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).
  - Empirics: How markups vary with income at the micro and macro level.
  - 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. Micro elasticity of markups to income.
    - Doubling income increases markups paid 2.0–3.4 percent.
    - 2x previous estimates that compare prices paid for identical products alone.
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    - Macro elasticity of 8–15 percent.

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  - 2. Spillovers and macro elasticity of markups to income.
    - Macro elasticity of 8–15 percent.
- **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: high-income shoppers increase markups for low-income by 6pp.
  - 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?
  - Income distribution 1950–2018 accounts for 11pp rise in retail markup.
    - Accelerates after 1980 due to $\uparrow$ income dispersion.
    - Increase due to within-firm markup changes *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).
    - → 1. Measure micro elasticity accounting for basket composition (2x as large).
  - *Income/wealth and price elasticity*: Harrod (1936), Lach (2007), Anderson, Rebelo, and Wong (2018), Stroebel and Vavra (2019), DellaVigna and Gentzkow (2019), Jaimovich, Rebelo, and Wong (2019), Argente and Lee (2021), Handbury (2021), Faber and Fally (2022), Gupta (2020), Auer et al. (2022).
  - *Trade / IO*: Alessandria and Kaboski (2011), Simonovska (2015); Nevo (2001), etc.
    - → 2. Measure macro elasticity, accounting for markups across products/firms.
- **Search in product markets**
  - Stigler (1961), Varian (1980), Burdett and Judd (1983), Alessandria and Kaboski (2011), Pytka (2018), Kaplan et al. (2019), Albrecht et al. (2021), Menzio (2021), Nord (2022).
- **Evolution of retail markups**
  - Neiman and Vavra (2019), Brand (2021), Döpper et al. (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.
  - Baseline assumption: Retailers' other costs (rent, labor) fixed at short horizons.
    E.g., Gopinath et al. (2011), Anderson et al. (2018).
  - To be extra sure: Elasticities of markups to income controlling for store/county to absorb local costs.
  - Strongly correlated with Berry, Levinsohn, and Pakes (1995) markups in one module.
- Average (cost-weighted) markup is 32%.
  - All calculations winsorize markups at 1%.

Wholesale price uniformity $\rightarrow$

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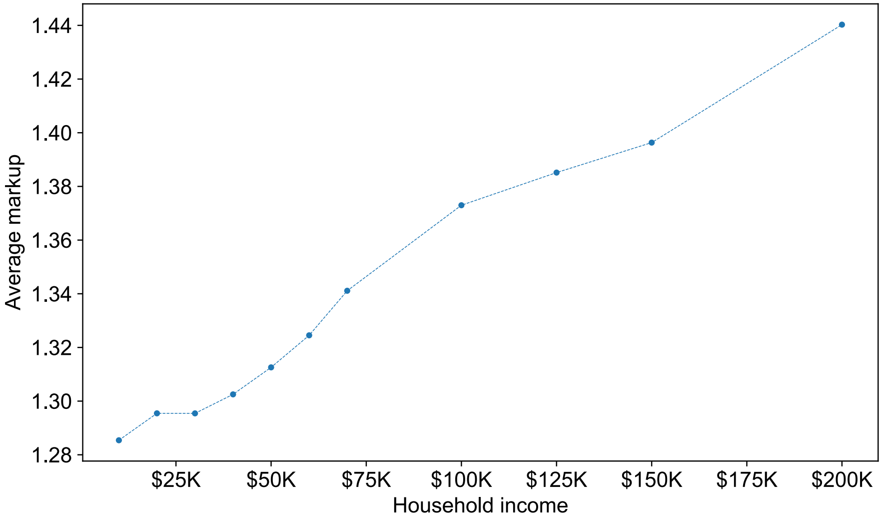
Descriptive evidence: Markup measure increases with household income

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



Within store, 7pp gap in markups paid

$$\text{Markup}_{ik} = \sum_{\ell} \beta_\ell 1\{i \text{ has income level } \ell\} + \underbrace{\gamma' X_i}_{\text{Demographic controls}} + \underbrace{\alpha_{\text{Store}}}_{\text{Store FEs}} + \varepsilon_{ik}.$$

