Markups Across the Income Distribution: Measurement and Implications

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Disclaimer

This presentation contains my own analyses 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 author 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.

Household Income and Firm Markups: Micro Evidence, Macro Effects

- Evidence of rising markups has heightened focus on determinants of markups.
  e.g., De Loecker et al. (2020), Barkai (2020), Autor et al. (2020), Gutiérrez (2017).

- Prevailing focus on changes to competition, conduct, and production.
  - E.g., lax antitrust enforcement, rise of superstar firms, structural technological change.
    e.g., Gutiérrez and Philippon (2018), Autor et al. (2017), De Loecker et al. (2021).

- This paper: Role of changes in demand (income levels and inequality).
  - Micro evidence $\rightarrow$ macro implications.

Household Income and Firm Markups: Micro Evidence, Macro Effects

- **Micro evidence**:
  - Explore using retail markups (price $/$ wholesale cost) on 26M transactions.
  - High-income households pay 15pp higher markups on average.
    - Within store, high-income pay 7pp higher markups.
    - Markup gap is 2x gap in prices paid for identical goods.
  - Markups paid depend positively on incomes of other households.
    - “Macro” elasticity of markups to income $>$ micro elasticity.
- **Search model of income and markups**:
  - Heterogeneous households with Burdett and Judd (1983) search.
  - Quantitatively accounts for patterns in the data.
  - Theoretical results: Conditions under which $\uparrow$ income levels, inequality raise markups.

Household Income and Firm Markups: Micro Evidence, Macro Effects

- **Macro implications**:
  - Search spillovers: wealthy shoppers increase markups paid by low-income by 5–9pp.
  - Costs of inequality for all households.
  - Across cities, $\uparrow$ income level and inequality lead to $\uparrow$ markups, as in the data.
- **Counterfactual**: How do changes in income distribution affect markups over time?
  - Model-free estimates: Income distribution 1950–2018 accounts for $\uparrow$ 13–23pp markup.
  - Model: Predicts 10–14pp rise in retail markup.
    - Markup increase accelerates after 1980 due to $\uparrow$ income dispersion.
    - Increase due to within-firm markups *and* reallocation to high-markup firms.
    - Magnitude consistent with rise in retail markups in the data.

Selected Literature

- **Prices paid and price sensitivity**
  - *Differences in prices paid*: Aguiar and Hurst (2007), Broda, Leibtag, and Weinstein (2009), Kaplan and Menzio (2015), Handbury (2021), Diamond and Moretti (2021)
  - *Price elasticities over time or across groups*: Harrod (1936), Lach (2007), Anderson, Rebelo, and Wong (2018), Stroebel and Vavra (2019), DellaVigna and Gentzkow (2019), Faber and Fally (2022), Jaimovich, Rebelo, and Wong (2019), Argente and Lee (2021), Handbury (2021), Gupta (2020), Auer, Burstein, Lein, and Vogel (2022)
  - *Trade literature*: Alessandria and Kaboski (2011), Simonovska (2015).
- **Search in product markets**
  - Stigler (1961), Varian (1980), Burdett and Judd (1983), Alessandria and Kaboski (2011), Kaplan and Menzio (2016), Pytka (2018), Kaplan, Menzio, Rudanko, and Trachter (2019), Albrecht, Menzio, and Vroman (2021), Menzio (2021), Bhardwaj, Ghose, Mukherjee, and Singh (2022), Nord (2022), Menzio (2023)
- **Evolution of retail markups**
  - Neiman and Vavra (2019), Brand (2021), Döpper, MacKay, Miller, and Stiebale (2021).

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Data

1. Nielsen Homescan.
   - 62 million transactions by 60,000 households in 2007.
   - Nationally representative sample across 2700 counties.
   - Panelist incentives (e.g., sweepstakes) for accurate reporting.
   - Track purchases of fast-moving consumer goods.
2. PromoData Price-Trak.
   - Weekly monitoring service of wholesale list prices and promotional discounts.
   - Data from 12 wholesalers on 67,000 UPCs.
   - Covers 43% of transactions (37% expenditures) in Homescan data.

Coverage by income →

Retail markups calculated using wholesale cost

- Calculate Retail Markup $=$ Price$/$Wholesale Cost.
  (Gopinath et al. 2011; Anderson et al. 2018.)
  - Differences in markups paid **within store** since wholesale costs, distribution costs, and overhead may differ across stores.
  - Strongly correlated with markups estimated à la Berry et al. (1995) in one module.
- Average (sales-weighted) markup is 32%.
  - Stroebel and Vavra (2019) report 35% for large retailer.
  - (All calculations winsorize markups at 1%.)

Wholesale price uniformity →

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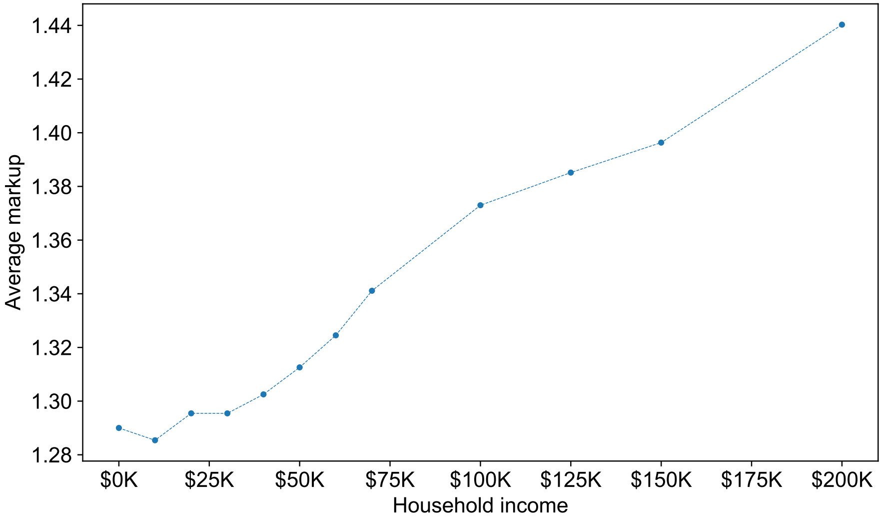
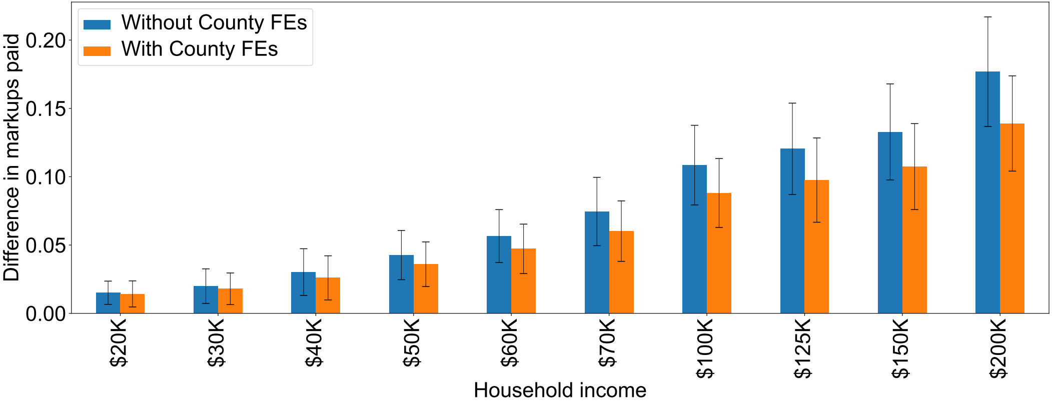
Average markup paid increases with household income

Figure: Aggregate (cost-weighted average) markup paid by income group.



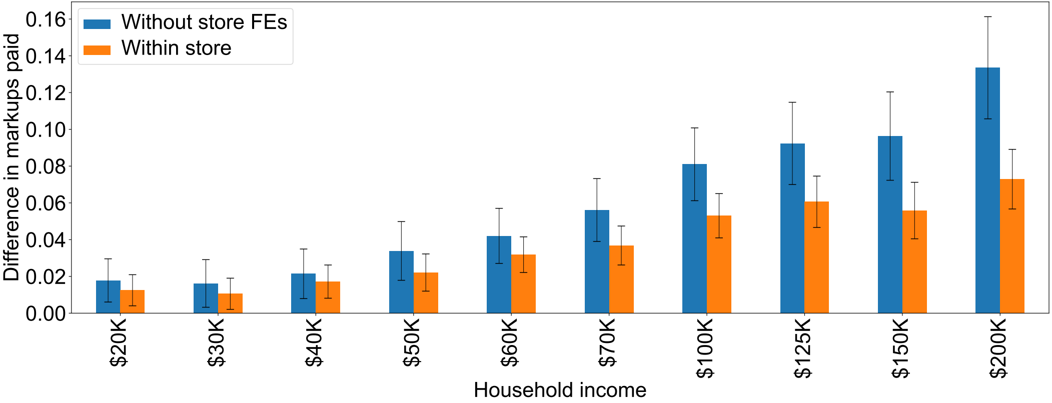
14pp gap in markups paid within county



$$\text{Markup}_{i,g} = \sum_{\ell} \tilde{\beta}_\ell 1\{i \text{ has income } \ell\} + \underbrace{\gamma' X_i}_{\text{Demographic controls}} + \underbrace{\delta_{\text{County}}}_{\text{County FEs}} + \varepsilon_{i,g}.$$

Graph shows FEs relative to group with <$20K reported income. Standard errors two-way clustered by brand and county.

7pp gap in markups paid within store



$$\text{Markup}_{i,g} = \sum_{\ell} \tilde{\beta}_{\ell} 1\{i \text{ has income } \ell\} + \underbrace{\gamma' X_i}_{\text{Demographic controls}} + \underbrace{\alpha_{\text{Store}}}_{\text{Store FEs}} + \varepsilon_{i,g}.$$

Graph shows FEs relative to group with $<$\$20K reported income. Standard errors two-way clustered by brand and county.

Robustness of markup gap

Markup gap (pp) relative to <$20K	Demographics $100K	Demographics $200K	Within County $100K	Within County $200K	Within Store $100K	Within Store $200K
Baseline	10.8	17.7	8.8	13.9	5.3	7.3
Weighting by sales	10.4	17.8	7.8	12.7	4.5	6.1
Using PromoData base price	9.7	16.0	8.0	12.7	5.6	7.9
Using PromoData market-level price	8.5	16.3	6.6	11.7	5.8	8.9
With day-of-week fixed effects	10.6	17.5	8.6	13.8	5.1	7.1
With supply-side controls	10.6	17.4	8.5	13.6	5.2	7.2
Excluding perishable items	10.5	17.1	8.4	13.4	4.8	6.7

- Volume discounts at large retailers? Markup gap stable if we remove large retailers.
- Selection? Unit prices for products without cost data exhibit larger covariance with income.
- External validity? Similar link between De Loecker et al. (2020) markups and buyer income.

Volume discounts → Connected set → Noise in wholesale costs → Selection → DLE markups and buyer income →

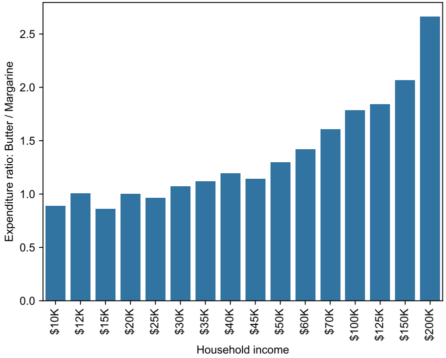
Accounting for the markup gap

1. **High-income households pay higher prices for identical products.**
   (Aguiar and Hurst 2007, Broda et al. 2009, Kaplan and Menzio 2015.)
   - Exploiting price variation over time and across stores. (Coupons play a negligible role.)
   - Responsible for just under 50% of markup gap.
2. **High-income households' baskets are composed of high markup products.**
   - Across-product component of markup gap could be positive or negative in theory.
     (e.g., Mussa and Rosen 1978, Tirole 1988.)
   - Wholesale cost data uniquely allows for this comparison across products.
   - Responsible for just over 50% of markup gap.

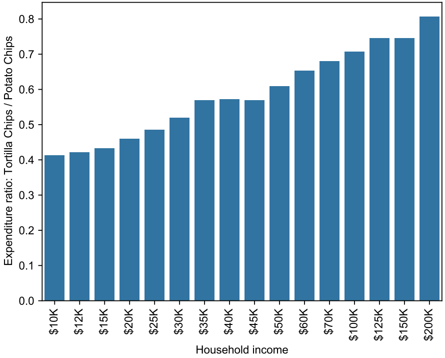
- $\Rightarrow$ Markup gap is 2x larger than gap in prices paid for identical products.

Decomposition → Within-store markup gap decomposition → Elasticities →

Example: Products consumed by rich have higher markups



(a) Expenditures on butter vs. margarine.

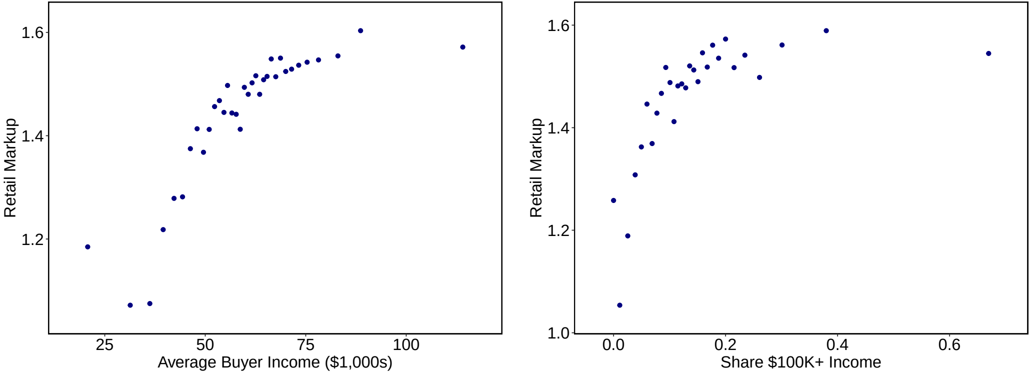


(b) Expenditures on tortilla chips vs. potato chips.

