merchandisers</td>
<td>0.214</td>
<td>0.218</td>
</tr>
<tr>
<td>Grocery Stores</td>
<td>0.219</td>
<td>0.217</td>
</tr>
<tr>
<td>Drug Stores</td>
<td>0.088</td>
<td>0.117</td>
</tr>
<tr>
<td><strong>Other Broad-Basket Retail Channels</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Warehouse Club</td>
<td>0.090</td>
<td>0.094</td>
</tr>
<tr>
<td>Dollar Stores</td>
<td>0.015</td>
<td>0.026</td>
</tr>
<tr>
<td><strong>Other Consumer Product Retail Channels</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Convenience Stores, Department Stores, Apparel, etc.</td>
<td>0.374</td>
<td>0.328</td>
</tr>
<tr>
<td><strong>Combined Share of Focal Channels</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Among All Consumer Products</td>
<td>0.522</td>
<td>0.552</td>
</tr>
<tr>
<td>Among Broad-Basket Retailers</td>
<td>0.833</td>
<td>0.822</td>
</tr>
</tbody>
</table>

**Notes:** Data reflects revenues of the largest 100 U.S. retailers. We exclude restaurants, home improvement stores, and auto parts stores. The included retailers represent $1.4 trillion in revenues in 2007 and $2.0 trillion in 2019.
Exploring Potential Mechanisms

Declining price sensitivity from 2006 to 2019 → higher markups

What might cause consumers to become less price sensitive?

1. Changing retail patterns (online, warehouse clubs)
2. Firm-level investments in marketing, R&D, or new products
3. Secular/exogenous changes to consumer preferences
Exploring Potential Mechanisms

Declining price sensitivity from 2006 to 2019 → higher markups

What might cause consumers to become less price sensitive?

1. Changing retail patterns (online, warehouse clubs)
2. Firm-level investments in marketing, R&D, or new products
3. Secular/exogenous changes to consumer preferences

What indicators could point to an exogenous change?

- Look for auxiliary data related price sensitivity
- Collect data on total coupons issued and redeemed in the U.S. across all formats (e.g., FSIs, online) from 1980 through 2020
Figure 9: Coupon Redemptions: 1980–2020

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

Consumer shopping time declined from 2006 to 2019

- For adults 25 to 54, declined 21 percent (from 3.0 to 2.4 hours per week)
- 5 percent fewer shoppers each day, 16 percent less time when shopping
- Decline is sharper among women
Core Finding #2

A decline in consumer price sensitivity, potentially due to exogenous shifts in preferences

- Trend is mirrored by longer-run decline in coupon usage and reduced time spent shopping
- Could reflect stronger brand preferences or increases in the opportunity cost of time spent comparison shopping
### What are the Welfare Impacts of Rising Markups?

#### Table 5: Annual Surplus and Welfare per Capita

(a) 2006 Preferences and Costs

<table>
<thead>
<tr>
<th>Specification</th>
<th>CS</th>
<th>PS</th>
<th>W</th>
<th>% change CS</th>
<th>% change W</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>628</td>
<td>261</td>
<td>889</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Markups Scaled to 2019 Levels</td>
<td>551</td>
<td>267</td>
<td>818</td>
<td>-12.2</td>
<td>-8.0</td>
</tr>
</tbody>
</table>

Notes:
The table reports consumer surplus per capita based on estimated demand parameters (“Baseline”) and for counterfactual scenarios that hold fixed preferences and marginal costs and vary the price levels.

- Factoring in changes in marginal costs and preferences, consumer surplus rises from $628 to $974 per capita (i.e., about 3 percent annually).
### Table 5: Annual Surplus and Welfare per Capita

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#### (b) 2019 Preferences and Costs

<table>
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</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>974</td>
<td>371</td>
<td>1345</td>
<td>0.0</td>
<td>0.0</td>
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<td>Markups Scaled to 2006 Levels</td>
<td>1106</td>
<td>280</td>
<td>1386</td>
<td>13.5</td>
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**Notes:** The table reports consumer surplus per capita based on estimated demand parameters (“Baseline”) and for counterfactual scenarios that hold fixed preferences and marginal costs and vary the price levels.
### Table 5: Annual Surplus and Welfare per Capita

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**Notes:** The table reports consumer surplus per capita based on estimated demand parameters (“Baseline”) and for counterfactual scenarios that hold fixed preferences and marginal costs and vary the price levels.