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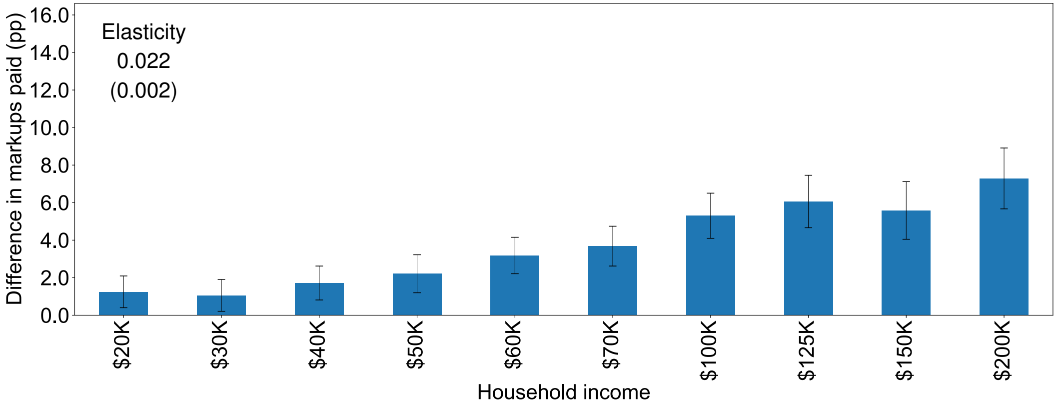

For household i, transaction k. FEs relative to group with $<$\$20K income. Std. errors two-way clustered by brand and county.

Inclusive of cross-store differences, 13pp markup gap

$$\text{Markup}_{ik} = \sum_{\ell} \beta_{\ell} 1\{i \text{ has income level } \ell\} + \gamma' X_i + \underbrace{\phi_{\text{County}}}_{\text{County FEs}} + \underbrace{\delta' W_k}_{\text{Retailer–product controls}} + \varepsilon_{ik}.$$

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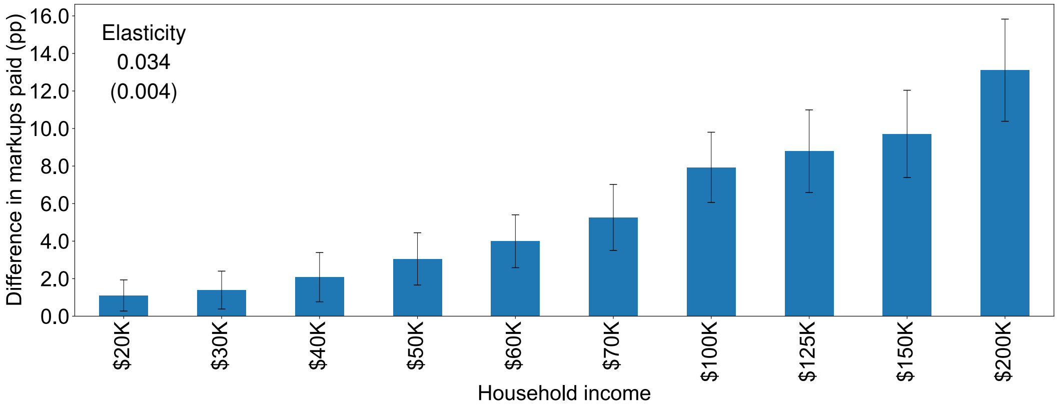

For household i, transaction k. FEs relative to group with <$20K income. Std. errors two-way clustered by brand and county.

Robustness: Micro elasticity of markups to income

Elasticity of markups paid to income (percent)	Within store	Overall
Baseline	2.2	3.4
Using PromoData base price	2.5	3.6
Using PromoData market-level price	2.3	2.7
Excluding perishable categories	2.0	3.3
With day-of-week fixed effects	2.1	3.4
With supply-side controls	2.1	3.3
Instrumenting for household income	3.8	6.9
With additional retailer–product controls	2.1	3.3

- 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? Even stronger link btwn 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.**
   (Prices for identical products documented by 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 $\rightarrow$

