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 markups rising for several decades.
  De Loecker et al. (2020), Barkai (2020), Autor et al. (2020), Gutiérrez (2017).

- Prevailing explanations: changes to competition, conduct, or production.
  - E.g., lax antitrust enforcement, rise of superstar firms, structural technological change.
    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**:
  - Retail markups (price / wholesale cost) on 26M transactions.
  - 1. High-income households pay 15pp higher markups.
    - Within store, high-income pay 7pp 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)
  - 2. Markups paid depend positively on incomes of other households.
    - "Macro" elasticity of markups to income $>$ micro elasticity.

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  - 2. 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.
  - Analytic results: Conditions under which $\uparrow$ income levels, inequality raise markups.

Household Income and Firm Markups: Micro Evidence, Macro Effects

- **Macro implications**:
  - Spillovers: wealthy shoppers increase markups for low-income by 5–9pp.
  - Inequality: Raises markups 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 12pp rise in retail markup.
    - Accelerates after 1980 due to $\uparrow$ income dispersion.
    - 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).
    - Accounting for basket composition doubles markup gap.
  - *Varying price elasticities*: 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).
  - *IO literature*: Nevo (2001), Villas-Boas (2007), Nakamura and Zerom (2010), etc.
    - Measuring micro- vs. macro-level relationships.
- **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), Nord (2022), Menzio (2023).
    - How income distribution affects markups in heterogenous-household model.
- **Evolution of retail markups**
  - Neiman and Vavra (2019), Brand (2021), Döpper, MacKay, Miller, and Stiebale (2021).

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Data

1. NielsenIQ Homescan.
   - 62 million transactions by 60,000 households in 2007.
   - Nationally representative sample across 2700 counties.
   - Panelist incentives (e.g., sweepstakes) for accurate reporting.
   - Fast-moving consumer goods covering 35% of CEX nondurables. (Broda and Parker 2014.)
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 Berry, Levinsohn, and Pakes (1995) markups in one module.
- Average (cost-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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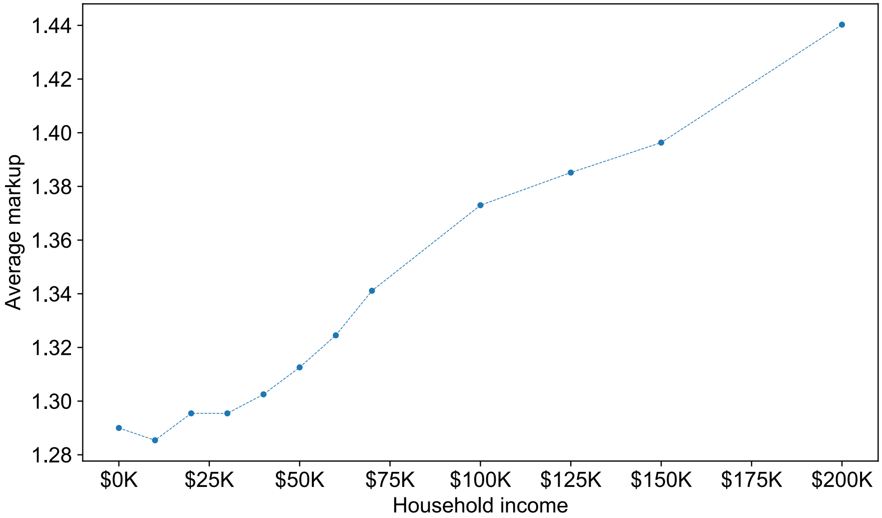
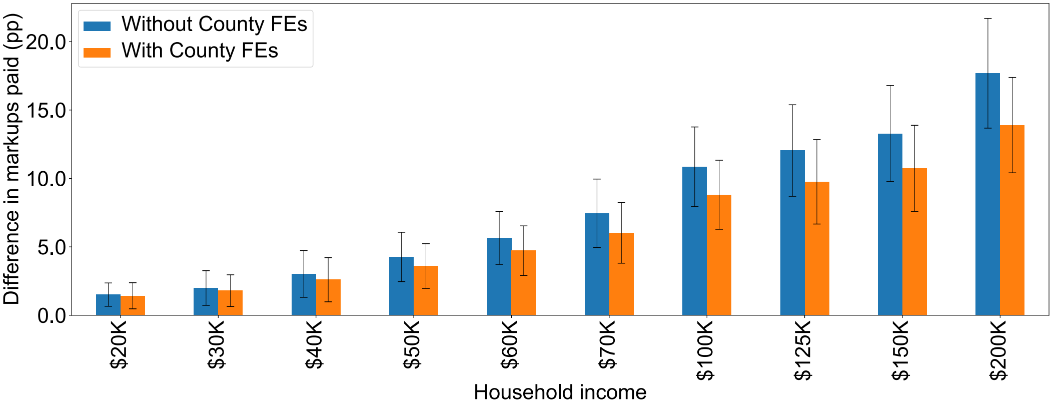
Average markup paid increases with household income