- Factoring in changes in marginal costs and preferences, consumer surplus *rises* from $628 to $974 per capita (i.e., about 3 percent annually)
Figure 10: Consumer Surplus By Income Quartile

Notes: The figure reports coefficients and 95 percent confidence intervals of a regression of the log of consumer surplus by purchase on year dummies, controlling for module fixed effects, separately for different quartiles of the income distribution.
Core Finding #3

Consumer surplus increases despite rising markups and prices

Consumer surplus rises because preferences change

- However, these gains were concentrated among the wealthy
- Philosophical question of how to treat changing preferences
Conclusion

Markups in consumer products have increased by more than 25 percent from 2006 to 2019

- Changes within products, not reallocation... the whole distribution shifts over time
- Mainly due to falling real marginal costs, not rising real prices
- Role of consumer preferences: consumers became less price sensitive over time
- Consumer surplus may be increasing despite rising markups, mainly among high-income households
Thank You
Addressing Price Endogeneity

Firms may increase prices in response to higher demand

Can address with instruments or covariance restrictions

• Difficult to find valid instruments for many product categories
  ▷ BLP (1995) and Gandhi and Houde (2020) instruments require non-price product attributes, and relevance might not be satisfied

• With covariance restrictions, directly incorporate how firms adjust markups to demand (MacKay and Miller, 2022)
  ▷ Plausible with fixed effects (e.g., control for quality)
  ▷ Exploits all the endogenous price and quantity variation, so there is no relevance condition
A Primer on Covariance Restrictions

Drawing on MacKay and Miller (2022), consider monopoly pricing with linear demand and constant marginal cost.

Equilibrium can be recast as a system of equations:

\[ q^d_t = \alpha + \beta p_t + \xi_t \quad \text{(demand)} \]
\[ q^s_t = \gamma - \beta p_t + \nu_t \quad \text{(supply)} \]
\[ q^d_t = q^s_t \quad \text{(equilibrium)} \]

Notice that the price coefficient in the demand schedule also determines the slope of the supply schedule.
Figure 11: The Slope of Demand and Supply are Linked
A Primer on Covariance Restrictions

Figure 12: The Slope of Demand and Supply are Linked
A Primer on Covariance Restrictions

Consistent estimate given by:

$$\hat{\beta} = -\sqrt{\frac{\text{Var}(q)}{\text{Var}(p)}}$$

Generalizes beyond monopoly with linear demand—the relative variance of quantity and price identifies the price parameter under uncorrelatedness.
Covariance Restrictions vs Hausman Instruments

Figure 13: Distributions of Median Own-Price Elasticities
Covariance Restrictions vs Hausman Instruments

Figure 14: Differences in Own-Price Elasticities
Covariance restrictions for RTE Cereals in 2006

Candidate Price Parameter

Contribution of Covariance Restrictions

DMMS Rising Markups 52
Covariance restrictions for RTE Cereals 2006-2019
Results for RTE cereals

DMMS Rising Markups
Nielsen Retail Scanner Data

• Price & quantity data, 2006-2019, at the UPC-store-week level
• Connects stores to their retail chain and their region (“DMA”)
• We define products at the brand level; this consolidates thousands of UPCs into a more manageable set
• We include the 20 highest-revenue products in the estimation sample, and collapse the rest into a “fringe” product
• We include the top 200 categories by revenue, and we screen out categories that include highly dissimilar products
• Baseline sample includes 133 product categories
• Categories in the baseline sample cover 55 percent of revenues; the top 200 cover 74 percent (out of over 1,000 categories)
### Table 6: Product Categories in the Scanner Data

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

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

- Household level information on income and children
- We generate consumer-specific demographic draws by sampling 2,000 consumers for each DMA and year (with replacement)
- We use projection weights provided by Nielsen
- Restrict sample to the 22 DMAs with at least 500 panelists
- For micro-moments, we obtain the average values of the observed demographics for each product, region, and year
  - e.g., What is the average income of a household that buys Coca-Cola in the Boston DMA in Q1 2014?
Additional Data

Ownership data

- Capital IQ: ultimate parent for each product in 2019
- Zephyr (Bureau van Dijk): Ownership changes via mergers and acquisitions

Accounting data

- Compustat: R&D and marketing expenses for listed firms

Price index

- CPI for All Urban Consumers: All Items Less Food and Energy in U.S. City Average
A Structural Decomposition

For a broad class of oligopoly models, we can write price-cost margins in terms of $\alpha$ and inverse supply ($\lambda$)

$$p_{jcr} - c_{jcr}(x_{crt}; \theta) = -\frac{1}{\alpha_t} \lambda_{jcr}(q_{crt}, p_{crt}, D_{crt}, \eta_{crt}; \theta)$$

Taking the quantity-weighted average, divide by average prices to obtain the aggregate Lerner index,

$$L_t = \frac{p_t - c_t}{p_t} = -\frac{1}{\alpha_t} \lambda_t$$

Taking logs, we obtain the decomposition:

$$\ln L_t = \ln(\lambda_t) - \ln(-\alpha_t)$$
A Structural Decomposition

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A Structural Decomposition

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Taking logs, we obtain the decomposition:

$$\ln(\bar{L}_t) = \ln\left(\frac{\bar{\lambda}_t}{\bar{p}_t}\right) - \ln(-\alpha_t)$$

