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.

Research Question

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

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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$\times$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

Modeling Framework

Rely on the workhorse models of industrial organization:

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

$\longrightarrow$ 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

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

- Heterogeneity in consumer-specific coefficients
  - Price (α_i^*): depends on income and an indicator for children
  - Intercept (β_i^*): depends on income, children, and an unobserved N(0,1) "demographic" variable
  - No product characteristics $\longrightarrow$ 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

$$p_{crt} = \underbrace{mc_{crt}}_{\text{Marginal cost}} + \underbrace{\left(-\Omega_{crt} \circ \left[\frac{\partial s_{crt}(p_{crt})}{\partial p_{crt}}\right]'\right)^{-1} s_{crt}(p_{crt})}_{\text{Additive markup}}$$

- Vectors p_{crt}, s_{crt}, and mc_{crt} have prices, market shares, and marginal costs
- Ω_{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

$$mc_{jcrt} = \eta_{jr} + \eta_{cr} + \eta_t + \Delta\eta_{jcrt}$$

- Fixed effects for the product×region, chain×region, quarter
- The structural error term $\Delta\eta_{jcrt}$ 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)

$\longrightarrow$ Exogenous variation in $\Delta\eta_{jcrt}$ 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 (Π, Σ)
- Use empirical patterns of purchasing habits: micro-moments (Berry and Haile, 2020)

Second step:

- Estimate mean price parameter (α)
- Assume (residual) demand and cost shocks are uncorrelated:

$$\mathbb{E}\left[\Delta\xi_{jcrt}(\theta)\Delta\eta_{jcrt}(\theta)\right] = 0$$

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)

Details

Table 1: Sample of Product Categories

Rank	Product Category	Observations	Revenue ($ Millions)	Retailer-DMA Combinations	Brands Per Market	Share Top 20 Brands	Share Private Label
1	Cereal - Ready To Eat	231,178	22,557	333	19.3	0.58	0.08
2	Candy - Chocolate	229,065	16,162	335	18.9	0.54	0.03
3	Candy - Non-Chocolate	225,336	9,420	334	18.6	0.61	0.14
4	Deodorants - Personal	221,618	7,186	333	18.3	0.79	0.00
5	Soap - Specialty	214,153	5,563	355	17.5	0.68	0.05
6	Tooth Cleaners	212,056	7,343	333	17.6	0.71	0.00
7	Shampoo - Liquid/Powder	202,923	7,490	332	16.8	0.65	0.04
8	Cookies	202,880	17,191	334	16.8	0.64	0.18
9	Sanitary Napkins	201,864	5,128	333	16.7	0.79	0.18
10	Cold Remedies - Adult	201,134	9,111	332	16.6	0.85	0.40
20	Bottled Water	160,454	23,333	335	13.2	0.90	0.38
40	Baby Formula	133,082	10,616	323	12.1	0.76	0.05
60	Nuts - Bags	107,314	6,500	334	8.9	0.79	0.24
80	Fresh Muffins	85,228	3,899	332	7.6	0.85	0.17
100	Tuna - Shelf Stable	68,711	4,099	332	5.7	0.98	0.13
120	Cream - Refrigerated	52,297	3,402	330	4.6	0.70	0.30
130	Frozen Poultry	33,428	2,145	300	3.9	0.86	0.27
133	Fresh Mushrooms	25,510	2,772	246	3.4	0.95	0.28
	Mean Values	108,442	6,766	319	9.8	0.84	0.16

Estimated Marginal Costs

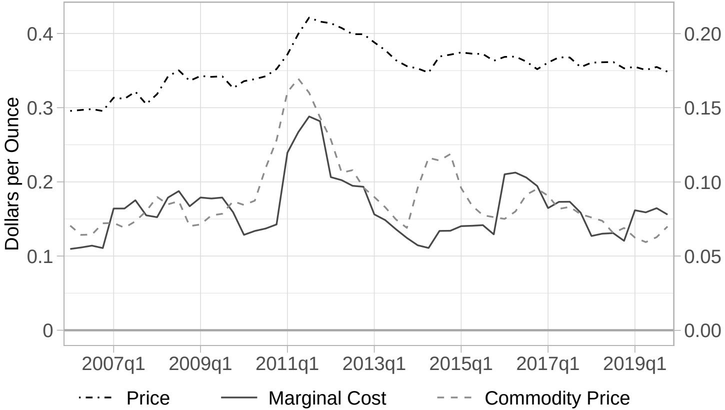

Figure 1: Ground and Whole Bean Coffee

$\Longrightarrow$ Our marginal cost estimates track commodity prices

Comparisons to the Literature

Table 2: Average Own-Price Elasticities of Demand

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

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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