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



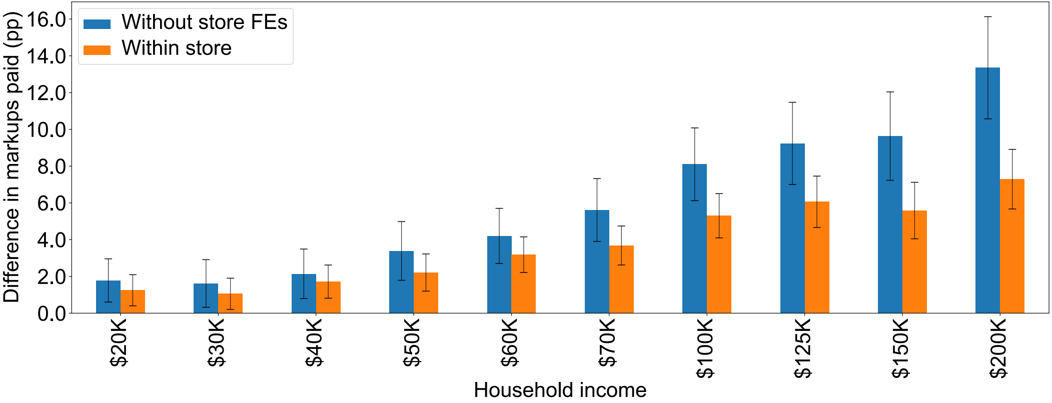
14pp gap in markups paid within county



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

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	Within County	Within Store
Baseline	17.7	13.9	7.3
With supply-side controls	17.4	13.6	7.2
Weighting by sales	17.8	12.7	6.1
Using PromoData base price	16.0	12.7	7.9
Using PromoData market-level price	16.3	11.7	8.9
With day-of-week fixed effects	17.5	13.8	7.1
Excluding perishable items	17.1	13.4	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 →

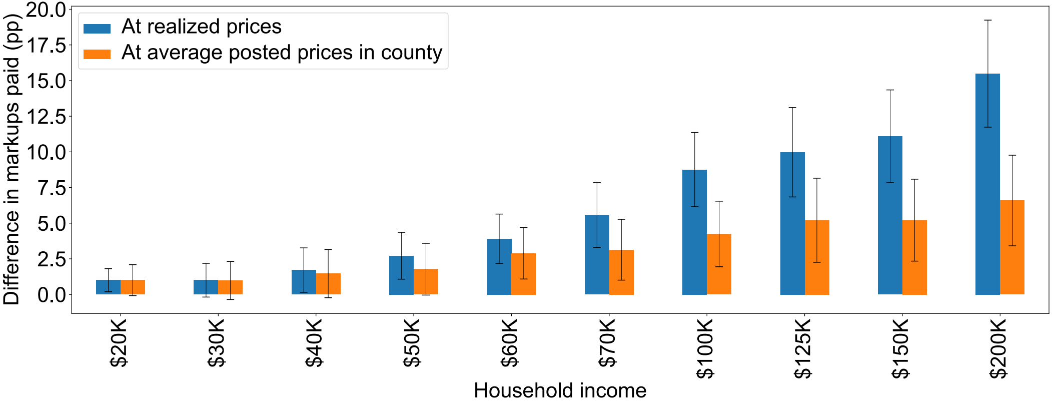
Accounting for the markup gap

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 $\approx$ 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.)
   - Cost data uniquely enables comparison across products.
   - Responsible for $\approx$ 50% of markup gap.

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

Decomposition $\rightarrow$ Within-store markup gap decomposition $\rightarrow$ Elasticities $\rightarrow$

Decomposition: Basket composition vs. search



- Construct avg. posted price for UPC in county using Retail Scanner data.
- Markup gap at avg. posted price removes search, isolates basket composition.

Accounting decomposition →

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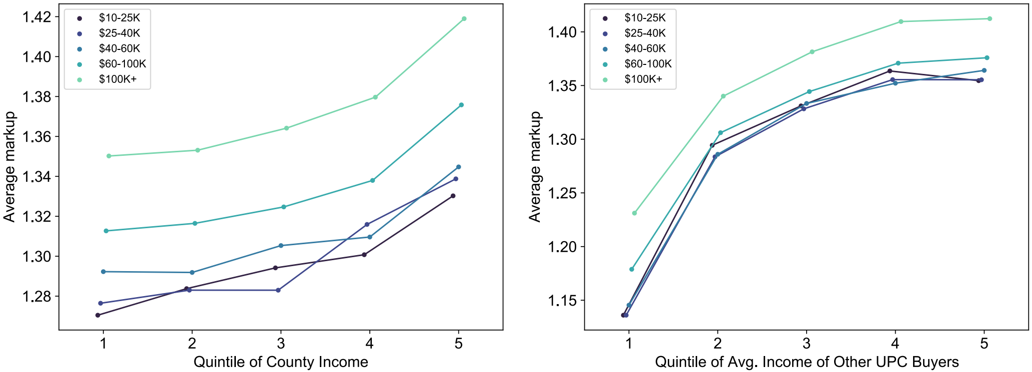
Conditional on income, markups rise with income of other buyers



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

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

Identifying spillovers

- Construct retail markups using wholesale cost data from 2006–2012.
- Exploit time series variation in other buyers' incomes (with household & store FEs).

Identifying spillovers

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1. Variation in local CBSA income:

$$\log \text{Markup}_{i,s,t,k} = \beta_1 \log \text{CBSA Income}_{\text{CBSA}(i),t} + \underbrace{\gamma_{i,\text{IncomeLevel}(i,t)} + \alpha_s + \delta_t}_{\substack{\text{Household} \times \text{Income FEs} \\ \text{Store FEs} \\ \text{Year FEs}}} + \varepsilon_{i,s,t,k}.$$

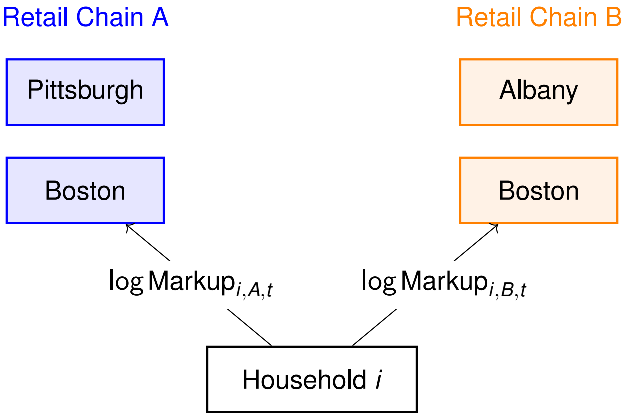
2. Variation in avg. income at retail chain's locations:

$$\log \text{Markup}_{i,s,t,k} = \beta_2 \log \text{Income at Retailer Locations}_{\text{Retailer}(s),t} + \underbrace{\gamma_{i,t} + \alpha_s + \phi_{\text{County}(s),t}}_{\substack{\text{Household-Year FEs} \\ \text{Store FEs} \\ \text{County-Year FEs}}} + \varepsilon_{i,s,t,k}.$$

- Controls for unobserved household characteristics ($\gamma_{i,t}$), store-level costs (α_s), time-varying local costs ($\phi_{\text{County}(s),t}$).