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From Micro to Macro

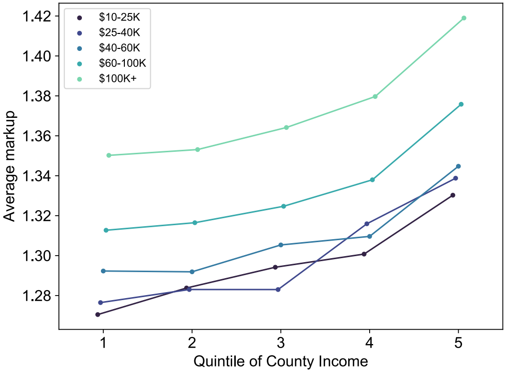
- Suppose markups depend on own income and aggregate income, $\mu_i(z_i, z_{-i})$.
- Aggregate markup is cost-weighted average $\mu^{agg} = \mathbb{E}_c[\mu_i(z_i, z_{-i})]$.
- To a first order, "macro elasticity of markups to income" is...

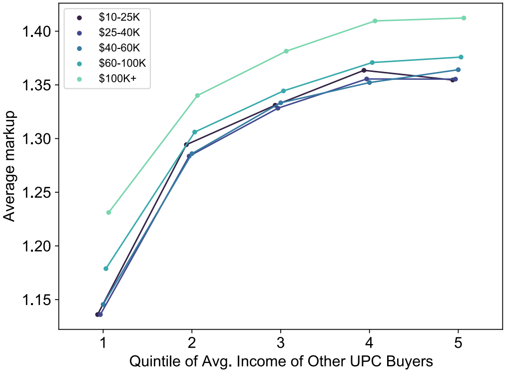
$$\frac{\partial \log \mu^{agg}}{\partial \log z} \approx \underbrace{\mathbb{E}_c\left[\frac{\partial \log \mu_i}{\partial \log z_i}\right]}_{\text{"Micro" elasticity (2-3\%)}} + \underbrace{\mathbb{E}_c\left[\frac{\partial \log \mu_i}{\partial \log z_{-i}}\right]}_{\text{Spillovers}}.$$

- Classic "missing intercept" problem of going micro to macro.
  - My approach: Measure spillovers directly in data.

Micro to macro aggregation →

Descriptive evidence: Markups rise with income of other buyers





- Positive dependence on others' incomes $\rightarrow$ "macro" elasticity $>$ micro elasticity.
- Two concerns: (1) Unobserved local costs, (2) Manski (1993) reflection problems.

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

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

$$\log \text{Markup}_{istk} = \beta_1 \log \text{CBSA Income}_{\text{CBSA}(i,t),t} + \gamma_{i,\text{Income}(i,t)} + \alpha_s + \delta_t + \varepsilon_{istk}.$$

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

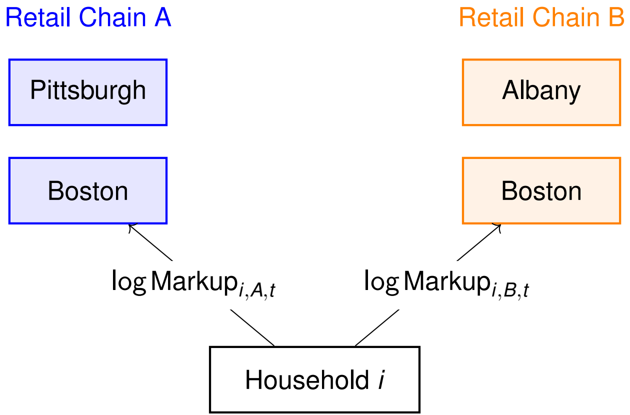
$$\log \text{Markup}_{istk} = \beta_3 \log \text{Income of UPC Buyers}_{\text{UPC}(k),t} + \gamma_{it} + \psi_{st} + \varepsilon_{istk}.$$

for transaction k by household i at store s in year t.

- Controls for unobserved household characteristics (γ_{it}), store-level costs (α_s), time-varying local costs (e.g., $\phi_{\text{County}(s),t}$, ψ_{st}).