$\rightarrow$ Nearly identical markups

Estimated Demand Elasticities

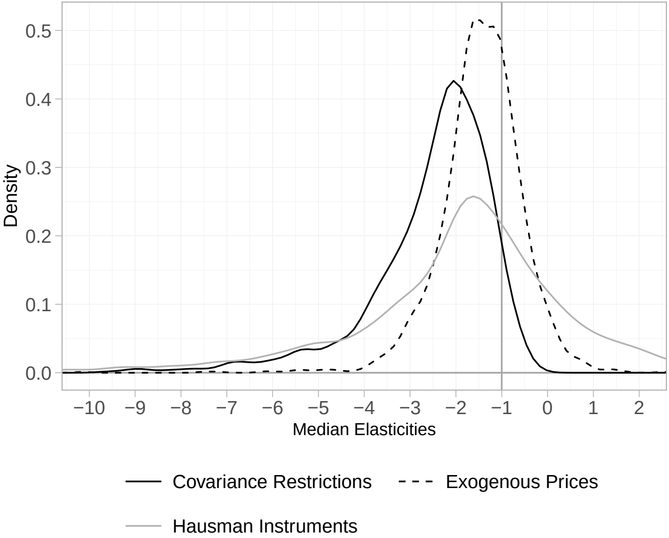

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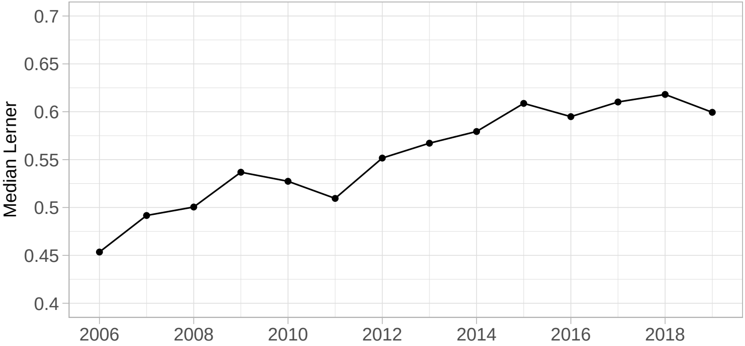
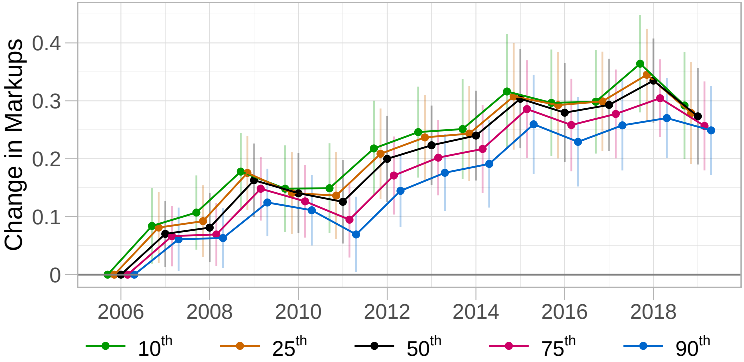
Figure 2: Evolution of Markups Across Product Categories



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.

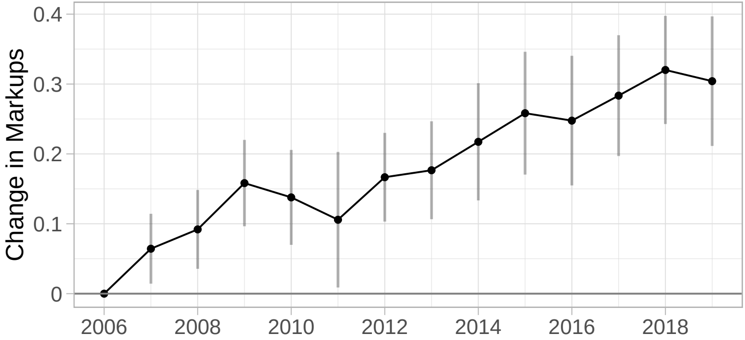
Figure 3: Changes in the Distribution of Markups



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.