- Butter has higher markups than margarine (average 45% vs. 33%).
- Tortilla chips have higher markups than potato chips (average 50% vs. 19%).

Substitution across brands →

UPCs with high-income customers have high retail markups



- ↑ 10pp share of buyers with $100K income associated with ↑ 7pp retail markup.

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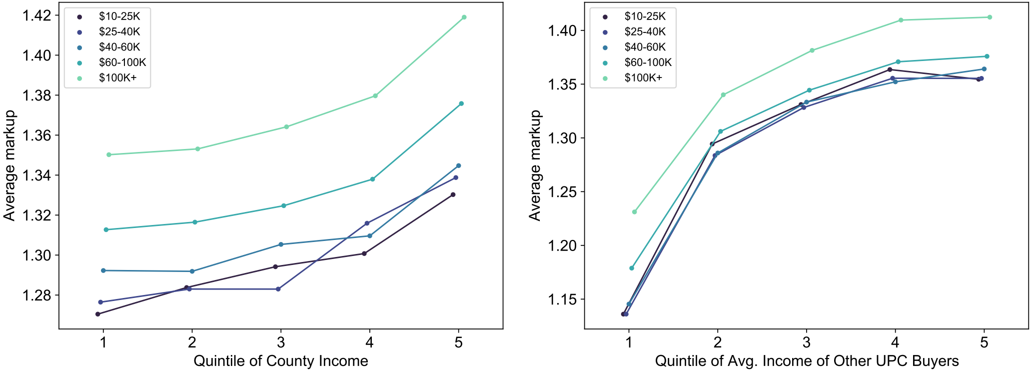
Conditional on income, markups rise with income of other buyers



$$\varepsilon^{\text{Agg}}_{\mu,\text{Income}} = \varepsilon^{\text{individual}}_{\mu,\text{Own Income}} + \varepsilon^{\text{individual}}_{\mu,\text{Others' Incomes}}.$$

- Positive dependence on others' incomes $\rightarrow$ "macro" elasticity $>$ micro elasticity.

Markups higher in high-income areas, retail chains, customer base

	OLS	IV	OLS	IV	OLS	IV
Log Household Income	0.032**	0.053**	0.020**	0.038**	0.013**	0.024**
	(0.004)	(0.008)	(0.003)	(0.007)	(0.001)	(0.003)
Log Avg. CBSA Income	0.102**	0.092**				
	(0.011)	(0.011)				
Log Avg. Income: Retailer's Other Locations			0.137**	0.129**		
			(0.036)	(0.036)		
Log Avg. Income: Other UPC Buyers					0.146**	0.178**
					(0.043)	(0.043)
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FEs			Yes	Yes	Yes	Yes
Store FEs					Yes	Yes
N (millions)	23.8	23.8	9.0	9.0	14.0	14.0
R^2	0.01	0.02	0.03	0.03	0.10	0.09

** is significant at 5%. Standard errors two-way clustered by brand and county.

- IV for household income corrects for potential bias from measurement error.

Spillovers using 2006–2012 variation place macro elasticity between 8–15%

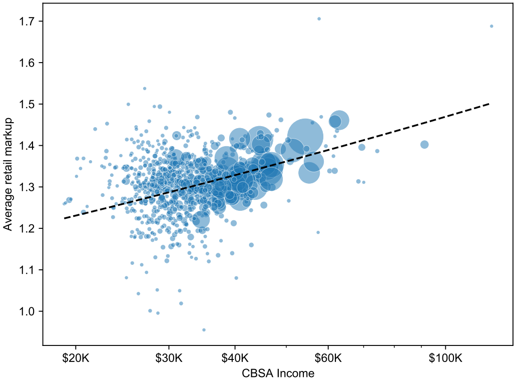
Log Retail Markup	(1)	(2)	(3)
Log Avg. CBSA Income	0.069**		
	(0.014)		
Log Avg. Income: Retailer's Other Locations		0.071**	
		(0.021)	
Log Avg. Income: Other UPC Buyers			0.159**
			(0.042)
Household FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes
Store FEs	Yes	Yes	Yes
N (millions)	91.9	50.9	97.0
R^2	0.18	0.18	0.18

- Store FEs control for store-level costs; household FEs control for unobserved traits.
- Short time horizon? Extend analysis using unit prices from 2004–2019.
- Time series vs. cross section? Similar magnitudes for both markups and unit prices.

Additional FEs → Unit prices 2004–2019 → Time series vs. cross-section markups → Time series vs. cross-section unit prices → Income vs. house prices →

Macro elasticity of 8–15% consistent with markups across CBSAs, prior work

Figure: CBSA average retail markup vs. income.



Log CBSA Retail Markup	(1)	(2)
Log Avg. CBSA Income	0.109^{**}	0.091^{**}
	(0.016)	(0.012)
Top 10% Income Share		0.105^{**}
		(0.043)
N	881	881
R^2	0.27	0.29

- Simonovska (2015): Elasticity of markups to per-capita income of export destination = 12–24%.
- Bhardwaj et al. (2022): Elasticity of prices to hourly wages = 10%.

Table: Avg. income and inequality across CBSAs →

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Search Model of Income and Markups

- Micro-foundation: Households exert search effort to find low prices.
  Aguiar and Hurst (2007), Alessandria and Kaboski (2011), Kaplan and Menzio (2016), Pytka (2018).
  - Differences in price sensitivity arise endogenously, rather than from static utility primitives.
- Quantifiable model with heterogeneous products:
  - Account for the patterns in the data:
    - High-income households pay higher markups.
    - Markup gap $>$ gap in prices paid for identical products.
    - Positive spillovers of others' incomes on markups paid.
  - Generates new predictions:
    - Search intensity decreasing in household income, increasing in others' incomes.
- For exposition, begin with single-product model.

Household Search Technology

- Households know the distribution of prices, but not which firms sell at which price.
- Household i has probability mass function over number of price quotes $\{q_{i,n}\}_{n=1}^{\infty}$,
  - Observes only one quote with probability $q_{i,1}$,
  - Observes two quotes with probability $q_{i,2}$, etc.
- For each purchase, households buy iff min price $p \leq$ reservation price R.
  Redraw n quotes costlessly if $p > R$.

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  Redraw n quotes costlessly if $p > R$.

- Endogenous search decision: Household i chooses search intensity s_i.

- Mapping function from search intensity to probability of observing n price quotes,
  $\mathscr{S} : s_i \mapsto \{q_{i,n}\}_{n=1}^{\infty}$.

Conditions on $\mathscr{S}$ →

Household Problem

$$\max_{l_i, s_i} u(c_i) \quad \text{s.t.} \quad \begin{cases} t_i(c_i, s_i) + l_i = 1 & \text{(Time constraint)} \\ p_i c_i = z_i l_i. & \text{(Budget constraint)} \end{cases}$$

where

- c_i is units of good consumed,
- l_i is time spent working with labor productivity z_i.
- $t_i(c_i, s_i)$ is the time it takes to shop for c_i units with search intensity s_i.
- p_i is the average price paid by i (deterministic over continuum of units).

- First order condition:

$$\underbrace{-\partial p_i / \partial s_i}_{\text{Marginal savings}} = \underbrace{\phi_i}_{\text{Opportunity cost}}$$

where opportunity cost of increasing search intensity $\phi_i = z_i \cdot \frac{1}{c_i} \frac{\partial t(c_i, s_i)}{\partial s_i}$.

Shopping time increases with basket size →

Firm Problem

- Mass M of firms pay entry cost $f_e \cdot w$.
- Constant returns production with marginal cost w.
- Define aggregate search behavior $\bar{q}$,

$$\bar{q}_n = \int_0^\infty q_n(z) d\Lambda(z), \qquad \text{for all } n,$$

  where $H(z) =$ income CDF, consumption $C = \int_0^\infty c(z) dH(z)$, and $d\Lambda(z) = \frac{c(z)}{C} dH(z)$.

- Firms set prices to maximize profits, taking as given $\bar{q}$ and distribution of prices F:

$$\max_p \pi(p) = (p - w) \underbrace{\frac{C}{M} \sum_{n=1}^{\infty} n\bar{q}_n (1 - F(p))^{n-1}}_{\text{Firm's demand at price } p},$$

Dispersed Price Equilibrium (Burdett and Judd 1983)

- Dispersed price eq: $F(p)$ where firms make identical profits for any $p \in \text{supp}(F)$.

- Given $\{\bar{q}_n\}_{n=1}^{\infty}$ with $\bar{q}_1 \in (0,1)$, the unique equilibrium price distribution $F(p)$ is

$$F(p) = \begin{cases} 0 & \text{if } p < \underline{p} \\ 1 - \Psi\left[\left(\frac{R-w}{p-w}\right)\bar{q}_1\right] & \text{if } \underline{p} \leq p \leq R \\ 1 & \text{if } p > R \end{cases}$$

  where the lowest price $\underline{p}$ is

$$\underline{p} = w + \frac{\bar{q}_1}{\sum_{n=1}^{\infty} n\bar{q}_n}(R-w),$$

  and $\Psi(\cdot)$ is the inverse of the strictly increasing, C^{∞} function $y(x) = \sum_{n=1}^{\infty} n\bar{q}_n x^{n-1}$.

- Mass of firms M adjusts to ensure zero profit condition, $\pi = f_e w$.

Equilibrium

- Equilibrium $(F, \{s(z)\}, M)$ such that (1) $s(z)$ maximizes utility given F for all z, (2) F is a dispersed price eq. given $\bar{q}$, (3) $\pi = f_e$, (4) markets clear.
  - Assume all households choose interior $s(z)$.
  - Focus on comparative statics of stable equilibrium.
- For two parameterizations of search mapping $\mathscr{S}$ (general conditions in paper):
  - Two quote (Alessandria and Kaboski 2011; Pytka 2018; Kaplan, Menzio, Rudanko, and Trachter 2019).
  - Poisson (Albrecht, Menzio, and Vroman 2021; Menzio 2021).

Proposition (Shift in Buyers' Incomes)

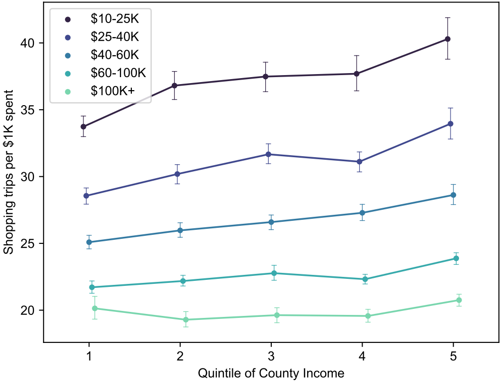
Aggregate markup (total sales / total costs) weakly increases if

- *First-order stochastic shift in $\Lambda(z)$ and opp. cost of search $\phi(z)$ increasing.*
- *Mean-preserving spread in $\Lambda(z)$ and opp. cost of search $\phi(z)$ increasing and convex.*

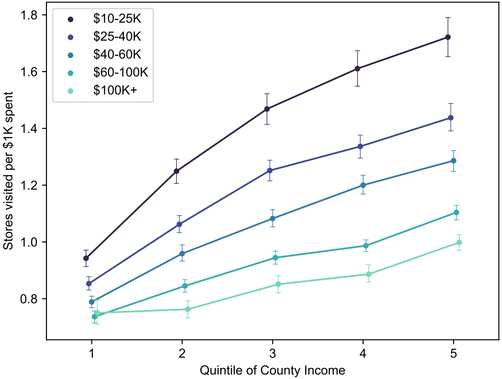
Functional forms → Intuition →

Model predictions on search behavior

- Model: In stable equilibrium, households' search intensities are strategic substitutes.
- Search intensity (Kaplan and Menzio 2015) falls w/ income, rises w/ county income.



(a) Shopping trips per $1K expenditures.



(b) Unique stores visited per $1K expenditures.

Variance of markups →

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Heterogeneous products: Tastes correlated with income

- Suppose household i has utility for segment $k \in \{1, \ldots, K\}$:

$$u_{ik} = \underbrace{\alpha_k(z_i)\delta_k}_{\substack{\text{Common to households} \\ \text{with income } z_i}} + \underbrace{\varepsilon_{ik}}_{\text{Idiosyncratic}},$$

with $\varepsilon_{ik} \sim e^{-e^{-x}}$. Households only buy segment that maximizes per-purchase utility.

(Neiman and Vavra 2019, Li 2021, Handbury 2021.)

- Fraction of households with income z purchasing from segment k is

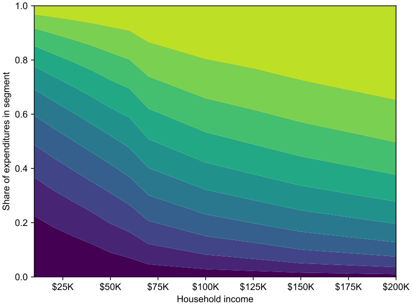
$$\text{Share}_k(z) = \frac{\exp(\alpha_k(z)\delta_k)}{\sum_{k'} \exp(\alpha_{k'}(z)\delta_{k'})}$$

By choosing $\alpha_k(z)$, δ_k, match any shares by income $\times$ segment.