Identifying spillovers: Example

$$\log \text{Markup}_{i,s,t,k} = \beta_2 \log \text{Income at Retailer Locations}_{\text{Retailer}(s),t} + \gamma_{i,t} + \alpha_s + \phi_{\text{County}(s),t} + \varepsilon_{i,s,t,k}.$$



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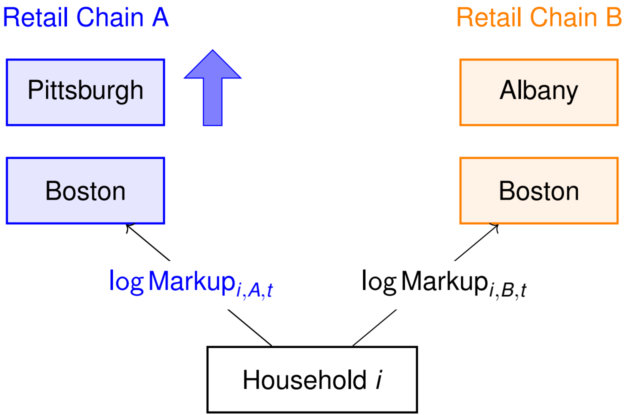

Spillovers using 2006–2012 variation: Macro elasticity between 8–15%

Log Retail Markup	(1)	(2)	(3)
Log CBSA Income	0.071**		
	(0.013)		
Log Income at Retailer's Locations		0.068**	
		(0.030)	
Log Income of Other UPC Buyers			0.142**
			(0.038)
Household $\times$ Income Level in Year FEs	Yes		
Year FEs	Yes		
Household-Year FEs		Yes	Yes
Store FEs	Yes	Yes	
Store County-Year FEs		Yes	
Store-Year FEs			Yes
N (millions)	91.9	50.8	97.0
R^2	0.19	0.21	0.21

Regression weighted by sales. SEs two-way clustered by brand & county.

- Macro elasticity $=$ 2–3% (elasticity to own income) $+$ 6–14% (spillovers).

Additional FEs → Cross-section →

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Search Model of Income and Markups

- 1. Households have different tastes for goods.
    - $\Rightarrow$ Basket composition varies across households.
- 2. Households have different (endogenous) search intensities.
  Aguiar and Hurst (2007), Alessandria and Kaboski (2011), Kaplan and Menzio (2016), Pytka (2018).
    - Tug-of-war between opportunity cost of time and search productivity.
    - $\Rightarrow$ Price dispersion for identical products (spatial / intertemporal).
- PE effects: Search $+$ basket composition.
- GE effects: Composition of buyers $\rightarrow$ distribution of firm markups.

Household Preferences Over Goods

- Utility for household i comes from consumption of goods $k = 1, ..., K$:

$$u(\{c_{ik}\}) = \left(\sum_{k=1}^{K} (\beta_{ik} c_{ik})^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}},$$

  where β_{ik} is a taste shifter for good k and c_{ik} is i's consumption of k.

- Taste shifters β_{ik} will determine different basket composition across households.
  - Allowing σ to vary with i is isomorphic in cross-section (but not time series).

Household Search Technology

- For each good, households know the price distribution, but not firms' individual prices.
- Household i buying good k has probability mass function over no. of quotes $\{q_{ik,n}\}_{n=1}^{\infty}$,
  - Observes only one price quote with probability $q_{ik,1}$,
  - Observes two price quotes with probability $q_{ik,2}$, 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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- For each purchase, households buy iff min price $p \leq$ reservation price R.
  Redraw n quotes costlessly if $p > R$.
- Endogenous search decision: Household i chooses search intensity s_{ik} for each k.
- Mapping function from search intensity to probability of observing n price quotes,
  $\mathscr{S} : s_{ik} \mapsto \{q_{ik,n}\}_{n=1}^{\infty}$.

Household Problem

$$\max\ u(\{c_{ik}\}) \qquad \text{s.t.} \qquad \begin{cases} \sum_k t_i(c_{ik}, s_{ik}) + l_i = 1, & \text{(Time constraint)} \\ \sum_k p_{ik} c_{ik} = z_i l_i. & \text{(Budget constraint)} \end{cases}$$

where

- c_{ik} is units of good k consumed,
- l_i is time spent working with labor productivity z_i.
- $t_i(c_{ik}, s_{ik})$ is the time it takes i to shop for c_{ik} units with search intensity s_{ik}.
- p_{ik} is the average price paid by i for good k (deterministic over continuum of units).

- Let $t_i(c_{ik}, s_{ik}) = c_{ik} s_{ik} / a_i$.
  - Search productivity a_i can reflect technologies (e.g., car) or returns to scale in shopping.

- First order condition:

$$\underbrace{-\partial p_{ik} / \partial s_{ik}}_{\text{Marginal savings}} = \underbrace{\phi_i}_{\text{Opportunity cost}}$$

where opportunity cost of increasing search intensity $\phi_i = z_i / a_i$.