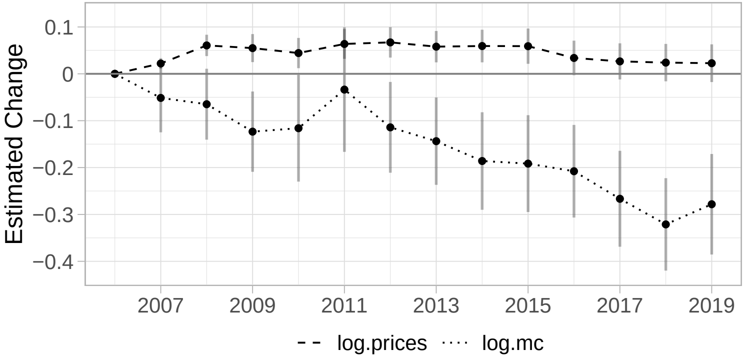
Absolute changes in markup distribution

Figure 4: Evolution of Markups at the Product Level



Notes: Regression of $\log((p-c)/p)$ on region×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 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.

Changes in nominal prices and costs

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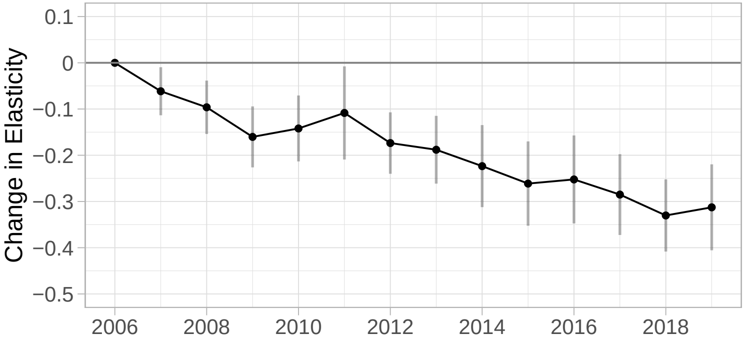
Why might we find falling costs with (modest) price increases?

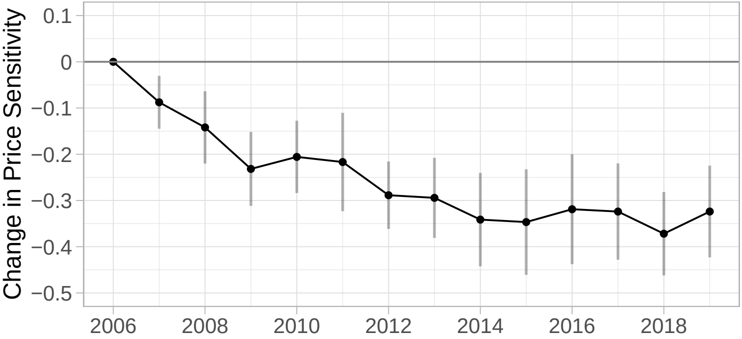
- Imperfect competition generates incomplete pass-through
- Mergers and acquisitions
- Demographic trends
- Perceived product quality
- Consumer preferences, including price sensitivity

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 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.

Table 3: Determinants of Markups Changes at the Product Level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Marginal Cost (Standardized)	−0.564***					−0.450***	−0.449***
	(0.024)					(0.023)	(0.023)
Price Sensitivity		−0.721***				−0.392***	−0.393***
		(0.030)				(0.022)	(0.022)
Quality (Standardized)			−0.142***			0.006	0.007
			(0.022)			(0.006)	(0.006)
Income (Log)				0.052**		0.059***	0.058***
				(0.025)		(0.013)	(0.013)
Children at Home				−0.175***		−0.076***	−0.083***
				(0.064)		(0.026)	(0.027)
Parent HHI					0.236		0.236***
					(0.186)		(0.046)
Brand HHI					0.091		−0.097**
					(0.178)		(0.048)
Retailer HHI					0.203***		0.074***
					(0.077)		(0.025)
Brand-Category-DMA-Retailer FEs	X	X	X	X	X	X	X
Time Period FEs	X	X	X	X	X	X	X
Observations	14,407,410	14,407,410	14,407,410	14,407,410	14,407,353	14,407,410	14,407,353
R^2 (Within)	0.719	0.468	0.047	0.000	0.003	0.826	0.827