Calibration: Segmentation directly from data, match markups paid

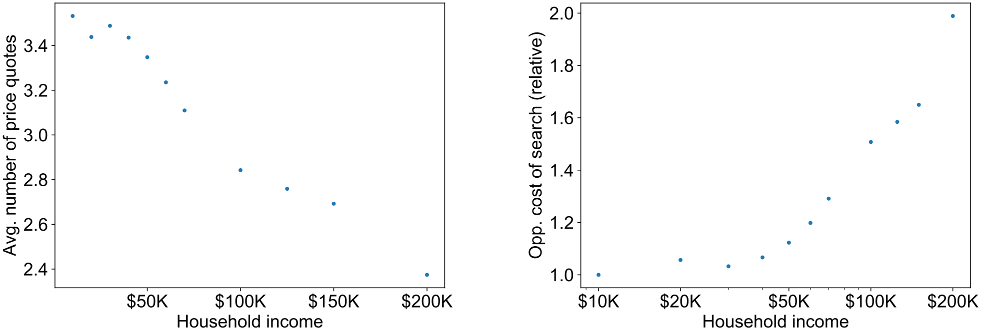
- Order UPCs by buyer income, split into K groups.
- Assume Poisson search mapping $\mathscr{S}$.
  (Albrecht et al. 2021, Menzio 2021.)
- Assume households $>$\$200K income have identical behavior to those with \$200K.
- Solve fixed point in $(\{F_k\}, \phi(z))$.
- **Extensions**:
  - Pro-competitive effects of entry in each segment. (Jaravel 2019, Handbury 2021).
  - Elasticities of substitution across segments.

Figure: Share of purchases in each segment, with $K = 10$ segments.



Pro-competitive effects setup →

Calibration: Price quotes received and opportunity cost of search



(a) Expected number of price quotes received $(s_i + 1)$.

(b) Opportunity cost of search effort $\phi(z)$.

- Doubling search time decreases prices paid 7–9%. (7–10% estimated by Aguiar and Hurst 2007.)
- Elasticity of search intensity to income is -11%. (-12% in McKenzie and Schargrodsky 2005.)

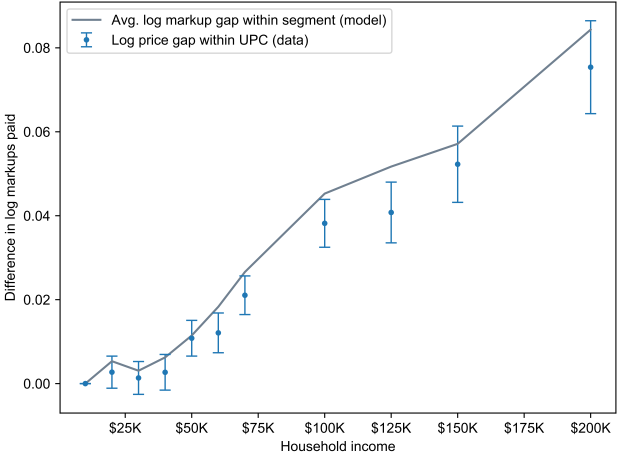
Comparison to Auer et al (2022) →

Magnitude of strategic interactions in model in line with data

	Log markup				*Search intensity*			
	Data		Model		Data		Model	
	OLS	IV	$K = 1$	$K = 10$	OLS	IV	$K = 1$	$K = 10$
Log Household Income	0.034	0.053	0.038	0.036	-0.26	-0.40	-0.19	-0.13
Log Others' Income	0.101	0.092	0.062	0.041	0.03	0.10	0.07	0.04

- For macro elasticity, simulate economies with income distributions from 1950 to 2018.
- "Micro elasticity" of markups matches the data.
- "Macro elasticity" of markups to income (7–10%) conservative relative to data.
- Strategic interactions in search match the data.

Within-segment markup gap $\approx$ gap in prices paid for identical products



- Untargeted moment: differences in prices paid for identical products.
- Overall markup gap $=$ within-segment price gap $+$ cross-segment markup gap.

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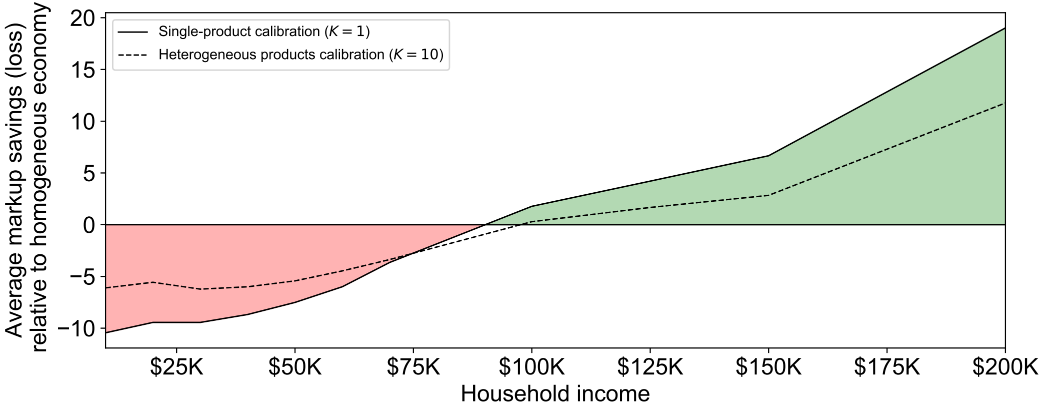
Macro Implications

1. Spillovers from shopping behavior across households.
2. Costs of inequality to all households.
3. Aggregate markups across cities.
4. Spillovers of regional income shocks.

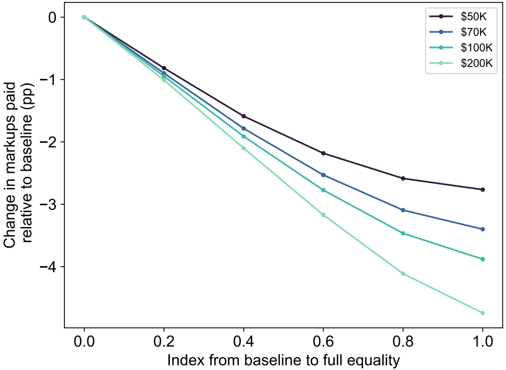
1. Spillovers from shopping behavior across households



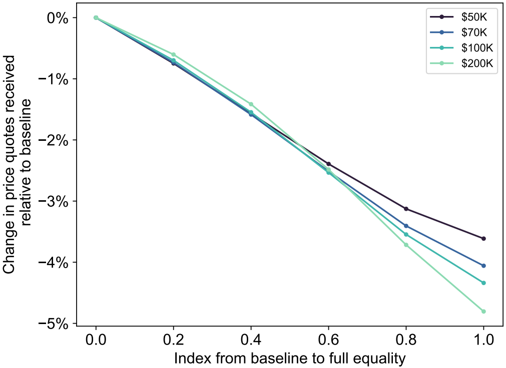
- Low-income pay 5–9pp higher markups due to presence of high-income shoppers.

Spillovers in \$ →

2. Income inequality is costly for all households



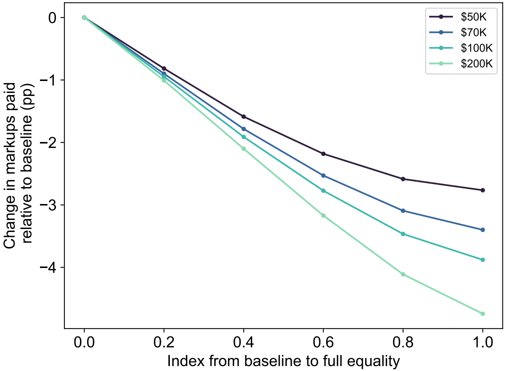
(a) Markups paid.



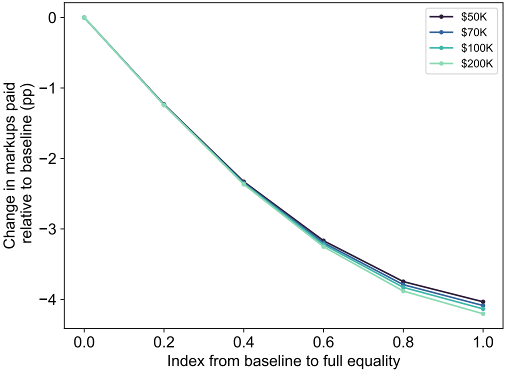
(b) Avg. price quotes received.

- Moving to full equality would reduce markups paid 2–5pp and search time 3–5%.

2. Differential costs for high-income households due to segmentation



(a) Model with segmentation ($K = 10$).



(b) Single-product model ($K = 1$).

- ↑ Inequality decreases agg. search more for products with high-income customers.
- With product segmentation, costs of inequality higher for high-income households.

3. Predicting markups across cities

- Apply calibrated search model to predict markups in granular markets.
  - Assume prices/markups set at retailer $\times$ product level (DellaVigna and Gentzkow 2019).
  - Use granular spending patterns data by retailer $\times$ product segment.
  - Out of sample test: Predict markups using $\phi(z)$ calibrated on aggregate data.
- For comparison, calculate markups predicted by standard nested CES calibration.
  - Approach frequently used to infer markups from market share / concentration data.
    (e.g., Atkeson and Burstein 2008, Smith and Ocampo 2023.)

3. Result: Model explains 35% of variation in CBSA markups

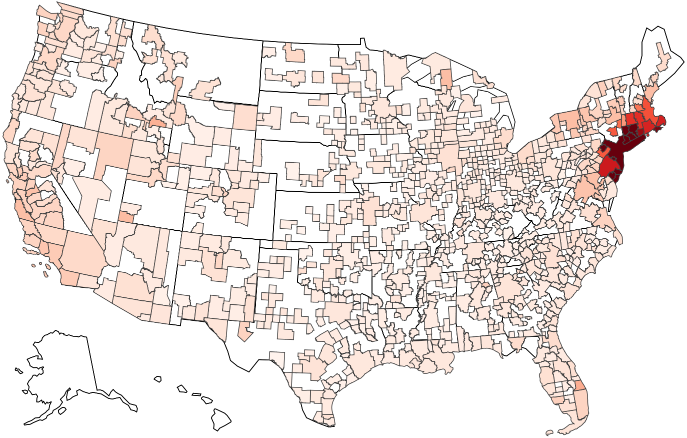
- Outperforms income measures alone as well as standard Nested CES calibration.
- Model-predicted markups across CBSAs increase with income level, inequality.

	Model-Predicted		Data			
Log CBSA Markup	(1)	(2)	(3)	(4)	(5)	(6)
Log CBSA Income	0.102**	0.095**	0.109**	0.091**		
	(0.006)	(0.007)	(0.016)	(0.012)		
Top 10% Income Share		0.041*		0.105**		
		(0.022)		(0.043)		
Log Model-Predicted Markup					0.918**	
					(0.109)	
Log Nested CES-Predicted Markup						-0.658**
						(0.153)
N	881	881	881	881	881	881
R^2	0.57	0.58	0.27	0.29	0.35	0.09

Binscatters →

4. Spatial spillovers: Effects of higher incomes among rich in New York

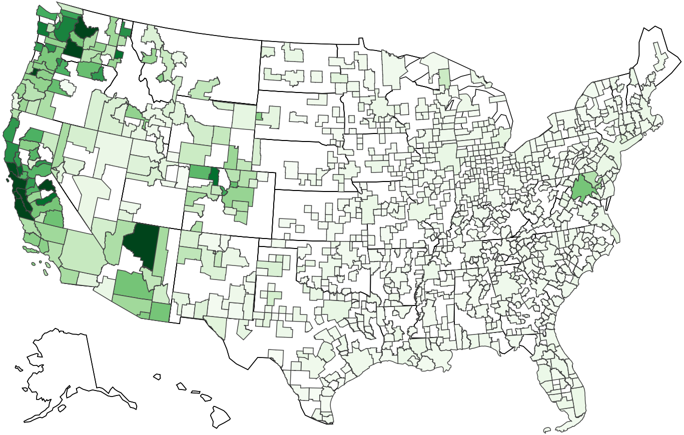
- Counterfactual exercises: permanently shock incomes of subset of households.
- #1: Double incomes of all households earnings over $100K in New York City.



CBSA	
New York - Newark - Jersey City, NY-NJ-PA	+5.49pp
Atlantic City - Hammonton, NJ	+1.80pp
Bridgeport - Stamford - Norwalk, CT	+1.74pp
Ocean City, NJ	+1.68pp
Trenton - Princeton, NJ	+1.47pp

4. Spatial spillovers: Effects of “Tech Recession”

- #2: Halve incomes of all households earnings over $100K in Bay Area.



CBSA	
San Jose - Sunnyvale - Santa Clara, CA	-6.19pp
San Francisco - Oakland - Berkeley, CA	-5.90pp
Santa Cruz - Watsonville, CA	-1.20pp
Yakima, WA	-1.18pp
Sonora, CA	-1.07pp

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Back-of-the-Envelope Estimates of Change in Markups over Time

1. Perfect price discrimination.
   - Households with post-tax real income z pay markup $\mu(z)$ in the data.

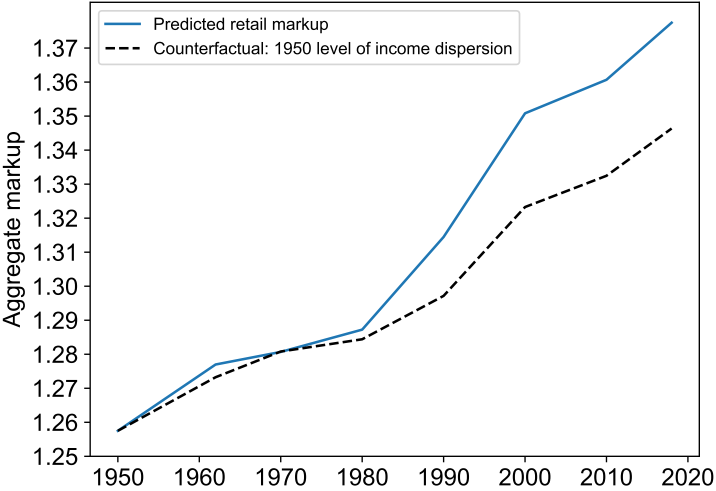
$$\Delta \text{ Income distribution 1950–2018} \to 6.4\text{pp}$$

2. Macro elasticity of markups to income in the data between 8–15%.
   - Per-capita post-tax real income grew 3.5x from 1950–2018.

$$1.32 \times \log(3.5) \times 0.08 = 13.2\text{pp}$$
$$1.32 \times \log(3.5) \times 0.15 = 23.2\text{pp}$$

   - Does not account for rising income dispersion ($\uparrow$).
   - May not fully account for strategic interactions in search intensity ($\downarrow$).