Shopping time increases with basket size →

Firm Problem

- Mass M_k of firms pay $f_e \cdot w$ to enter market for good k.
- Constant returns production with marginal cost w.
- Define aggregate search behavior for good k as $\bar{q}_k$,

$$\bar{q}_{k,n} = \int_0^\infty q_{k,n}(z) d\Lambda_k(z), \qquad \text{for all } n,$$

where $H(z) =$ CDF of household incomes, consumption $C_k = \int_0^\infty c_k(z) dH(z)$, and density of buyers' incomes for k is $d\Lambda_k(z) = \frac{c_k(z)}{C_k} dH(z)$.

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

$$\max_p \pi(p) = (p - w) \underbrace{\frac{C_k}{M_k} \sum_{n=1}^{\infty} n\bar{q}_{k,n} (1 - F_k(p))^{n-1}}_{\text{Firm's demand at price } p},$$

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 $(F_k, \{c_k(z), s_k(z)\}, M_k)$ such that (1) $c_k(z), s_k(z)$ maximize utility for all z, (2) F_k is a dispersed price eq. given $\bar{q}_k$, (3) $\pi_k = f_e$, (4) markets clear.
  - Assume all households choose interior $s_k(z)$.
  - Focus on comparative statics of stable equilibrium.

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  - Assume all households choose interior $s_k(z)$.
  - Focus on comparative statics of stable equilibrium.
- Assumptions on search mapping $\mathscr{S} : s \mapsto \{q_n\}$.
  - Ensure price is decreasing and convex in search intensity s, and $q_1''(z) > 0$ if $\phi''(z) > 0$.
  - Conditions satisfied by two common parameterizations:
    - Two quote. (Alessandria and Kaboski 2011; Pytka 2018; Kaplan et al. 2019.)
    - Poisson. (Albrecht, Menzio, and Vroman 2021; Menzio 2021.)

General conditions on $\mathscr{S}$ $\rightarrow$

Effects of own and others' incomes: Intuition

- Suppose identical households ($a_i = a, z_i = z, \beta_{ik} = \beta_k$). Markup $\mu_i = \mu(z_i, z_{-i})$.

Response to perturbation in own income z_i and others' incomes z_{-i}:

$$d\mu_i = \left(1 - \frac{d\log a}{d\log z}\right)\Bigg(\underbrace{\kappa_1 dz_i}_{\substack{\text{Own income:}\\ \text{Through search choice}}} + \underbrace{\kappa_2 \frac{\partial s_i}{\partial s_{-i}} dz_{-i}}_{\substack{\text{Others' incomes:}\\ \text{Through search choice}}} + \underbrace{\kappa_3 dz_{-i}}_{\substack{\text{Others' incomes:}\\ \text{Through price dist.}}} \Bigg),$$

with coefficients $\kappa_1, \kappa_2, \kappa_3 > 0$.

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with coefficients $\kappa_1, \kappa_2, \kappa_3 > 0$.

- (Lemma 1) Race between labor and search productivity ($\frac{d\log a}{d\log z} \lesseqgtr 1$) can lead to either:
  - $a(z)$ rises faster than z: "poverty premium." Caplovitz (1963), Prahalad and Hammond (2002).
  - $a(z)$ rises slower than z: markups paid increase with income.

κ coefficients $\rightarrow$

Effects of own and others' incomes: Intuition

- Suppose identical households ($a_i = a, z_i = z, \beta_{ik} = \beta_k$). Markup $\mu_i = \mu(z_i, z_{-i})$.

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with coefficients $\kappa_1, \kappa_2, \kappa_3 > 0$.

- Effect of others' incomes both through price dist. and effect on own search choice.
- (Lemma 2) If ϕ sufficiently low, search decisions are strategic substitutes $\frac{\partial s_i}{\partial s_{-i}} < 0$.
  - Strategic interactions in search *moderate* macro elasticity of markups to income.
  - In paper: Cross-sectional evidence of strategic substitutability in search.

κ coefficients $\rightarrow$

Comparative Statics: Changes in Income Distribution

- Analytic comparative statics for single-good model: $K = 1$.
    - Alternatively, Leontief preferences $\sigma = 0$ and identical tastes $\beta_k(z) = \beta_k$ for all k, z.
    - Single distribution of buyers' incomes $\Lambda(z)$.

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Proposition (Shift in Buyers' Incomes)

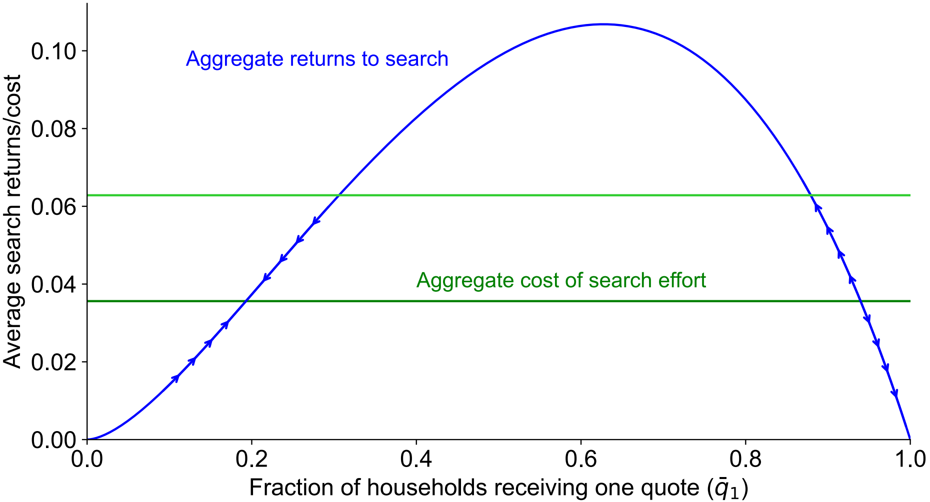
Aggregate markup (total sales / total costs) weakly increases if

- *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 →

Comparative Statics: Intuition

$$\int -p_s(s(z), \{\bar{q}_n\}) d\Lambda(z) = \int \phi(z) d\Lambda(z),$$



Balanced Growth?