Structural decomposition

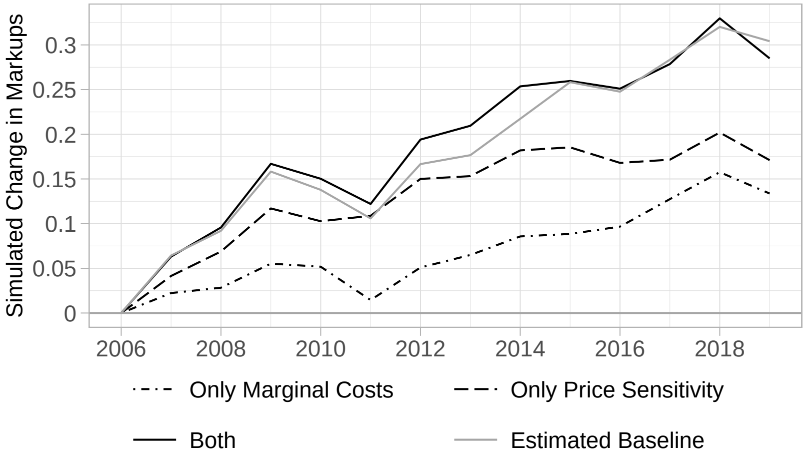
Core Finding #1

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



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Exploring Potential Mechanisms

Falling marginal costs from 2006 to 2019 $\rightarrow$ 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 $\rightarrow$ 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

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

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

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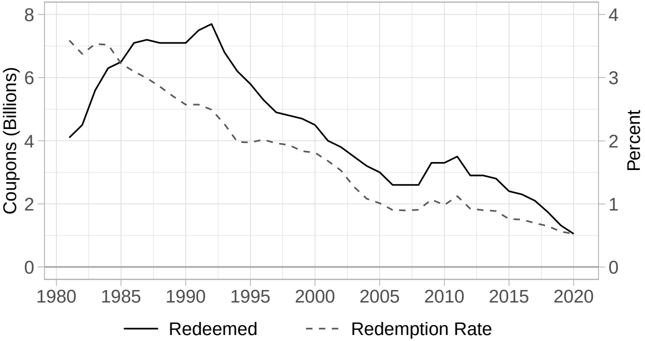
What indicators could point to an exogenous change?

- 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

Specification	CS	PS	W	% change CS	% change W
Baseline	628	261	889	0.0	0.0
Markups Scaled to 2019 Levels	551	267	818	-12.2	-8.0

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(b) 2019 Preferences and Costs

Specification	CS	PS	W	% change CS	% change W
Baseline	974	371	1345	0.0	0.0
Markups Scaled to 2006 Levels	1106	280	1386	13.5	3.1

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.

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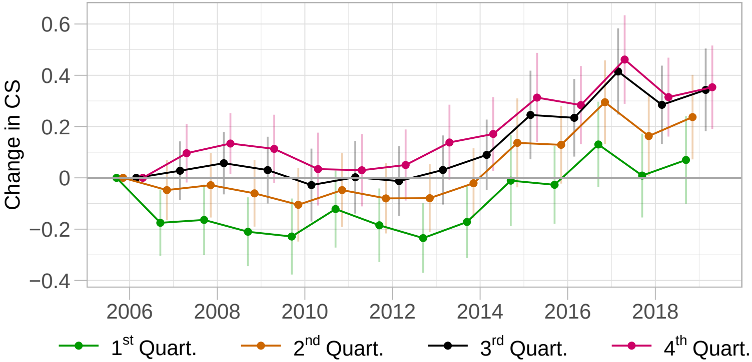
Notes: The table reports consumer surplus per capita based on estimated demand parameters ("Baseline") and for counterfactual scenarios that hold fixed preferences and marginal costs and vary the price levels.

- 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.