Counterfactual: Income distribution from 1950–2018

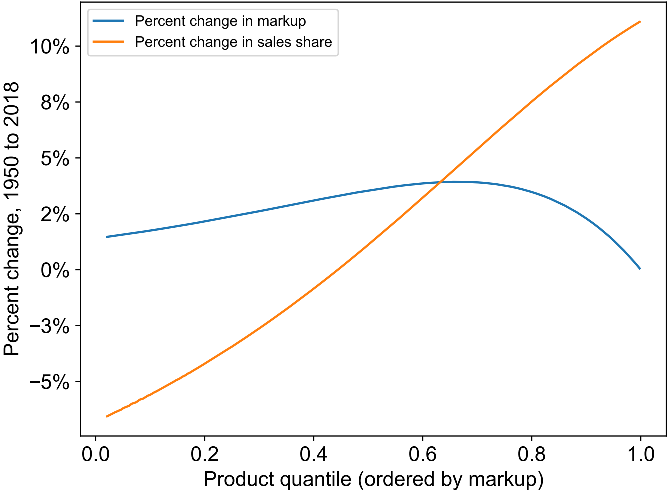


- 1950–2018 post-tax real income distribution from Saez and Zucman (2019).
- 12pp predicted increase in aggregate markup.
- Accelerates after 1980.
- After 1980, 30% due to ↑ income dispersion.

Table → Holding search fixed → Perfect price discrimination →

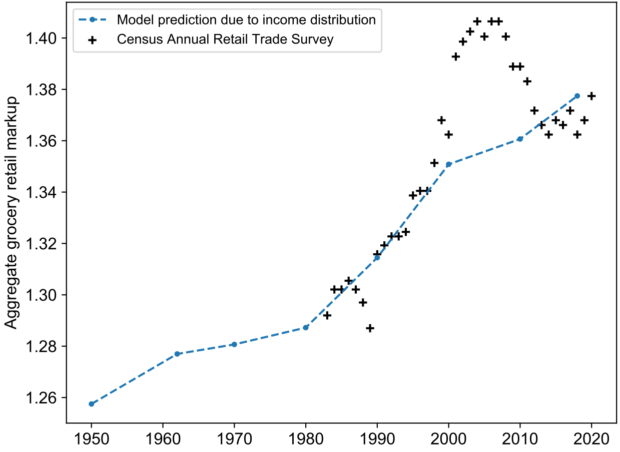
Reallocations across products vs. within-product changes

- Within segment, markups rise at all quantiles of distribution.
- Reallocation of sales to high-markup firms.
- 40% of increase due to cross-product reallocations.



Relative contributions →

Predicted rise in markups is quantitatively important



- Census Annual Retail Trade Stats. gross margins for retail grocery.
- Markup assuming constant returns.
- Effects of housing wealth (Stroebel and Vavra 2019) can explain markup boom-bust in 2000s.
- NBER calculations from 1869–1947 suggest rise in gross margins extends further back.

With Stroebel and Vavra (2019) effect → NBER & Census data on other sectors →

Broader questions

- **Does the rise in retail markups extend back before 1980?**
  - Sources: Historical NBER calculations (Barger 1955) and newly digitized Census of Annual Retail Trade Statistics from 1969–1977.
  - Suggest rise in markups extends further back before 1980.
- **Does the model predict markups will rise to infinity over time?**
  - Model suggests mild increases: e.g., doubling all incomes increases agg. markup 8pp.
  - As search intensities $\to 0$, markups approach Diamond (1971) limit.
- **What about the rise in markups in other sectors?**
  - Theory suggests $\downarrow$ price sensitivity can incr. markups upstream (Tirole 1988; Wu 2022).
  - Using upstream-downstream firm pairs from Compustat Customer Segments, I show that De Loecker et al. (2020) markups of suppliers increase with buyer income downstream.

Historical rise in markups $\to$ Future markups $\to$ Upstream-downstream analysis $\to$

Extensions

- **How important is modeling endogenous search decisions?**
  - Non-homothetic preferences model à la Handbury (2021) predicts 2x rise in markups.
  - Misses strategic interactions in search that moderate rise in markups.
- **Implications for level and evolution of consumption inequality.**
  - Gini index of consumption 2.5% lower than Gini of post-tax income.
  - Increase in Gini of consumption inequality from 1950 to 2018 is 5% lower.
- **How important is heterogeneity in tastes / segmentation?**
  - Varying $K = 1$ to 100, estimated rise in markups ranges from 11–16pp.
- **How important are pro-competitive effects of entry?**
  - With pro-competitive effects calibrated to Jaravel (2019), rise in markups of 10–13pp.

Non-homothetic preferences $\rightarrow$ Evolution of consumption inequality $\rightarrow$ Pro-competitive effect calibration $\rightarrow$ Varying K and ζ $\rightarrow$

Conclusion

- Conceptually, price elasticity depends on two things:
  - 1. Availability of alternatives (supply-side)
  - 2. Consumer propensity to switch to alternatives (demand-side)
- This paper: Income matters for #2.
- Changes in income distribution can generate large changes in markup distribution.
- Reallocations, $\uparrow$ markups occur without changing nature of production or competition.

Extra Slides

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Harrod's Law of Diminishing Elasticity of Demand

- *[...] the search for cheapness entails special efforts made on special occasions. During the growing affluence of the boom habits become hardened, part of the extra means are taken out in wastage due to not bothering too much. When incomes begin to fall people are forced to economize; cherished habits have to be abandoned willy-nilly. At this point they are shaken out of their lethargy; they begin to sit up and take notice. They resent and resist the curtailment of their wonted pleasures and become willing to take great pains to seek ways and means for mitigating their hardships. Their efforts to find cheapness become strenuous and eager.*

  Harrod (1936), pg. 86-87.

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PromoData Price-Trak UPC data coverage by income level

Table: Coverage of UPC wholesale costs data by income level.

Income group	Percent matched to wholesale cost data: Transactions	Percent matched to wholesale cost data: Expenditures	Average price index ($\hat{p}$): Matched	Average price index ($\hat{p}$): Unmatched
\$10–25K	41	38	-0.02	-0.05
\$25–40K	42	38	0.00	-0.02
\$40–60K	43	38	0.04	0.02
\$60–100K	44	37	0.09	0.09
Over \$100K	44	35	0.17	0.17
All	43	37	0.06	0.05

← Back

E-commerce shares by year

Table: E-commerce shares by year (Census Annual Retail Trade Survey).

	2002	2007	2012	2017	2021
All retail trade	1.4%	3.4%	5.4%	9.1%	14.6%
Food and beverage stores	$<$ 0.1%	0.2%	0.2%	0.5%	n/a
General merchandise stores	$<$ 0.1%	$<$ 0.1%	$<$ 0.1%	0.1%	n/a
Health and personal care stores	$<$ 0.1%	0.1%	$<$ 0.1%	$<$ 0.1%	n/a

← Back

Uniformity of wholesale prices across markets

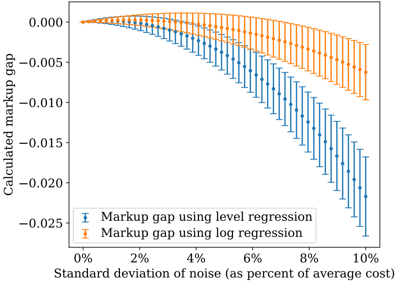
Table: Uniformity of wholesale prices across markets.

	Measure of wholesale cost	
	Base Price	Deal Price
Percent of items sold:		
At modal price ($\hat{w}^{x}_{i,m,t} = 1$)	80.3	78.5
Within 5% of modal price ($\lvert \hat{w}^{x}_{i,m,t} - 1 \rvert \leq 0.05$)	90.7	86.4
Within 10% of modal price ($\lvert \hat{w}^{x}_{i,m,t} - 1 \rvert \leq 0.10$)	95.1	90.9

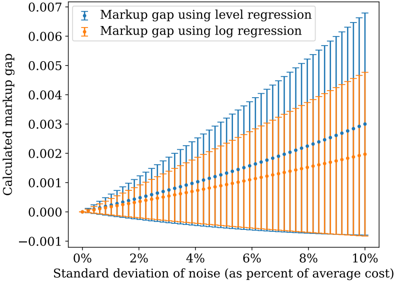
← Back

Noise in wholesale costs would not produce observed markup gap

- Concern: Wholesale costs are measured with noise.
  - Unit prices paid positively correlated with income $\Rightarrow$ upward bias in markup gap?
  - Monte Carlo simulations for additive and multiplicative noise with two groups, where average price paid by group 2 is 2x that of group 1.



(a) Case 1: $c^{\text{observed}} = c + \varepsilon$.



(b) Case 2: $c^{\text{observed}} = c(1 + \varepsilon)$.

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Share of sample used to estimate income FEs

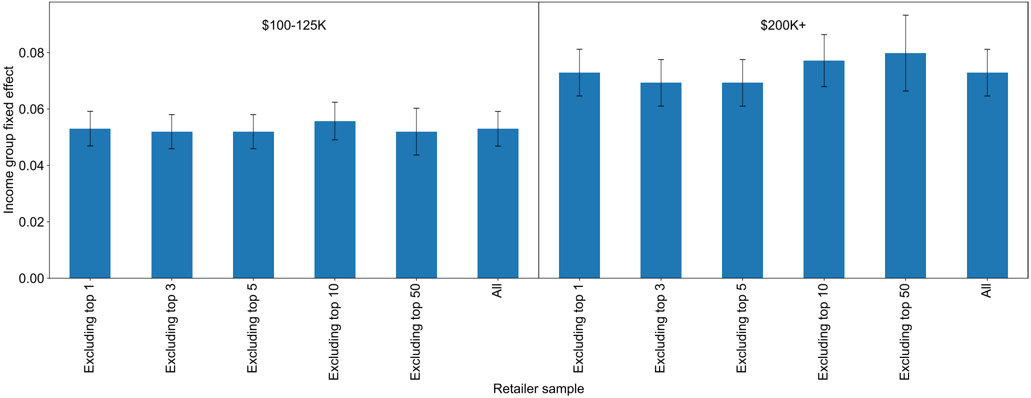
Table: Number of distinct income groups observed by split of data.

Income groups observed	County #	County %	Store #	Store %	Store-Group #	Store-Group %	Store-Module #	Store-Module %	Store-UPC #	Store-UPC %
1	522	22.4	5521	18.6	596789	46.6	2467644	66.5	10633656	91.0
2	395	17.0	5266	17.7	288777	22.6	718813	19.4	689980	5.9
3	285	12.2	4515	15.2	164995	12.9	284222	7.7	137352	1.2
4	239	10.3	3854	13.0	99343	7.8	127176	3.4	56502	0.5
5	178	7.6	3250	11.0	59608	4.7	60719	1.6	34727	0.3
6	168	7.2	2586	8.7	35415	2.8	29523	0.8	27564	0.2
7	162	7.0	2016	6.8	20084	1.6	13661	0.4	25053	0.2
8	135	5.8	1430	4.8	9987	0.8	5603	0.2	25522	0.2
9	87	3.7	798	2.7	3905	0.3	1840	0.0	22262	0.2
10	64	2.7	339	1.1	1188	0.1	525	0.0	19318	0.2
11	93	4.0	95	0.3	333	0.0	1067	0.0	18909	0.2
Share ≥ 1		77.6		81.4		53.4		43.5		9.0

← Back

No decline in within-store income effect excluding largest retailers

$$\text{Markup}_{i,g} = \sum_{\ell} \tilde{\beta}_{\ell} 1\{i \text{ has income level } \ell\} + \gamma' X_i + \alpha_{\text{Store}} + \varepsilon_{i,g}.$$



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Robustness of within-county and within-store markup gap

	Percent of markup gap within county (%)			Percent of markup gap within store (%)		
Income group	$70–100K	$100–125K	$200K+	$70–100K	$100–125K	$200K+
Baseline	74.8	76.4	73.4	66.6	66.1	53.1
Cost-weighted markups	82.6	82.5	79.5	70.1	69.5	59.2
Log markups	78.5	79.1	75.9	69.5	68.7	57.0
Using PromoData deal price	72.0	74.3	71.5	59.8	60.9	47.7
Using PromoData market data	69.8	77.6	78.8	69.7	70.7	62.1
Without demographic controls	84.5	77.1	73.8	77.4	69.8	52.4
Only top 100 product modules	74.3	76.2	73.3	71.5	70.3	60.0
Excluding perishable items	71.3	73.9	71.4	60.3	62.5	49.7

- Same result: ≈3/4 of markup gap persists within county, 1/2 within store.
- Link between income and markups not explained by UPC/brand sales shares, HHI.