Identifying spillovers: Example

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



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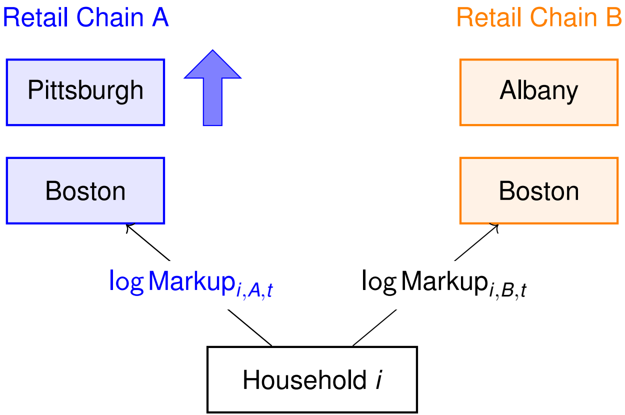


Consistent, positive spillovers across specifications: Macro elasticity 8–15%

Log Retail Markup	(1)	(2)	(3)
Log Income at Retailer's Locations	0.063**		
	(0.026)		
Log CBSA Income		0.070**	
		(0.012)	
Log Income of Other UPC Buyers			0.142**
			(0.012)
Fixed effects	Household-Year, Store, County-Year	Household-Income, Store, Year	Household-Year, Store-Year
N (millions)	50.9	91.9	97.0
R^2	0.21	0.19	0.21

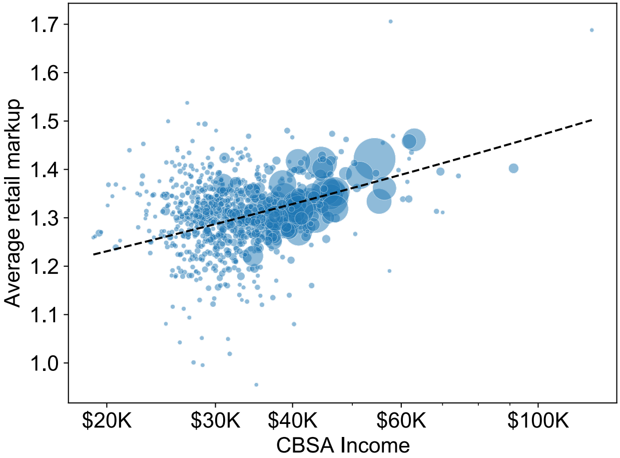
Regression weighted by sales. SEs two-way clustered by brand & county.

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

Robustness to FEs → Cross-section →

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

Figure: CBSA average retail markup vs. income.



- Elasticity across CBSAs = 11%.
- Rent/wage data suggest bias from local costs is small.
- Trade: Elasticity of markups to income at export destination = 12–24% (Simonovska 2015).

Table: Avg. income and inequality across CBSAs → Local costs bias → Similar elasticities in cross-section and time series →

Empirical Results: Taking Stock

- “**Micro elasticity**” of markups to household income of 2–3% (i.e., 15pp markup gap).
  - Partly due to differences in basket composition.
  - Partly due to differences in prices paid for identical products.
  - $\Rightarrow$ Need search frictions (i.e., cannot match with BLP / non-homothetic preferences only).
- “**Macro elasticity**” of markups to income of 8–15%.
  - Larger due to “missing intercept” from spillovers of other buyers’ incomes.

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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.
  - $\Rightarrow$ Price dispersion for identical products (spatial / intertemporal).
- Search choice (Aguiar and Hurst 2007) $+$ firm pricing (Burdett and Judd 1983).
  - In PE, diff prices for identical products $+$ basket composition.
  - In GE, composition of buyers $\rightarrow$ distribution of firm markups.

Comparison to other models $\rightarrow$

Basket Composition: 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} 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 amount of good k consumed (mass of infinitesimal purchases),
- 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.

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- 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, cross-section → Time series →

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: $F_k(p)$ where firms make identical profits for any $p \in \text{supp}(F_k)$.
- 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_k adjusts to ensure $\pi_k = f_e w$.

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.
- In paper: 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 $\mathscr{S}$ → Parameterizations →

Markups and Search in the Cross-Section

Lemma (Markups and search across income groups)

If $\phi(z)$ is increasing in z, then...

- *1. Search intensity for a good k is decreasing in income.*
- *2. Markups paid for a good k are increasing in income.*

Moreover, if $\phi(z)$ sufficiently small for all z, search decisions are strategic substitutes.

- Recall $\phi(z) = z/a(z)$. Race between labor and search productivity leads to either:
  - If $a(z)$ rises faster than z: “Poverty premium”. Caplovitz (1963), Prahalad and Hammond (2002).
  - If $a(z)$ rises slower than z: Markups paid increase with income.
- In paper: Evidence of strategic substitutability in search in the data.