Consumer Surplus By Income Decile

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

Back

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:

$$
\begin{aligned}
q_t^d &= \alpha + \beta p_t + \xi_t && \text{(demand)} \\
q_t^s &= \gamma - \beta p_t + \nu_t && \text{(supply)} \\
q_t^d &= q_t^s && \text{(equilibrium)}
\end{aligned}
$$

Notice that the price coefficient in the demand schedule also determines the slope of the supply schedule

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A Primer on Covariance Restrictions

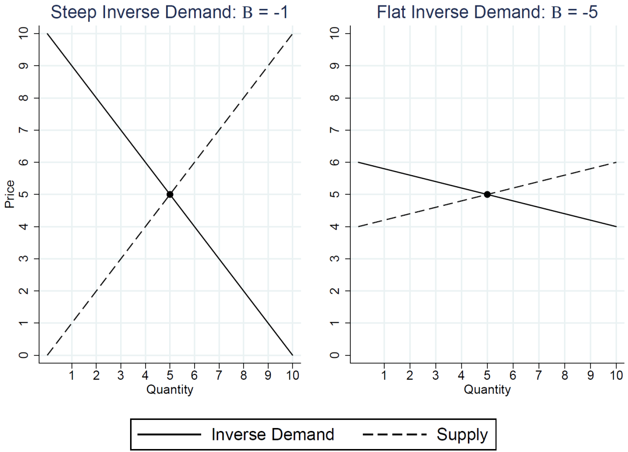

Figure 11: The Slope of Demand and Supply are Linked

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A Primer on Covariance Restrictions

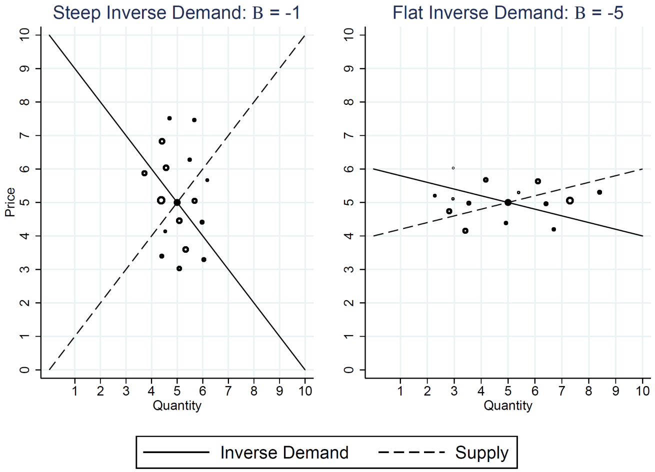

Figure 12: The Slope of Demand and Supply are Linked

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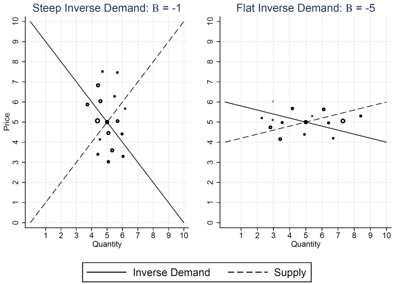
A Primer on Covariance Restrictions

Consistent estimate given by:

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

Generalizes beyond monopoly with linear demand—the relative variance of quantity and price identifies the price parameter under uncorrelatedness.



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Covariance Restrictions vs Hausman Instruments

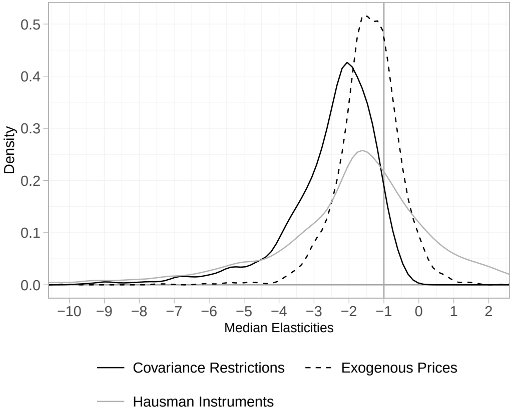

Figure 13: Distributions of Median Own-Price Elasticities

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Covariance Restrictions vs Hausman Instruments