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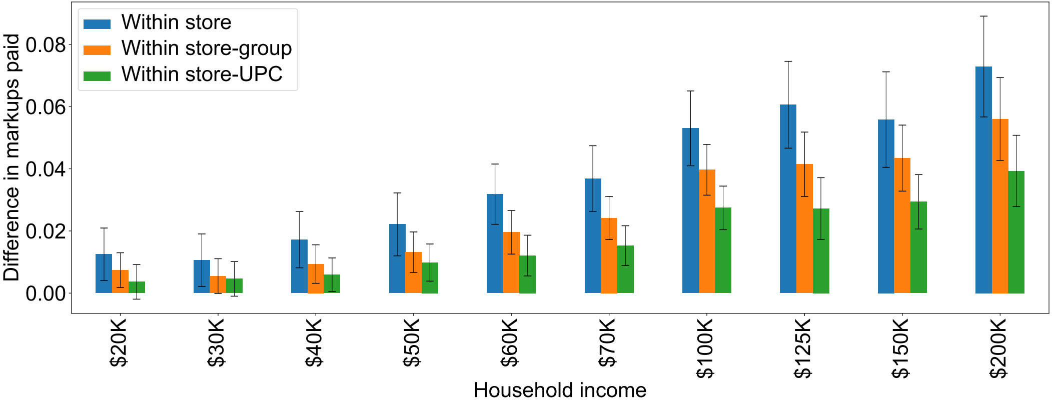
Understanding the gap in markups: Decomposition by module & UPC



$$\text{Markup}_{i,g} = \sum_{\ell} \tilde{\beta}_{\ell} 1\{i \text{ has income } \ell\} + \gamma' X_i + \underbrace{\alpha_{\text{Store}}}_{\text{Store FEs}} + \underbrace{\tilde{\alpha}_{\text{Store-Module}}}_{\text{Store-Module FEs}} + \underbrace{\hat{\alpha}_{\text{Store-UPC}}}_{\text{Store-UPC FEs}} + \varepsilon_{i,g}.$$

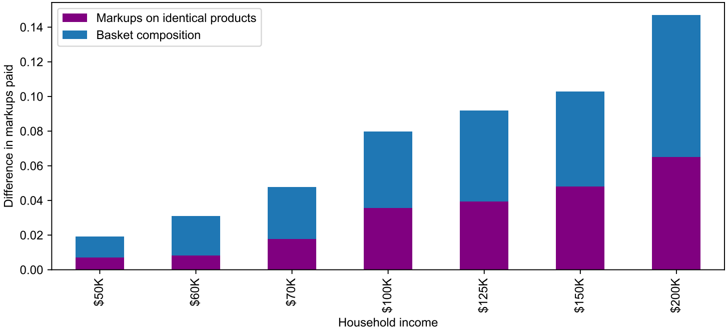
Graph shows FEs relative to group with <$20K reported income. Standard errors two-way clustered by brand and county.

← Back

Markups across goods account for over 50% of markup gap

- Decompose difference in sales-weighted markup between group i and o:

$$\mu_i - \mu_o = \sum_k \lambda_{ik}\mu_{ik} - \sum_k \lambda_{ok}\mu_{ok} = \underbrace{\sum_k \lambda_{ok}(\mu_{ik} - \mu_{ok})}_{\text{Differences in markups paid for identical goods}} + \underbrace{\sum_k \mu_{ik}(\lambda_{ik} - \lambda_{ok})}_{\text{Differences in basket composition}}$$



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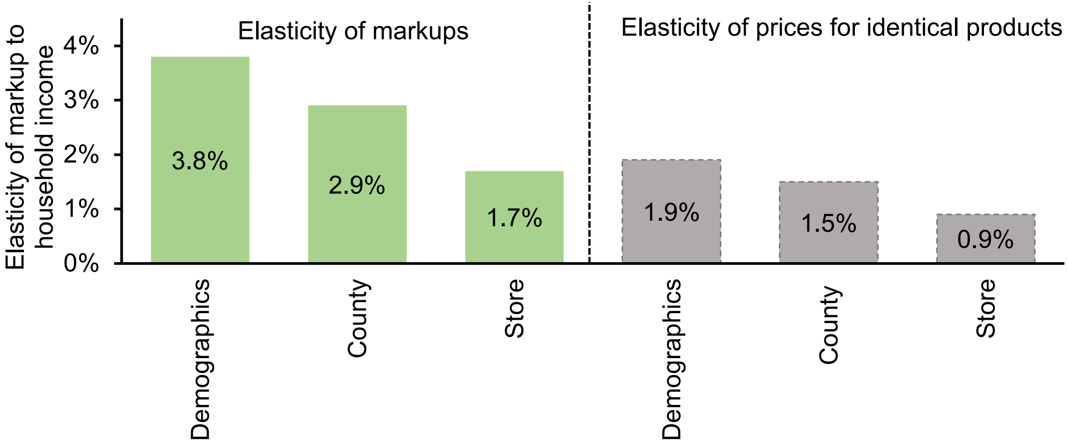
Why do high-income households pay higher markups?

- Markup gap is 2x larger than gap in prices paid for identical products.
  (Aguiar and Hurst 2007, Broda et al. 2009, Kaplan and Menzio 2015.)



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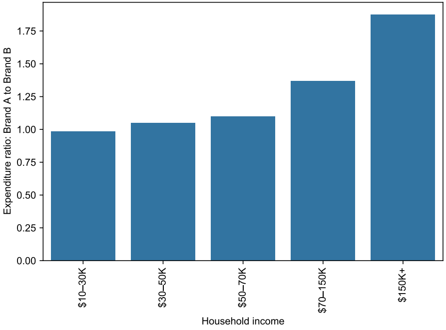
Within-household, over time elasticity of markups paid to income

- Nielsen Homescan records panelist income from two years prior to data collection.
- For households remaining in panel, get current income from reporting two years later.
- Result: Elasticity 0.1–0.3%.

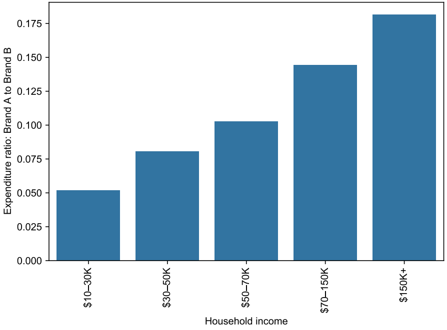
Log Retail Markup	(1)	(2)	(3)	(4)	(5)	(6)
Log Household Income	0.003**	0.001**	0.003**	0.001*	0.001	0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Household FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
County FEs			Yes	Yes		
Store FEs					Yes	Yes
UPC FEs		Yes		Yes		Yes
N (millions)	65.0	65.0	65.0	65	48.5	48.5
R^2	0.15	0.62	0.15	0.62	0.17	0.60

** is significant at 5%. Standard errors two-way clustered by brand and county.

Example: Within module, brands consumed by rich have higher markups



(a) Margarine brand 1 vs. brand 2.



(b) Potato chips brand 1 vs. brand 2.

- Margarine brand 1 has higher markups (average 38% vs. 23%).
- Potato chips brand 1 has higher markups (average 33% vs. 18%).

← Back

Elasticity of markups to own income and CBSA income

Log Retail Markup	(1)	(2)	(3)	(4)
Log Household Income	0.038**	0.033**	0.030**	0.020**
	(0.004)	(0.004)	(0.004)	(0.002)
Log Avg. CBSA Income		0.104**		
		(0.010)		
Demographic Controls	Yes	Yes	Yes	Yes
County FEs			Yes	Yes
Store FEs				Yes
N (millions)	25.8	23.8	25.8	14.0
R^2	0.00	0.01	0.02	0.08

** is significant at 5%. Standard errors two-way clustered by brand and county.

- Broda et al. (2009) elasticity of prices paid to income is 0.011–0.013.

Elasticity of markups to household income (IV)

Log Retail Markup	(1)	(2)	(3)	(4)
Log Household Income (fit)	0.057**	0.053**	0.051**	0.031**
	(0.008)	(0.008)	(0.005)	(0.003)
Log Avg. CBSA Income		0.092**		
		(0.011)		
Demographic Controls	Yes	Yes	Yes	Yes
County FEs			Yes	Yes
Store FEs				Yes
N (millions)	25.8	23.8	25.8	14.0
R^2	0.00	0.01	0.02	0.08

** is significant at 5%. Standard errors two-way clustered by UPC and household.

- IV for income: education and occupation category of heads of household.

← Back

De Loecker et al. (2020) markups increase with buyer income

- Buyer income of public retail firms from Baker et al. (2020).
- Sales shares of top firms in each NAICS-6 from 2012 Economic Census.

	All	Retail Firms (44–45)				
Log Production Function Markup	(1)	(2)	(3)	(4)	(5)	(6)
Log Avg. Buyer Income	0.229**	0.358**	0.439**	0.444**	0.443**	0.444**
	(0.085)	(0.067)	(0.094)	(0.094)	(0.094)	(0.095)
Top 4 Firms Sales Share			-0.101			
			(0.123)			
Top 8 Firms Sales Share				-0.067		
				(0.117)		
Top 20 Firms Sales Share					-0.082	
					(0.136)	
Top 50 Firms Sales Share						-0.071
						(0.139)
Year $\times$ NAICS-4 FEs	Yes	Yes	Yes	Yes	Yes	Yes
N	1706	898	693	693	693	693
R^2	0.76	0.71	0.68	0.68	0.68	0.68
Within R^2	0.02	0.17	0.21	0.21	0.21	0.21

** is significant at 5%. Standard errors two-way clustered by firm and year.

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Exploiting uniform retail pricing

- Retail chains tend to price uniformly across stores (DellaVigna and Gentzkow 2019) $\rightarrow$ households "pooled" with buyers in other counties shopping at same retail chain.
- Spillovers of buyers incomes at other locations, controlling for county.
- Threat to identification: Retail chains with stores in high-income counties locate at higher rent locations or buy more expensive factors within-county.
- Solution: Construct instrument for county income at other locations isolating only growth in county income at locations existing last year.

$$\text{Inc. at } \widehat{\text{Other Locations}} = \frac{1}{\text{\# Locations}} \sum_i \frac{\text{Inc. at Location } i \text{ in year } t}{\text{Inc. at Location } i \text{ in year } t-1}.$$

Exploiting uniform retail pricing: Results

- Macro elasticity OLS estimates in 8–15% range. IV estimates significantly higher.

Log Retail Markup	OLS	OLS	IV	IV
Log Household Income	0.020**	0.020**	0.017**	0.018**
	(0.003)	(0.003)	(0.003)	(0.003)
Log Avg. County Inc. at Other Retail Chain Locations	0.137**		0.547**	
	(0.036)		(0.132)	
Log Avg. County Inc. at Other Parent Locations		0.144**		0.372**
		(0.037)		(0.115)
Demographic Controls	Yes	Yes	Yes	Yes
County FEs	Yes	Yes	Yes	Yes
N (millions)	8.98	8.99	8.98	8.99
R^2	0.03	0.03	0.02	0.03

** is significant at 5%. Standard errors two-way clustered by brand and county.

Robustness for spillovers over time, 2006–2012

- Can include additional county-year FEs (uniform pricing) or store-year FEs (UPCs).

Log Retail Markup	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log Avg. CBSA Income	0.085**	0.069**					
	(0.017)	(0.014)					
Log(Income at Retailer Locations)			0.060**	0.071**	0.057*		
			(0.029)	(0.021)	(0.030)		
Log Avg. Income: Other UPC Buyers						0.159**	0.149**
						(0.042)	(0.039)
Household FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FEs	Yes		Yes				
Store FEs		Yes		Yes		Yes	
County-Year FEs					Yes		
Store-Year FEs							Yes
N (millions)	133	91.9	50.9	50.9	50.9	97	97
R^2	0.16	0.18	0.15	0.18	0.16	0.18	0.20

** is significant at 5%. Standard errors two-way clustered by brand and county.

← Back

Time series evidence consistent with macro elasticity in cross-section

- Use retail markups for all available years (2006–2012).
- Including CBSA FEs (δ_c) isolate changes over time:

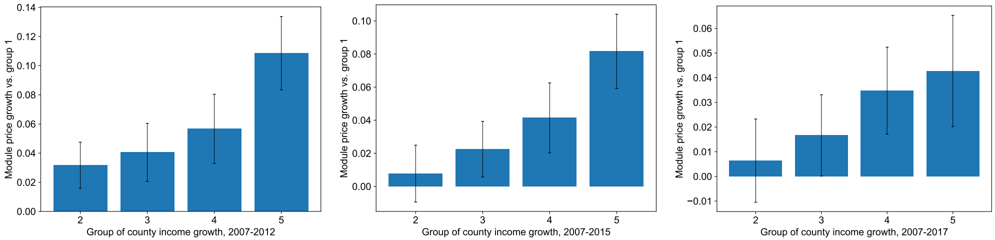
$$\text{Log CBSA Markup}_{c,t} = \beta \text{Log CBSA Income}_{c,t} + \alpha_t + \delta_c + \varepsilon_{c,t},$$

	Sales-weighted		Cost-weighted	
Log CBSA Markup	(1)	(2)	(3)	(4)
Log CBSA Income	0.114**	0.108**	0.088**	0.079*
	(0.019)	(0.026)	(0.015)	(0.036)
Year FEs	Yes	Yes	Yes	Yes
CBSA FEs		Yes		Yes
N	6101	6101	6101	6101
R^2	0.77	0.96	0.77	0.91

← Back

Time series evidence consistent with macro elasticity in cross-section

- Sort counties into quintiles of per-capita income from 2007–2017.
- Difference-in-differences: Unit price growth within product modules across counties.



- In paper: Cross-sectional and time series elasticities are similar in magnitude.