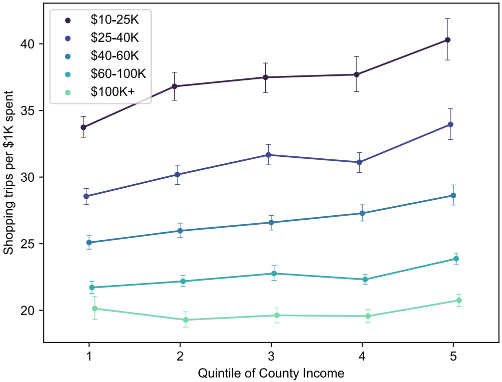
- (Corollary) Balanced growth if search productivity a_i grows 1:1 with labor prod z_i.
- In the data, markup growth from ↑ income **not offset** by add'l search prod growth.

Outcome	*Log Markup*		*Log Avg. Unit Price*			
Sample	2006–2012		2004–2019		2004 and 2019	
Log CBSA Income	0.104**	0.099**	0.127**	0.128**	0.097**	0.096*
	(0.017)	(0.026)	(0.026)	(0.030)	(0.045)	(0.052)
Year FEs	Yes	Yes		Yes		Yes
CBSA FEs		Yes	Yes		Yes	
Year-Product Module FEs			Yes		Yes	
CBSA-Product Module FEs				Yes		Yes
N (millions)	133	133	18.3	18.3	2.2	2.2
R^2	0.03	0.04	0.99	0.99	0.99	0.99

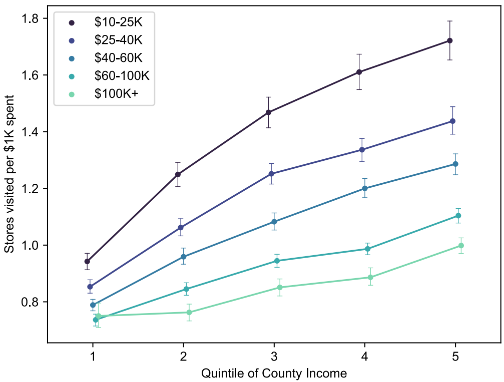
** is significant at 5%. Standard errors two-way clustered by year and CBSA.

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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Calibration approach

- Preferences over goods chosen to match spending shares in the data exactly.
- Search behavior chosen to match aggregate markups by income group exactly.
  - Assume households with $>$\$200K income have identical behavior to those with \$200K.

Parameter		Value	Source
Number of products	K	$10^{\dagger}$	Increasing $K > 10$ does not change results
Elasticity of substitution	σ	$1^{\dagger}$	Cobb-Douglas
Quality shifters	$\beta_k(z)$	-	Match spending shares exactly
Unit wage	w	1	Numeraire
Reservation price	R	$3.3^{\dagger}$	98th percentile of markups in the data
Search mapping	$\mathscr{S}$	Poisson	Albrecht et al. (2021), Menzio (2021)
Opp. costs of search	$\phi(z)$	-	Match avg. markup paid by income exactly
Search productivity	$a(z)$	-	Solved from $\phi(z) = z/a(z)$

† Paper reports robustness to parameter choice.

Calibration: Take spending shares directly from the data

- Order UPCs by buyer income, split into $K = 10$ groups.
- Note: Similar results if $K = 20, 50, 100$, etc.

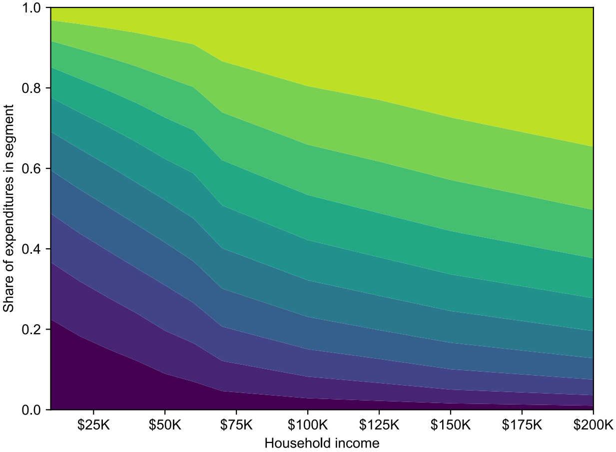
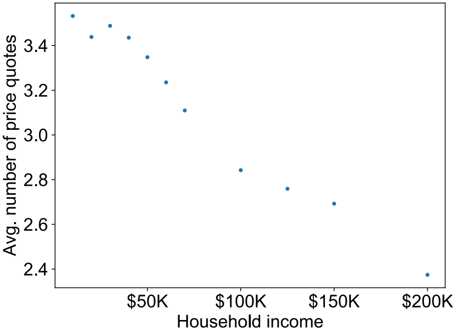
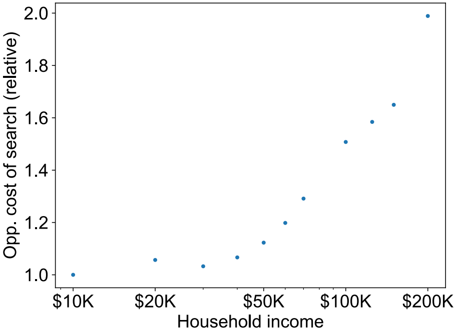


Figure: Spending shares over $K = 10$ groups.