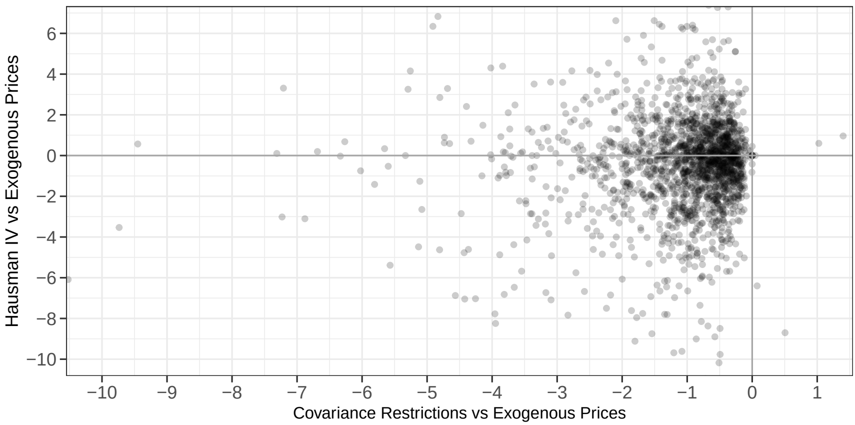

Figure 14: Differences in Own-Price Elasticities

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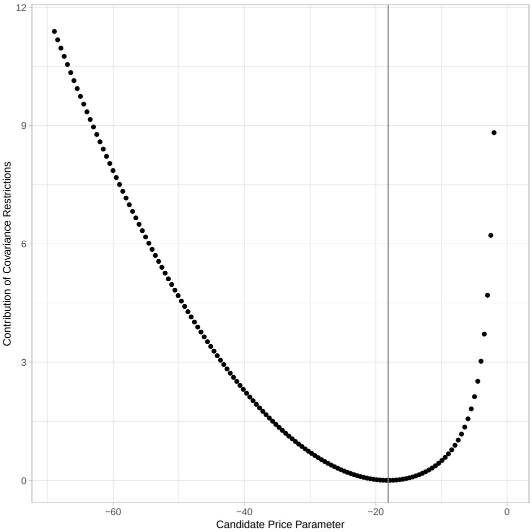
Covariance restrictions for RTE Cereals in 2006



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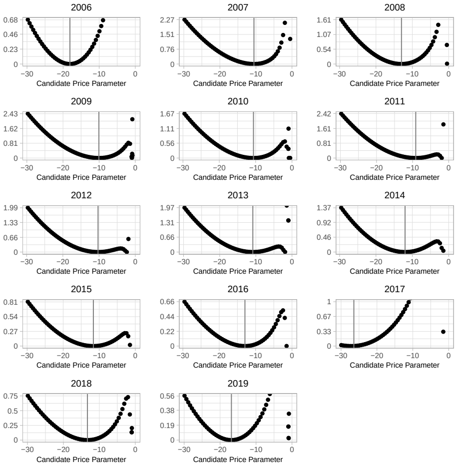
Covariance restrictions for RTE Cereals 2006-2019



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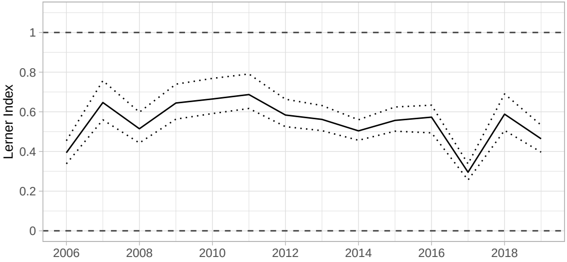
Results for RTE cereals



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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)

Nielsen Retail Scanner Data

Table 6: Product Categories in the Scanner Data

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

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

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 acquistions

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

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A Structural Decomposition

For a broad class of oligopoly models, we can write price-cost margins in terms of α and inverse supply (λ)

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

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

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

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Taking logs, we obtain the decomposition:

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

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Table 7: Price Sensitivity and Markups Across Product Categories

	(1) 2006 Log $\overline{L}$	(2) 2017 Log $\overline{L}$	(3) 2019 Log $\overline{L}$	(4) Δ Log $\overline{L}$
Price Sensitivity	-0.134^{***}	-0.200^{***}	-0.090^{***}	
	(0.027)	(0.029)	(0.029)	
Δ Price Sensitivity				-0.575^{***}
				(0.012)
Observations	133	133	133	1,729
R^2	0.162	0.268	0.070	0.571