← Back

Similar cross-sectional and time series elasticities of unit prices to income

- Extend analysis using unit prices from 2004–2019.
- Isolate time series (columns 1 and 3) and cross-sectional (cols 2 and 4) elasticities:

	Years 2004–2019		2007 and 2017	
Log Avg. Unit Price	(1)	(2)	(3)	(4)
Log CBSA Income	0.130**	0.120**	0.091*	0.097**
	(0.024)	(0.021)	(0.055)	(0.046)
Year FEs	Yes		Yes	
CBSA-Product Module FEs	Yes		Yes	
CBSA FEs		Yes		Yes
Year-Product Module FEs		Yes		Yes
N (millions)	25.6	25.6	3.27	3.27
R^2	0.99	0.99	0.99	0.99

← Back

Spillovers controlling for house price effects

Log Retail Markup	(1)	(2)	(3)	(4)	(5)	(6)
Log Avg. CBSA Income	0.069**	0.037**				
	(0.014)	(0.014)				
Log Avg. Income: Retailer's Other Locations			0.071**	0.061**		
			(0.021)	(0.022)		
Log Avg. Income: Other UPC Buyers					0.159**	0.160**
					(0.042)	(0.042)
Log House Price Index		0.024**		0.017**		0.028**
		(0.008)		(0.006)		(0.007)
Household FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Store FEs	Yes	Yes	Yes	Yes	Yes	Yes
N (millions)	91.9	91.9	50.9	50.8	97.0	96.8
R^2	0.18	0.18	0.18	0.18	0.18	0.18

** is significant at 5%. Standard errors two-way clustered by brand and county. Annual county-level price indices from the Federal Household Finance Agency (Bogin et al. 2019).

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CBSAs with higher inequality have higher markups

Log CBSA Markup	Sales-weighted markup (1)	(2)	(3)	(4)	Cost-weighted markup (5)	(6)	(7)	(8)
Log CBSA Income	0.130**	0.103**	0.104**	0.113**	0.109**	0.091**	0.092**	0.098**
	(0.020)	(0.014)	(0.015)	(0.015)	(0.016)	(0.012)	(0.013)	(0.013)
Top 10% Income Share		0.159**				0.105**		
		(0.052)				(0.043)		
Top 5% Income Share			0.127**				0.082*	
			(0.057)				(0.047)	
Top 1% Income Share				0.101				0.065
				(0.071)				(0.059)
N	881	881	881	881	881	881	881	881
R^2	0.33	0.36	0.34	0.33	0.27	0.29	0.28	0.28

- Top 10% income share, rather than inequality at extreme top end, matters most for CBSA markups.

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Conditional on income, households in rich counties search more

	Log Shopping Trips per \$1K			*Log Unique Stores per \$1K*		
	(1)	(2)	(3)	(4)	(5)	(6)
Log Household Income (IV)	−0.40**	−0.40**	−0.40**	−0.35**	−0.34**	−0.34**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Log Avg. County Income		0.19**	0.10**		0.65**	0.27**
		(0.02)	(0.02)		(0.07)	(0.07)
Log Grocery Estabs.			0.03**			0.11**
			(0.00)			(0.01)
State FEs		Yes	Yes		Yes	Yes
County FEs	Yes			Yes		
N	63350	62865	62859	63350	62865	62859
R^2	0.14	0.09	0.09	0.23	0.11	0.14

* is significant at 10%, ** at 5%. Standard errors clustered by county.
Grocery Estabs. are NAICS 445 establishments from Census Business Patterns (includes grocery stores, supermarkets, liquor stores, and specialty food stores.)

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Relationship between total shopping time, income in model

- Suppose time function is mult. separable (with notation abuse): $t(c_i, s_i) = s_i t(c_i)$.

- Then, first order condition $+$ time constraint yield:

$$I_i = \frac{1}{1 + \varepsilon_s^p},$$

where elasticity of prices to search intensity is $\varepsilon_s^p = \frac{-\partial p_i}{\partial s_i} \frac{s_i}{p_i}$.

- Unfortunately, the elasticity of prices to search intensity is not monotonic in i:
  - $\frac{-\partial p_i}{\partial s_i}$ increasing in i (less you search, higher returns are),
  - s_i decreasing in i and $1/p_i$ decreasing in i.

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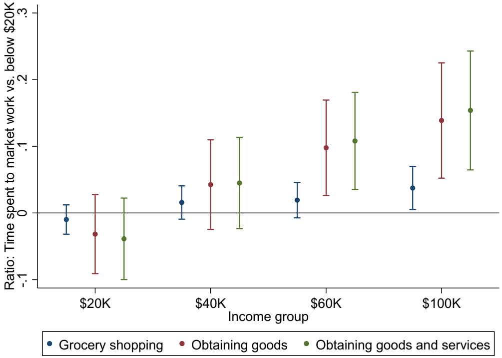
Ratio of total shopping time to market work time in ATUS

- Ratio of shopping time to market work time increasing in income.



$$(\text{ShoppingTime}/\text{MarketWorkTime})_{it} = \sum_{\ell} \beta_{\ell} 1\{i \text{ has income } \ell\} + \gamma' X_{it} + \alpha_t + \varepsilon_{it},$$

where X_{it} includes age, household size, race/ethnicity, and gender.

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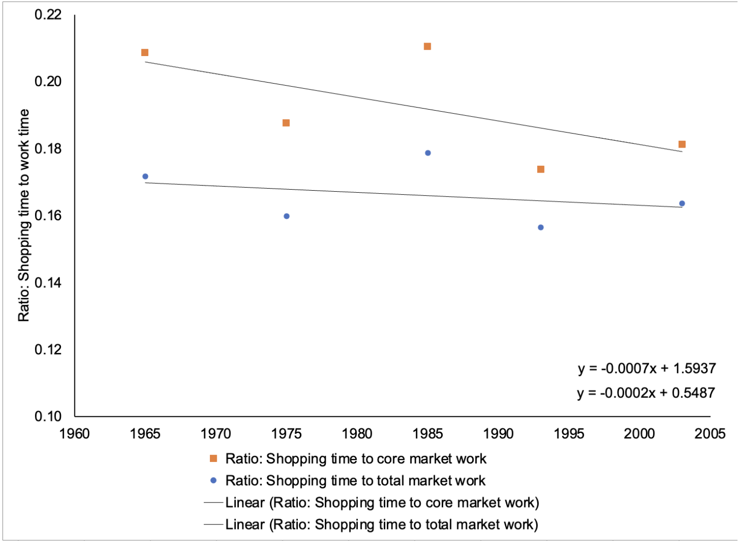
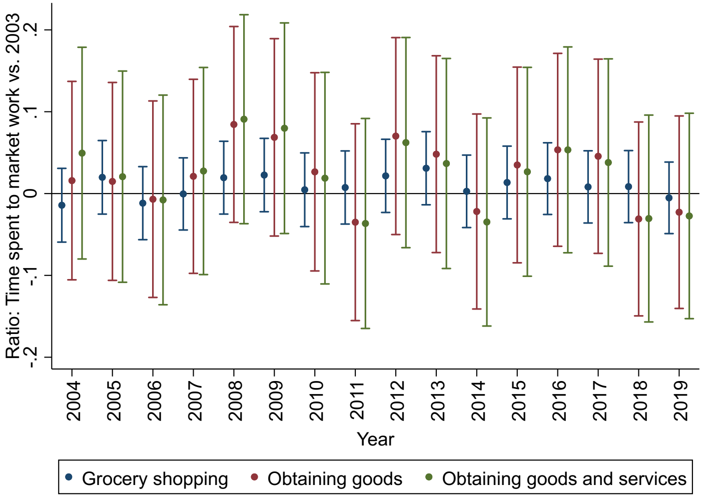
No strong trend in ratio of shopping time to work time in the data

Figure: Ratio of shopping time to work time from Aguiar and Hurst (2007b)



No trend in ratio of shopping time to market work time in ATUS 2003–19



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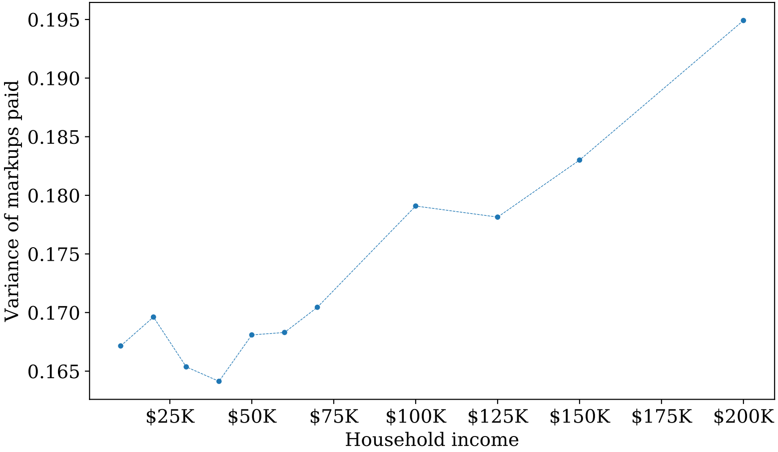
Variance of markups paid rises with income, consistent with search

Figure: Cost-weighted variance of markups paid by income group



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Model prediction: Comparative static on returns to scale α

- Calibration: High-income HHs have both higher labor prod. z and search prod. $a(z)$.
- However, $\frac{d}{dz}[a(z)c(z)^{\alpha-1}] < 1$, so opportunity cost $\phi(z)$ is still increasing in income:

$$\phi(z) = z/[a(z)c(z)^{\alpha-1}].$$

- Increasing α (returns to scale in search) should shrink differences in $\phi(z)$.
  - Thus, should reduce gradient of prices paid to income.
  - Use ticket size as empirical proxy for α: If search is a fixed cost, then returns to scale in search increase when ticket size is large relative to search cost.
- Prediction: $\gamma < 0$ in regression,

$$\text{Log(Price)}_{i,g,t} = \beta \log(\text{Income}_i) + \gamma \left(\text{Income}_i \times \text{AvgTicketSize}_g\right) + \varepsilon_{i,g,t}$$

Model prediction: Comparative static on returns to scale α

$$\text{Log(Price)}_{i,g,t} = \beta \log(\text{Income}_i) + \gamma \left(\text{Income}_i \times \text{AvgTicketSize}_g\right) + \varepsilon_{i,g,t}$$

Log Price	(1)	(2)	(3)	(4)	(5)
Log Household Income	0.017**	0.019**	0.017**	0.018**	0.015**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
Log Household Income × Log Ticket Size	−0.004**	−0.004**	−0.004**	−0.003**	−0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
UPC FEs	Yes	Yes	Yes	Yes	Yes
Demographic Controls		Yes	Yes	Yes	Yes
County FEs			Yes	Yes	Yes
Store FEs					Yes
N (millions)	59.8	59.8	59.8	29.6	29.6
R^2	0.99	0.99	0.99	0.98	0.98

* is significant at 10%, ** at 5%. Standard errors two-way clustered by brand and household county.

- Result: $\gamma < 0$. Price diff. across incomes $\downarrow$ as search cost falls relative to ticket size.

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Conditions on Mapping $\mathscr{S}$

$\mathscr{S} : s_i \mapsto \{q_{i,n}\}_{n=1}^{\infty}$ is such that the cumulative mass function $Q_{i,n}$ of $q_{i,n}$ satisfies:

1. If $s_i = 0$, $Q_{i,n} = 1$ for all n.
2. $Q_{i,n}(s_i)$ is weakly decreasing in s_i for all n and strictly decreasing for $n = 1$.
3. $Q_{i,n}(s_i)$ is C^{∞} for all n and all $s_i \geq 0$.

← Back

Two quote and Poisson mappings

- **Two quote**:

$$q_{i,1} = \exp(-s_i), \qquad q_{i,2} = 1 - q_{i,1}.$$

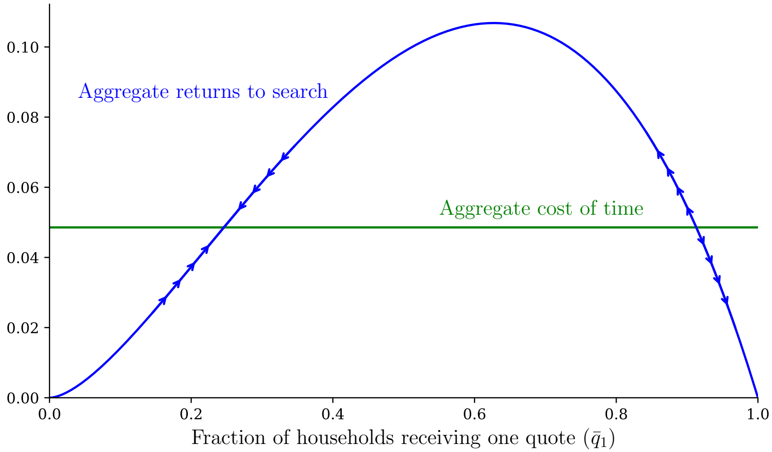
- **Poisson**:

$$q_{i,n+1} = \exp(-s_i)\frac{s_i^n}{n!}.$$

← Back

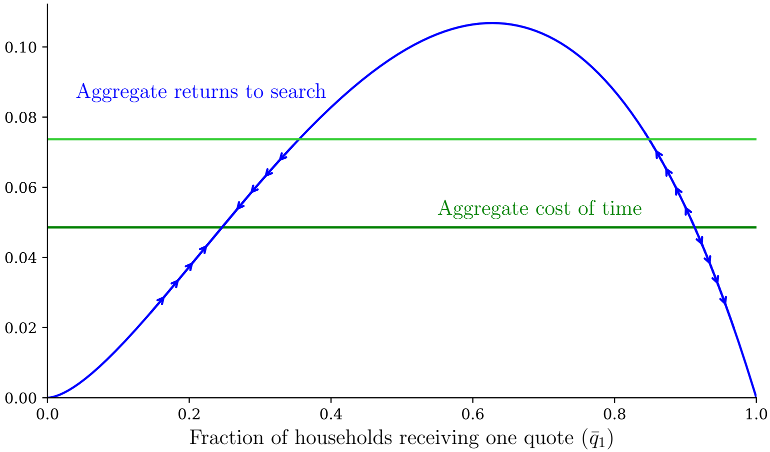
Stable Dispersed-Price Equilibrium

$$\underbrace{\int_0^{\infty} \sum_{n=1}^{\infty} \frac{-dQ_{i,n}}{ds_i} \left[\mathbb{E}\left[p|n\right] - \mathbb{E}\left[p|n+1\right]\right] d\Lambda(i)}_{\text{Aggregate returns to search}} = \underbrace{\int_0^{\infty} \phi_i d\Lambda(i)}_{\text{Aggregate cost of time}} \quad ,$$