Calibration: Price quotes received and opportunity cost of search



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

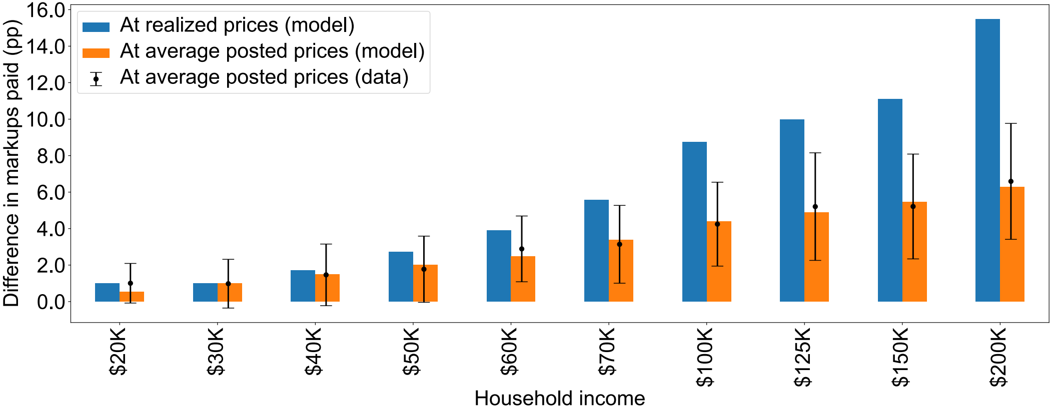


(b) Opportunity cost of search effort $\phi(z)$.

- 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) →

Decomposition: Basket composition vs. search



- Compare markup gap if households paid avg. posted price (i.e., no search) to data.
- Overall markup gap = markup gap due to basket composition + search effects.

Gap in prices paid for identical products →

Magnitude of strategic interactions in model in line with data

	Log markup			*Search intensity*		
	OLS	IV	Model	OLS	IV	Model
Log Own Income	0.032	0.054	0.032	-0.26	-0.40	-0.11
Log Others' Income	0.102	0.089	0.071	0.03	0.09	0.03

- Simulate economies with income distributions of 881 CBSAs.
- "Micro elasticity" of 3%, "macro elasticity" of 10%.
- Strategic substitutability in search.

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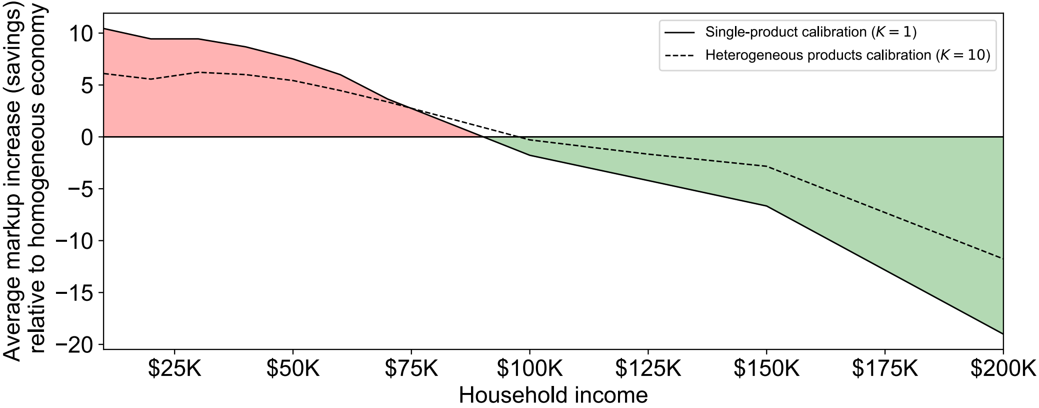
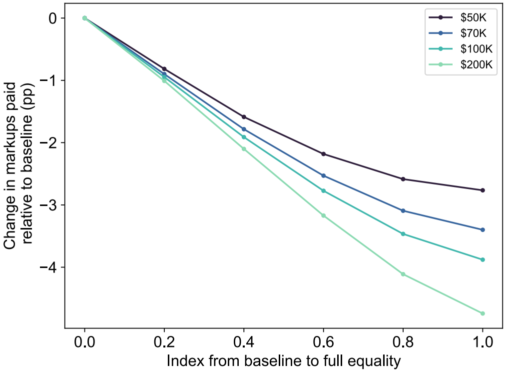
Spillovers from shopping behavior across households



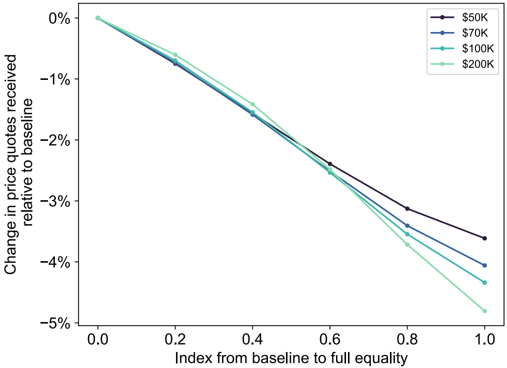
- Low-income pay 5–9pp higher markups due to presence of high-income shoppers.

Spillovers in $ → Welfare →

Markup and search spillovers from income inequality



(a) Markups paid.



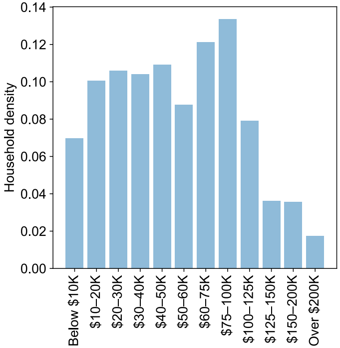
(b) Avg. price quotes received.