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

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A Structural Decomposition

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

In many cases, $\overline{\lambda}_t$ is "data"

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

A Structural Decomposition

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Let's plot the structural component

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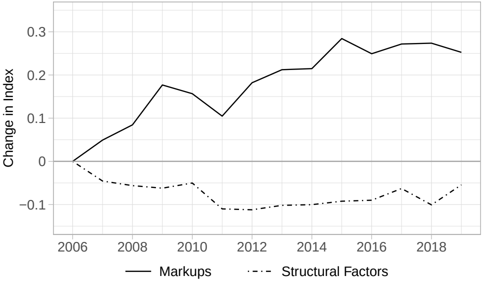
Figure 15: Decomposition of Markup Trends



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.

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Absolute Changes in Distribution of Markups

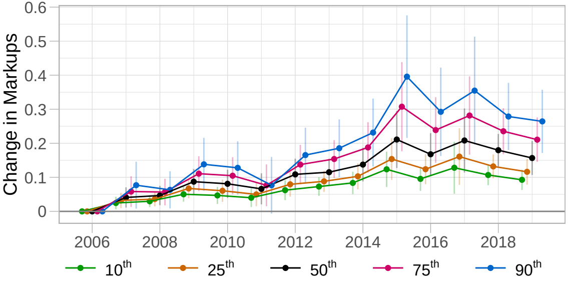

Figure 16: Changes in the Distribution of Markups

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.

Relative changes in markup distribution

Changes in Nominal Prices

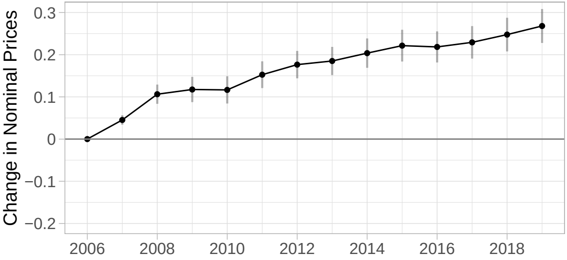

Figure 17: Product-Level Changes in Non-Deflated Prices

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.

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Changes in Nominal Marginal Costs

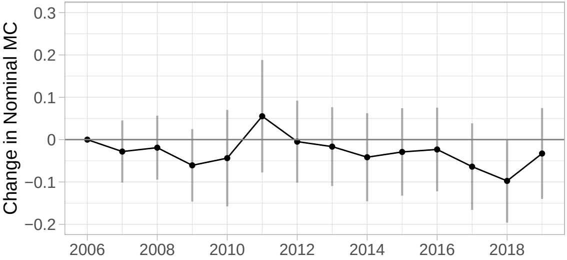

Figure 18: Product-Level Changes in Non-Deflated Marginal Costs

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.

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Changes in Perceived Product Quality

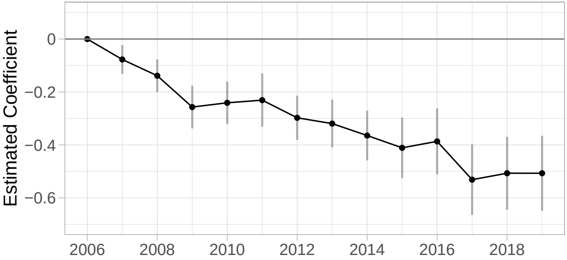

Figure 19: Product-Level Changes in Perceived Quality

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.

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Estimation of Consumer Surplus

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

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

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

To reduce influence of outliers, we use the average price coefficient within each consumer's income decile

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Consumer Surplus Over Time

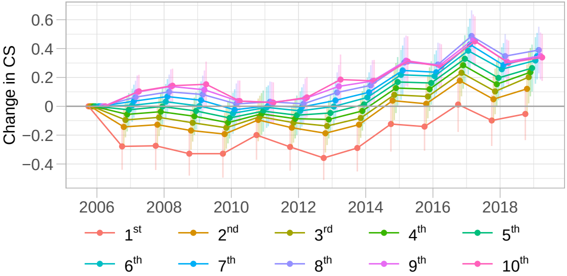

Figure 20: Consumer Surplus By Income Decile

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.

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