Stable Dispersed-Price Equilibrium: Comparative Statics

$$\underbrace{\int_0^{\infty} \sum_{n=1}^{\infty} \frac{-dQ_{i,n}}{ds_i} \left[\mathbb{E}\left[p|n\right] - \mathbb{E}\left[p|n+1\right]\right] d\Lambda(i)}_{\text{Aggregate returns to search}} = \underbrace{\int_0^{\infty} \phi_i d\Lambda(i)}_{\text{Aggregate cost of time}} ,$$



Fraction households with one quote is sufficient statistic for agg. markup

Lemma

In equilibrium, the aggregate markup is

$$\bar{\mu} = 1 + \left(\frac{R}{mc} - 1\right)\bar{q}_1 .$$

- **Intuition.** Firm with highest price R only sells to households that get no other quote.
- Since all firms have identical profits, we must have

$$\pi = \frac{1}{M}(R - mc)\,\bar{q}_1 .$$

- Aggregate markup is

$$\bar{\mu} = 1 + \frac{\int_{\underline{p}}^{R}(p - mc)\,D(p)dF(p)}{\int_{\underline{p}}^{R} mcD(p)dF(p)} = 1 + \int_{\underline{p}}^{R}\frac{\pi}{mc}dF(p) = 1 + \left(\frac{R}{mc} - 1\right)\bar{q}_1 .$$

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Conditions on General Mapping $\mathscr{S}$

Condition (1)

The mapping $\mathscr{S} : s_i \mapsto \{q_{i,n}\}_{n=1}^{\infty}$ *satisfies*

$$\sum_{n=1}^{\infty} \frac{d^2 Q_{i,n}}{ds_i^2} \left[\mathbb{E}\left[p|n;F\right] - \mathbb{E}\left[p|n+1;F\right]\right] > 0,$$

for any non-degenerate distribution F*, where* $Q_{i,n}$ *is the CMF of* $\{q_{i,n}\}_{n=1}^{\infty}$ *and where* $\mathbb{E}[p|n;F]$ *is the expected value of the minimum of n draws from* F*.*

Condition (2)

The mapping $\mathscr{S}$ *satisfies*

$$\sum_{n=1}^{\infty} \left(\frac{d^2 q_{i,1}}{ds_i^2} \frac{d^2 Q_{i,n}}{ds_i^2} - \frac{dq_{i,1}}{ds_i} \frac{d^3 Q_{i,n}}{ds_i^3} \right) \left[\mathbb{E}\left[p|n;F\right] - \mathbb{E}\left[p|n+1;F\right]\right] \geq 0,$$

for any non-degenerate distribution F*, where* $Q_{i,n}$ *and* $\mathbb{E}[p|n;F]$ *are as defined above.*

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Results varying segmentation (K) and pro-competitive effect (ζ)

Table: Calibration results varying number of UPC segments (K) and pro-competitive parameter (ζ).

No. segments (K)	Predicted Δ markup 1950–2018 $\zeta = 0$	Predicted Δ markup 1950–2018 $\zeta = 0.3$	Markup externality low-income $\zeta = 0$	Markup externality low-income $\zeta = 0.3$	Markup externality high-income $\zeta = 0$	Markup externality high-income $\zeta = 0.3$
1	15.7pp	12.8pp	+10pp	+8pp	-19pp	-11pp
3	12.6pp	10.9pp	+7pp	+6pp	-13pp	-6pp
5	12.2pp	10.7pp	+6pp	+6pp	-12pp	-6pp
10	12.0pp	10.6pp	+6pp	+6pp	-12pp	-5pp
20	11.9pp	10.6pp	+6pp	+6pp	-11pp	-5pp
50	11.8pp	10.5pp	+6pp	+6pp	-11pp	-5pp
100	11.8pp	10.5pp	+6pp	+6pp	-11pp	-5pp

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Pro-competitive effects of entry

- Jaravel (2019) and Handbury (2021) find that $\uparrow$ share of high-income households leads to $\downarrow$ relative prices for high-income households.

- Augment model with pro-competitive effect of firm mass on search productivity:

$$a_{ikt} = \bar{a}_i M_{kt}^{\zeta},$$

  where
  - a_{ikt} is search productivity of household i in segment k in market t,
  - M_{kt} is mass of firms in segment k in market t,
  - ζ is elasticity of search productivity to mass of firms.

- Intuition: More stores $\Rightarrow$ less costly to get many quotes.

- As $\uparrow$ share of high-income, entry into top segments reduces relative markups.

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Elasticity of markups to CBSA incomes greatest for high-income households

- Suggests pro-competitive parameter $\zeta \leq 0$.

	2007	All years, 2006–2012	
Log Retail Markup	(1)	(2)	(3)
Log Avg. CBSA Income	0.089**	0.071**	0.064**
	(0.011)	(0.018)	(0.016)
Log Avg. CBSA Income × Mid-Income Group	0.016*	0.022**	0.006
	(0.008)	(0.009)	(0.005)
Log Avg. CBSA Income × High-Income Group	0.030**	0.036**	0.010
	(0.013)	(0.013)	(0.008)
Year FEs	Yes	Yes	Yes
Demographic controls	Yes		
Household FEs		Yes	Yes
County FEs		Yes	Yes
Store FEs			Yes
N (millions)	23.8	133	92
R^2	0.01	0.16	0.18

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Comparison of markup distribution in data to model

Percentile of markup distribution	\$20–\$30K Data	\$20–\$30K Model	\$50–\$60K Data	\$50–\$60K Model	\$100–\$125K Data	\$100–\$125K Model	Over \$200K Data	Over \$200K Model
10	0.78	1.11	0.82	1.12	0.89	1.13	0.94	1.15
25	1.02	1.14	1.04	1.15	1.08	1.17	1.13	1.19
50	1.25	1.19	1.26	1.20	1.31	1.24	1.37	1.28
75	1.50	1.32	1.52	1.34	1.58	1.42	1.65	1.51
90	1.80	1.58	1.81	1.62	1.89	1.78	1.99	1.98

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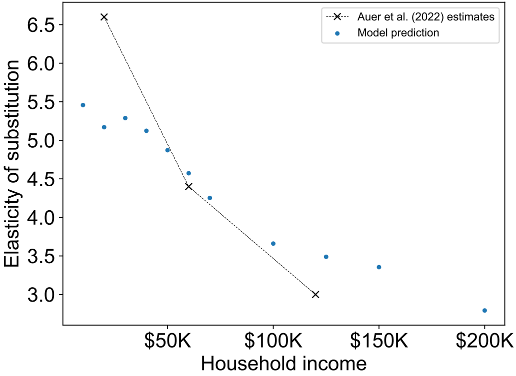
Comparison to estimates from Auer et al. (2022)

- Using agg. markup of economy with only households of type i, μ_i, construct equivalent elasticity of substitution $\sigma_i = \frac{\mu_i}{\mu_i - 1}$.



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Magnitude of markup spillovers across households

Table: Estimated savings (losses) relative to homogeneous income economies.

Income level	Markup savings (pp)	(%)	Average Nielsen expenditures ($K)	Estimated savings ($)
$10K	-6.1	-4.7	5.3	-254
$20K	-5.6	-4.3	6.2	-267
$30K	-6.2	-4.8	6.9	-332
$40K	-6.0	-4.6	7.4	-340
$50K	-5.4	-4.1	7.9	-328
$60K	-4.5	-3.4	8.3	-281
$70K	-3.4	-2.5	8.9	-223
$100K	0.3	0.2	9.5	20
$125K	1.7	1.2	9.7	116
$150K	2.8	2.0	10.6	216
$200K	11.8	8.2	10.6	863

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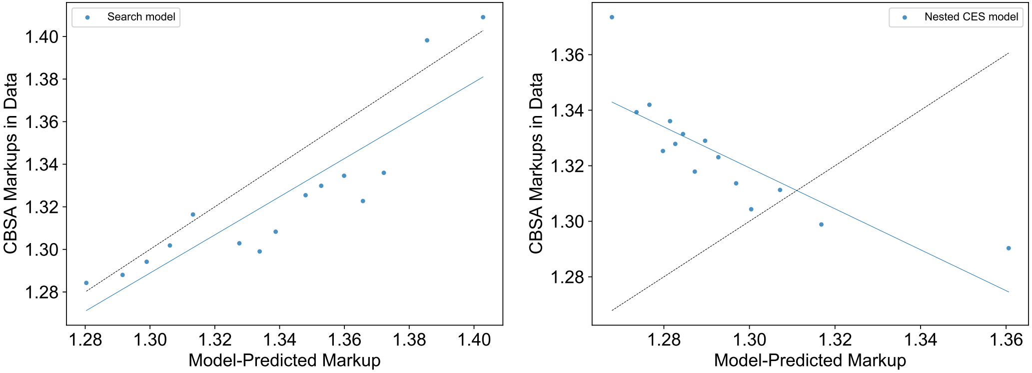
CBSA markups predicted by model vs. data: Binscatters



(a) Search model.

(b) Nested CES model.

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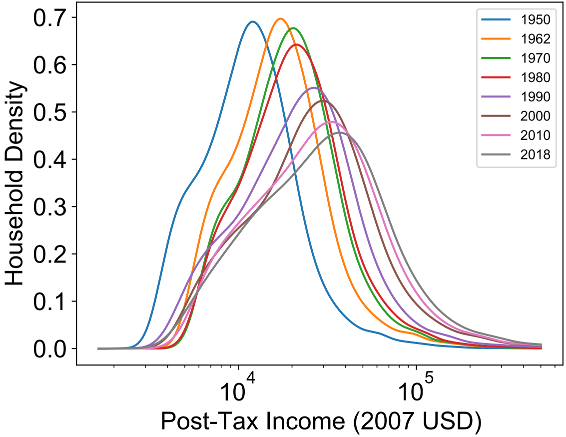
Income distribution from 1950–2018

Figure: Density $dH(i)$, constructed from data by Saez and Zucman (2019).



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Predicted change in aggregate retail markup from 1950–2018

Period	Predicted Δ in markup	Due to Δ Income level	Due to Δ Income dispersion	Due to Within-firm changes	Due to Cross-firm reallocations
1950–2018	12.0pp	8.9pp	3.1pp	6.7pp	5.3pp
1950–1980	3.0pp	2.7pp	0.3pp	1.7pp	1.3pp
1980–2018	9.0pp	6.2pp	2.8pp	5.3pp	3.7pp

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Predicted change in aggregate markup with perfect price discrimination

- Counterfactual: Perfect price discrimination.
- Average markup exactly reflects each income group's price elasticity.
- Macro elasticity $=$ micro elasticity. Result:

Period	Predicted Δ in markup	Portion due to Δ Income level	Portion due to Δ Income dispersion
1950–2018	6.4pp	5.1pp	1.3pp
1950–1980	1.9pp	1.7pp	0.2pp
1980–2018	4.5pp	3.3pp	1.2pp

← Back

Predicted change in aggregate markup, holding search constant

- Counterfactual: Search intensity fixed at 2007 calibration level.
- Since household search decisions are strategic substitutes, changes in search behavior attenuate change in markup in baseline model.
- Result: holding search intensity fixed augments predicted change in markup.

Period	Predicted Δ in markup	Portion due to Δ Income level	Portion due to Δ Income dispersion
1950–2018	15.5pp	11.3pp	4.2pp
1950–1980	3.8pp	3.5pp	0.4pp
1980–2018	11.6pp	7.8pp	3.9pp

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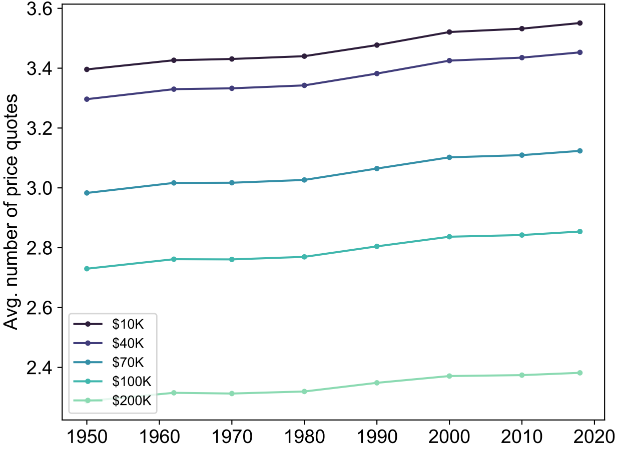
Predicted search intensities over time



- Since household search decisions are strategic substitutes, households' search intensity (conditional on income) rises as economy gets richer.

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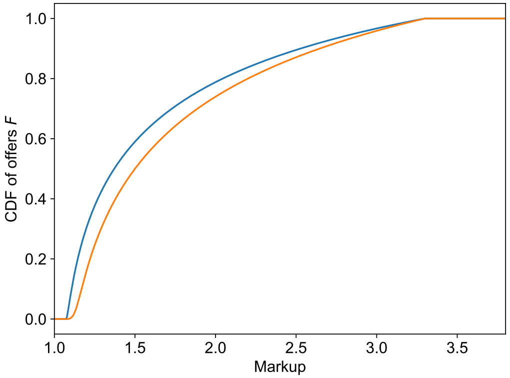
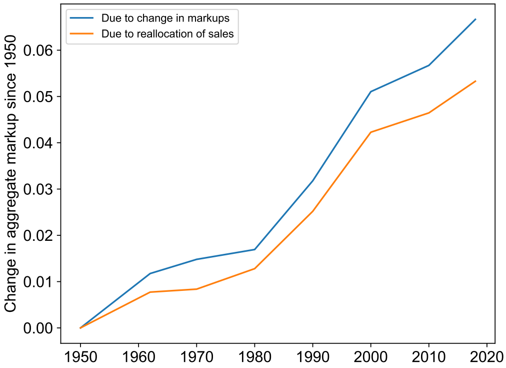
Within-firm markup changes and reallocations



(a) Predicted offer F in 1950 and 2018.