- Moving to full equality reduces markups paid 2–5pp and search time 3–5%.
- Note: One channel among several effects of inequality.

Differential effects due to segmentation →

Predicting markups across cities

- Predict markups across CBSAs.
  - CBSA income distributions from ACS 5-year survey.
  - Use $\phi(z)$ calibrated on aggregate data.
- Supply-side comparison: Nested CES model.
  - Macro literature inferring markups from market shares.
    (e.g., Atkeson and Burstein 2008, Smith and Ocampo 2023.)
  - Calibrate using retailer market shares in each CBSA.



Example: Income distribution in Jefferson City, MO CBSA.

Markups across space: Model predictions

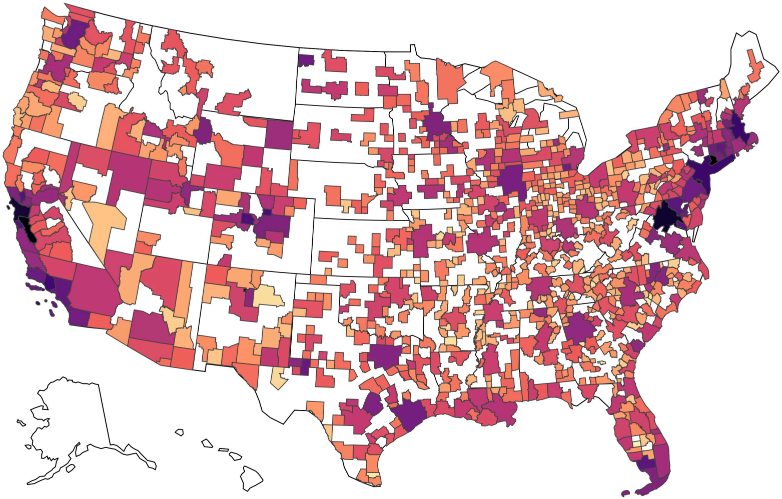


Figure: Predicted markups across CBSAs, based on CBSA income distributions.

Data →

Result: Model explains 31% of variation in CBSA markups

- Outperforms income measures alone and supply-side (nested CES) model.

	Model-Predicted		Data				
Log CBSA Markup	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log CBSA Income	0.102**	0.096**					
	(0.001)	(0.002)					
Gini Index		0.113**					
		(0.014)					
Log Model-Predicted Markup							
Log Nested CES Markup							
N	881	881					
R^2	0.84	0.85					

** is significant at 5%, * at 10%. Regressions weighted by CBSA sales.

Examples → Binscatters → Table: CBSA inequality robustness → Reallocation vs. within-product →

Result: Model explains 31% of variation in CBSA markups

- Outperforms income measures alone and Nested CES model.

	Model-Predicted		Data				
Log CBSA Markup	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log CBSA Income	0.102**	0.096**	0.110**	0.102**			
	(0.001)	(0.002)	(0.006)	(0.007)			
Gini Index		0.113**		0.153**			
		(0.014)		(0.057)			
Log Model-Predicted Markup					1.056**		
					(0.053)		
Log Nested CES Markup							
N	881	881	881	881	881		
R^2	0.84	0.85	0.27	0.28	0.31		

** is significant at 5%, * at 10%. Regressions weighted by CBSA sales.

Examples → Binscatters → Table: CBSA inequality robustness → Reallocation vs. within-product →

Result: Model explains 31% of variation in CBSA markups

- Outperforms income measures alone and Nested CES model.

	Model-Predicted		Data				
Log CBSA Markup	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log CBSA Income	0.102**	0.096**	0.110**	0.102**			0.018
	(0.001)	(0.002)	(0.006)	(0.007)			(0.015)
Gini Index		0.113**		0.153**			0.067
		(0.014)		(0.057)			(0.058)
Log Model-Predicted Markup					1.056**		0.824**
					(0.053)		(0.143)
Log Nested CES Markup						-0.720**	-0.122*
						(0.072)	(0.074)
N	881	881	881	881	881	881	881
R^2	0.84	0.85	0.27	0.28	0.31	0.10	0.31

** is significant at 5%, * at 10%. Regressions weighted by CBSA sales.

Examples → Binscatters → Table: CBSA inequality robustness → Reallocation vs. within-product →

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Model-Free 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.

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

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.

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

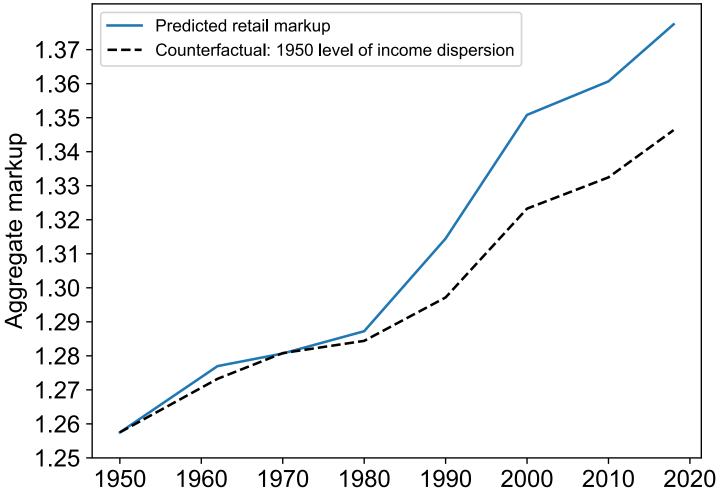
   - Note: Does not account for rising income dispersion ($\uparrow$).