\text{Structural Factors} \quad \text{Price Sensitivity}
### Table 7: Price Sensitivity and Markups Across Product Categories

<table>
<thead>
<tr>
<th></th>
<th>(1) 2006 Log $L$</th>
<th>(2) 2017 Log $L$</th>
<th>(3) 2019 Log $L$</th>
<th>(4) $\Delta$ Log $L$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price Sensitivity</td>
<td>$-0.134^{***}$</td>
<td>$-0.200^{***}$</td>
<td>$-0.090^{***}$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.027)</td>
<td>(0.029)</td>
<td>(0.029)</td>
<td></td>
</tr>
<tr>
<td>$\Delta$ Price Sensitivity</td>
<td></td>
<td></td>
<td></td>
<td>$-0.575^{***}$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.012)</td>
</tr>
<tr>
<td>Observations</td>
<td>133</td>
<td>133</td>
<td>133</td>
<td>1,729</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.162</td>
<td>0.268</td>
<td>0.070</td>
<td>0.571</td>
</tr>
</tbody>
</table>

Notes: This table reports regression results to examine the cross-sectional and time series relationships of markups and price sensitivity. Columns (1) and (2) capture cross-sectional variation using the year 2006 for our baseline sample (133 product categories) and the extended sample (200 categories). Columns (3) and (4) capture the time series variation by estimating the model in first differences from 2007 through 2019. The regressions are motivated by the decomposition in equation (59). Standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

- Structural factors explain most of the cross-sectional variation
- Changes in price sensitivity explain most of the variation over time
A Structural Decomposition

\[
\ln \bar{L}_t = \ln \left( \frac{\bar{\lambda}_t}{\bar{p}_t} \right) - \ln (-\alpha_t)
\]

Structural Factors - Price Sensitivity

In many cases, \( \bar{\lambda}_t \) is “data”

- Linear demand + single-product firms: \( \bar{\lambda}_t = \bar{q}_t \)
- Constant elasticity demand: \( \bar{\lambda}_t = \bar{p}_t \)
- BLP: \( \bar{\lambda}_t \) reflects shares of unobserved types, can be obtained from micromoments only (first step of estimation)
A Structural Decomposition

\[ \ln L_t = \ln \left( \frac{\lambda_t}{\bar{p}_t} \right) - \ln (-\alpha_t) \]

Structural Factors - Price Sensitivity

In many cases, \( \lambda_t \) is “data”

- Linear demand + single-product firms: \( \lambda_t = \bar{q}_t \)
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Let’s plot the structural component
Figure 15: Decomposition of Markup Trends

Notes: This figure shows the decomposition of changes to the aggregate log Lerner Index into the two components specified by equation (59). The first component, labeled “structural factors,” incorporates observable changes in prices and the distribution of market shares. The second component, the negative value of the price sensitivity, reflects mean price parameter across categories. A larger value of this (negative) component means that consumers are less price sensitive.
Figure 16: Changes in the Distribution of Markups

Notes: The figure shows coefficients and 95 percent confidence intervals of regressions of percentiles of the markup distribution at the product category level on year dummies using the year 2006 as the base category.
Figure 17: Product-Level Changes in Non-Deflated Prices

Notes: The figure shows coefficients and 95 percent confidence intervals of a regression of log prices at the product-level on year dummies using the year 2006 as the base category.
Changes in Nominal Marginal Costs

Figure 18: Product-Level Changes in Non-Deflated Marginal Costs

Notes: The figure shows coefficients and 95 percent confidence intervals of a regression of log marginal costs at the product-level on year dummies using the year 2006 as the base category.
Changes in Perceived Product Quality

Figure 19: Product-Level Changes in Perceived Quality

Notes: The figure shows coefficients and 95 percent confidence intervals of a regression of perceived product quality (standardized) at the product-level on year dummies using the year 2006 as the base category.
The expected value of consumer surplus ($CS$) in our model is (Small and Rosen, 1981):

$$CS = -\frac{1}{N} \sum_i \frac{1}{\alpha_i} \ln \left( \sum_j \exp(v_{ij}) \right)$$

$$v_{ij} = x_j' \beta_i^* + \alpha_i^* p_{jcr} + \xi_{jr} + \xi_{cr} + \xi_t + \Delta \xi_{jcrt}$$

To reduce influence of outliers, we use the average price coefficient within each consumer’s income decile.
Figure 20: Consumer Surplus By Income Decile

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