(b) Decomposition of change in agg. markup.

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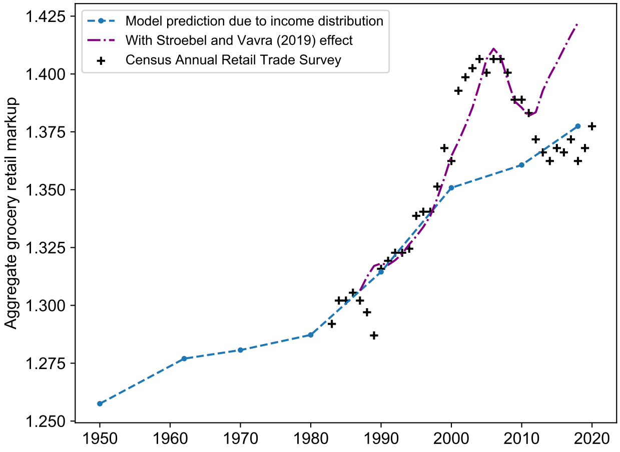
Including house price effect from Stroebel and Vavra (2019)



- Census Annual Retail Trade gross margins for retail grocery.
- Median OLS estimates from Stroebel and Vavra (2019) explain boom-bust in 2000s.

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Implications for level and evolution of consumption inequality

- Extrapolate markups paid on observed goods to rest of consumption bundle to estimate inequality in consumption (i.e., in costs of goods purchased).
- Result: Gini index of consumption 2.5% lower than Gini of post-tax income.
- Counterfactuals: Inequality in consumption grows slower than post-tax income.

Gini indices	Baseline year		1950	2018	Change	
Post-tax income	46.6	–	34.0	48.7	+14.7	–
Consumption net of markups						
Baseline ($\zeta = 0$)	45.5	*-2.5%*	33.6	47.5	+14.0	*-5.1%*
Pro-competitive effect ($\zeta = 0.3$)	45.5	*-2.5%*	33.6	47.5	+13.9	*-5.6%*

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Shopping time increases with basket size

- Conditional on income, demographics, and markups paid, higher basket size → more shopping time.
- Use household size as an IV for basket size.

	Log Shopping Trips		*Log Unique Stores*		*Log Unique Retailers*	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Log Expenditures	0.588**	0.617**	0.176**	0.044**	0.432**	0.159**
	(0.004)	(0.013)	(0.004)	(0.012)	(0.004)	(0.013)
Log Avg. Markup Paid	−0.688**	−0.694**	−0.172**	−0.144**	−0.344**	−0.285**
	(0.025)	(0.025)	(0.028)	(0.028)	(0.025)	(0.025)
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes
Income Level FEs	Yes	Yes	Yes	Yes	Yes	Yes
County FEs	Yes	Yes	Yes	Yes	Yes	Yes
N	63300	63300	63300	63300	63300	63300
R2	0.39	0.39	0.38	0.36	0.33	0.25

** is significant at 5%. Standard errors two-way clustered by firm and year.

← Back

Macro elasticity in IO models (I/II)

- Demand systems typically estimated in IO using Berry et al. (1995) preferences,

$$s_{ij} = \frac{\exp(\delta_{ij} - \alpha_i p_j)}{\sum_k \exp(\delta_{ik} - \alpha_i p_k)}, \qquad \text{where} \qquad \alpha_i = \bar{\alpha} + \pi_{yp} \log y_i + \varepsilon_i,$$

  where δ_{ij} is a demand-shifter for good j for household i and $\log y_i$ is i's log income (normalized to mean zero).

- Approximate macro elasticity of markups to income by considering how markups change if we take an economy with representative household and its perturb y_i.

$$\frac{\partial \log \mu}{\partial \log y_i} \approx -\frac{\mu - 1}{\mu} \frac{1}{\bar{\alpha}} \pi_{yp}.$$

Macro elasticity in IO models (II/II)

- Results for a few IO studies:

Paper	Industry	Estimates used μ	$\bar{\alpha}$	π_{yp}	Source	Est. Macro Elasticity
Nevo (2001)	Cereal	1.730	23.37	-1.12	Tables V, VIII	2.02%
Villas-Boas (2007)	Yogurt	1.409	5.8	-0.68	Tables 7, 9	3.40%
Nakamura and Zerom (2010)	Coffee	1.583	17.76	-3.24	Tables 5, 6	6.72%

- NOTE: To add estimates from my demand estimation in margarine.
- These estimates are small relative to estimates from the data (8–15%) and estimates in the trade literature (e.g., 12–24% in Simonovska 2015).
- Effect on markups within product category misses substitution to other categories, effect on aggregate markup.

Suggestive evidence: Income downstream can affect upstream markups

- In supply chains, $\downarrow$ elasticity at retailer $\uparrow$ markups upstream (Tirole 1988, Ch. 4).
- Wu (2022) shows that same intuitions hold in general production network.
- Empirically, markups of suppliers increase with buyer income at downstream firms.
  - Identify upstream-downstream firm pairs from Compustat Customer Segments data.
  - Firm markups from De Loecker et al. (2020), buyer income from Baker et al. (2020).

Markup at Upstream Firm	(1)	(2)	(3)	(4)
Log Avg. Buyer Income of Downstream Firm	0.103	0.078^{**}	0.085^{**}	0.076^{**}
	(0.119)	(0.033)	(0.031)	(0.033)
Year FEs	Yes	Yes	Yes	Yes
Year-Upstream Industry FEs		Yes	Yes	
Year-Downstream Industry FEs			Yes	
Year-Upstream Industry-Downstream Industry FEs				Yes
N	9092	8919	8484	7765
R^2	0.00	0.74	0.76	0.80

← Back

Country-level markups exhibit similar relationship with income

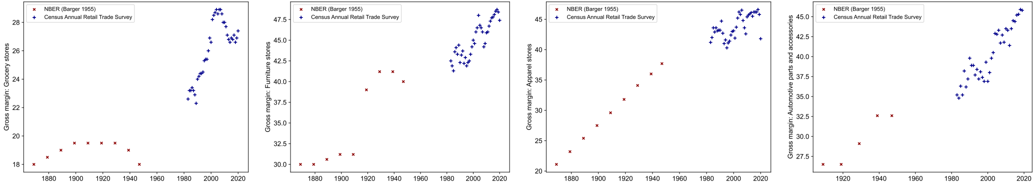
- Country-level markups estimated by De Loecker and Eeckhout (2018) (not limited to retail firms) also increase with income level and inequality.

	All years			2016 only
Log Country Markup	(1)	(2)	(3)	(4)
Log Per-Capita Income (PPP-adjusted)	0.073^{**}	0.214^{**}	0.062^{*}	0.136^{**}
	(0.035)	(0.088)	(0.031)	(0.052)
Gini Index	1.015^{**}	1.991^{**}	0.993^{**}	0.276
	(0.220)	(0.657)	(0.197)	(0.640)
Country FEs		Yes		
Year FEs			Yes	
N	642	642	642	29
R^2	0.15	0.64	0.30	0.12

← Back

Were markups rising before 1980?

- Combine digitized data on gross margins from Census Annual Retail Trade 1983–2019 with historical data from NBER report by Barger (1955).
- Digitized data from Census Annual Retail Trade for 1969–1977 also follows trend.



(a) Grocery stores. (b) Furniture stores. (c) Apparel stores. (d) Auto accessories.

← Back

Predictions for future markups

- Model suggests mild increases in the aggregate markup as incomes continue to rise.
  - Doubling all incomes (25 years at 3% growth) increases aggregate markup 12pp.
  - Making avg. income equal to Jackson Hole, WY would increase aggregate markup to 1.5.
- Even in the limit as all search intensities approach zero, markups are bounded. (Approach Diamond 1971 monopoly price.)
- Offset by decreases in income inequality, improvements in search technology.

← Back

Elasticity of retail establishments to income

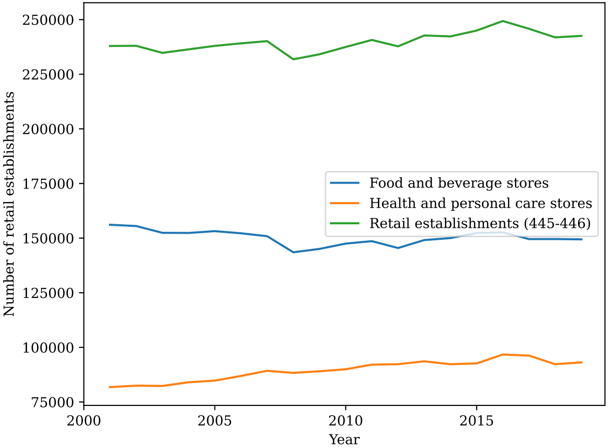
Log Retail Establishments	(1)	(2)	(3)
Log County Income (deflated)	0.395**	0.582**	−0.586**
	(0.080)	(0.070)	(0.082)
Log Population	0.930**	0.925**	0.671**
	(0.017)	(0.016)	(0.072)
Year FEs		Yes	
County FEs			Yes
N	57 185	57 185	57 185
R^2	0.92	0.92	0.98

Notes: Retail establishments include all NAICS 445 and 446 establishments (supermarkets, grocery, convenience, health, and personal care stores) from Census Business Patterns 2000–2019. Standard errors two-way clustered by state and year. ** indicates significance at 5%.

← Back

Total number of retail establishments

Figure: Total retail establishments in the U.S., from Census Business Patterns.



← Back

Robustness of results to elasticity of substitution across segments

Table: Calibration results varying elasticity of substitution across segments.

No. segments (N)	Elasticity of substitution across segments	Predicted Δ markup, 1950–2018
5	0	10.778pp
5	0.5	10.778pp
5	1	10.778pp
5	2	10.778pp
5	5	10.778pp
5	10	10.779pp
5	20	10.781pp
5	50	10.789pp

- Changes in elasticity of substitution across segments do not materially change results.

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Intuition: Why elasticity of substitution across segments has little effect?

- Consider CES case, where aggregate elasticity of demand in segment k is:

$$\sigma_k = \frac{\int_z \sigma(z)\lambda(z)\text{Share}_{zk}}{\int_z \lambda(z)\text{Share}_{zk}}.$$

In response to change in income distribution $\lambda(z)$, assuming $\sigma(z)$ fixed, we get

$$\begin{aligned} d\log\sigma_k &= \int_z \left[\frac{\sigma(z)\lambda(z)\text{Share}_{zk}}{\int_{z'}\sigma(z')\lambda(z')\text{Share}_{z'k}} - \frac{\lambda(z)\text{Share}_{zk}}{\int_{z'}\lambda(z')\text{Share}_{z'k}}\right](d\log\lambda(z) + d\log\text{Share}_{zk}) \\ &\approx \int_z \left[\frac{\sigma(z)\lambda(z)\text{Share}_{zk}}{\int_{z'}\sigma(z')\lambda(z')\text{Share}_{z'k}} - \frac{\lambda(z)\text{Share}_{zk}}{\int_{z'}\lambda(z')\text{Share}_{z'k}}\right] d\log\lambda(z), \end{aligned}$$

if $d\log\text{Share}_{zk} = -\varepsilon(d\log\frac{p_{ik}}{P_i}) \approx$ const across all z.

← Back

Non-homothetic CES model

- Suppose non-homothetic utility as in Handbury (2021):

$$\max C_i = \left[\int_0^1 \left[q_k(C_i) \right]^{\frac{1}{\sigma(C_i)}} \left(c_{ik} \right)^{\frac{\sigma(C_i)-1}{\sigma(C_i)}} Mdk \right]^{\frac{\sigma(C_i)}{\sigma(C_i)-1}} .$$

- Calibrate σ_i and $q_{i,k}$ across 100 segments to match average markups by income group and purchase shares in each segment. Result:

Period	Predicted Δ agg. markup	Portion due to Δ Income level	Portion due to Δ Income dispersion
1950–2018	21.6	12.8	8.8
1950–1980	3.8	3.5	0.3
1980–2018	17.7	9.2	8.5

- Larger increase in agg. markup because no strategic increase in search intensity.

← Back

Search and other non-homotheticities: Role in within-store markup gap

	(1)	(2)	(3)	(IV)
Log Household Income	0.020**		0.007**	0.187**
	(0.002)		(0.002)	(0.009)
Log Shopping Trips per $1K Purchases		-0.055**	-0.053**	
		(0.002)	(0.003)	
Demographic Controls	Yes	Yes	Yes	Yes
County FEs	Yes	Yes	Yes	Yes
Store FEs	Yes	Yes	Yes	Yes
N (millions)	14.0	14.0	14.0	14.0
R^2	0.08	0.09	0.09	0.03

** is significant at 5%. Standard errors two-way clustered by brand and county.

- Household search effort associated with lower markups paid within store.
- After controlling for search, income still plays role in markups paid.

← Back

Related models of income and markups: Comparison

Model	Comparison to data
Oligopolistic competition e.g., Atkeson and Burstein (2008)	Sales shares and concentration do not explain link between income and retail markups.
Bounded marginal utility e.g., Simonovska (2015), Neiman and Vavra (2019)	Markup is decreasing in share of households purchasing product.
Differentiation and finicky tastes e.g., Hummels and Lugovskyy (2009), Brand (2021)	No clear relationship between markup and measures of module differentiation.
Heterogeneous price-elasticities by product	Conditional on product purchased, household income still associated with markup paid.
Perfect price discrimination	Markup paid depends on income of other UPC buyers, county income.
Sales-based discrimination e.g., Varian (1980)	Markups paid by households at all income levels increase with county and other buyer income.
Non-homothetic CES e.g., Handbury (2021), Faber and Fally (2022)	Price dispersion within products.

← Back

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