Simulating markups over time through the model

- 1950–2018 post-tax real income distribution from Saez and Zucman (2019).
- Need to take a stand on how search productivity evolves over time.
  - Baseline: $a(z)$ grows with z according to cross-sectional relationship.
  - Robustness: Trend growth in search productivity to match elasticity of markups to income over time in the data. (Very similar.)
- Extensions:
  - Pro-competitive effects of entry in each segment.
    (Jaravel 2019, Handbury 2021).
  - Departing from Cobb-Douglas ($\sigma \neq 1$) $\rightarrow$ endogenous changes in segmentation.

Pro-competitive model setup $\rightarrow$ Pro-competitive empirics $\rightarrow$ Varying σ $\rightarrow$

Counterfactual: Income distribution from 1950–2018

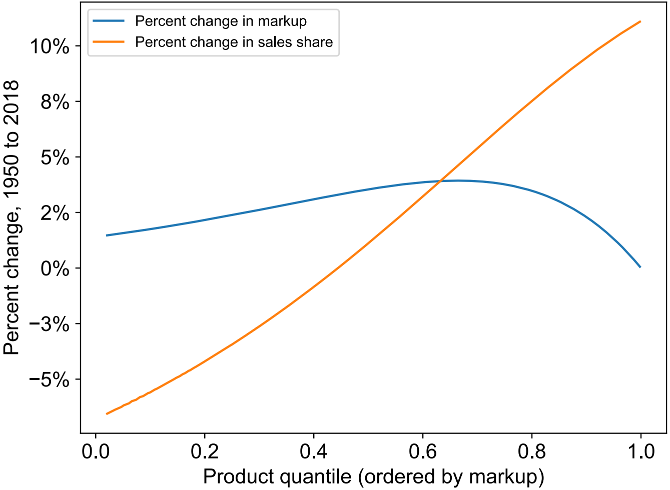


- Post-tax real income from Saez and Zucman (2019).
- 12pp predicted increase in aggregate markup.
- After 1980, 30% due to ↑ income dispersion.

Table → Holding search fixed → Perfect price discrimination →

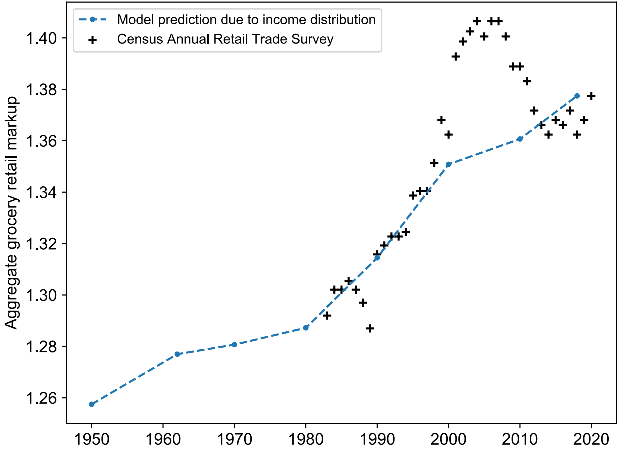
Reallocations across products vs. within-product changes

- Within product, markups rise for all stores.
- Sales reallocated to high-markup products/stores.
- 40% of increase due to reallocations.



Relative contributions →

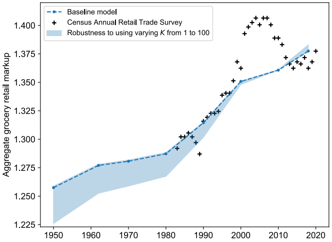
Predicted rise in markups is quantitatively important



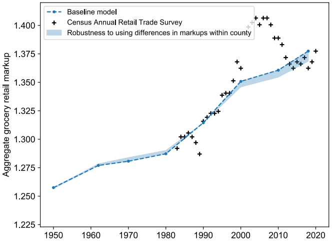
- Census Annual Retail Trade Survey gross margins for retail grocery.
- Markup assuming constant returns.
- Effects of housing wealth (Stroebel and Vavra 2019) can explain markup boom-bust in 2000s.

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

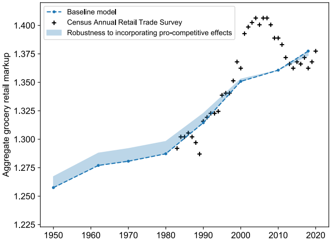
Rise in markups: Robustness to calibration choices



(a) Varying number of products $K = 1$ to 100.



(b) Using within-county differences in markups paid.



(c) With pro-competitive effects (Jaravel 2019).

- Within-county markup gap $\Rightarrow$ 11pp rise in markups.
- Pro-competitive effects calibrated to Jaravel (2019) $\Rightarrow$ 10–13pp rise in markups.
- In paper: Vary number of products K, elasticity σ, reservation price R.

Varying K and ζ $\rightarrow$ Varying σ $\rightarrow$

Broader questions

- **Does the rise in retail markups extend back before 1980?**
  - Sources: Newly digitized Census Annual Retail Trade Surveys from 1969–1977 and historical NBER calculations (Barger 1955).
  - Suggest rise in retail markups extends further back before 1980.

Broader questions

- **Does the rise in retail markups extend back before 1980?**
  - Sources: Newly digitized Census Annual Retail Trade Surveys from 1969–1977 and historical NBER calculations (Barger 1955).
  - Suggest rise in retail markups extends further back before 1980.
- **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 $\rightarrow$ Future markups $\rightarrow$ Upstream-downstream analysis $\rightarrow$

Extensions

- **How important is modeling endogenous search decisions?**
  - Non-homothetic preferences model à la Handbury (2021) predicts 2x macro elasticity.
  - 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.
- **Spillovers of regional changes in income due to uniform pricing.**
  - E.g., doubling top-end incomes in NY increase markups paid in NJ, CT up to 2pp.

Non-homothetic preferences → Evolution of consumption inequality → Spatial spillovers NY → SF →

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.