Perturbation example →

Comparative Statics: Changes in Income Distribution

- Analytic comparative statics for single-good model: $K = 1$.
    - 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.*

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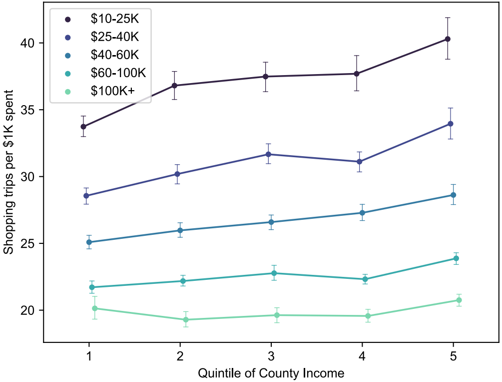
- (Corollary) Balanced growth if search productivity a_i grows 1-for-1 with labor prod z_i.
- In the data, elasticity of markups to income across space $\approx$ over time.

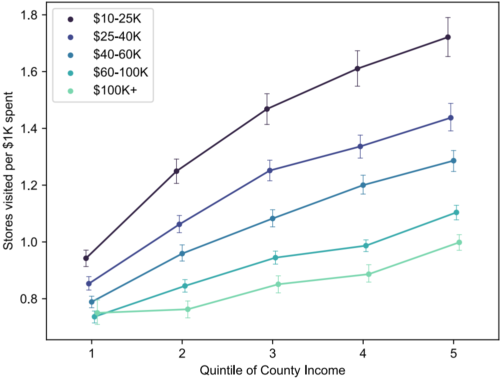
Intuition $\rightarrow$ Evidence against balanced growth $\rightarrow$

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.

Robustness to other definitions of basket size → Variance of markups →

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Calibration approach

- Outer loop: Preferences to match spending shares in the data exactly.
- Inner loop: Search behavior to match markups gaps across income groups 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
Taste shifters	$\beta_k(z)$	-	Match spending shares exactly
Unit wage	w	1	Numeraire
Reservation price	R	$3.0^{\dagger}$	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 outer loop: 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.

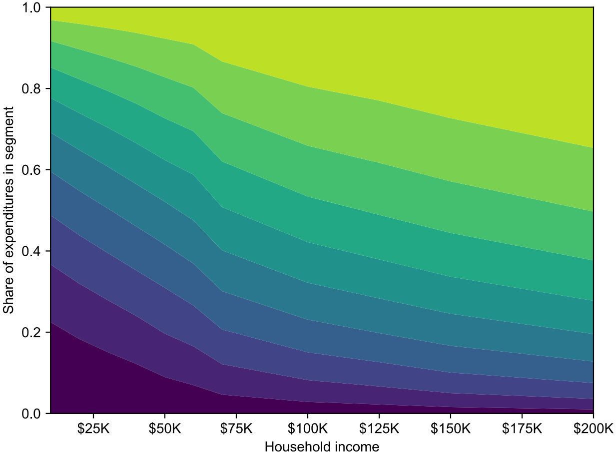
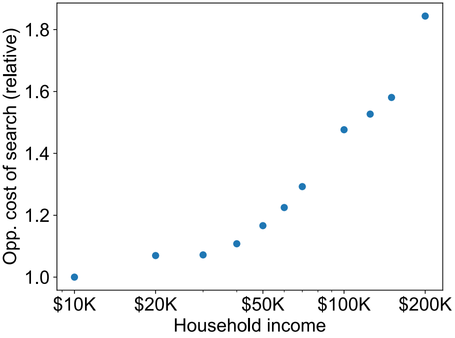
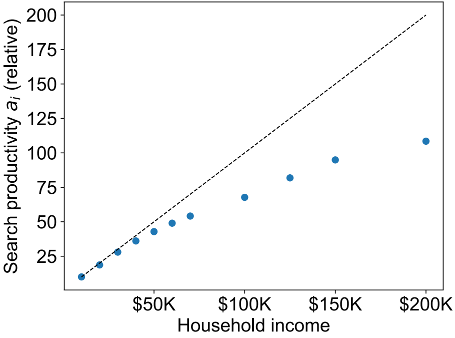


Figure: Spending shares over $K = 10$ groups.

Calibration inner loop: Search parameters to match markups



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

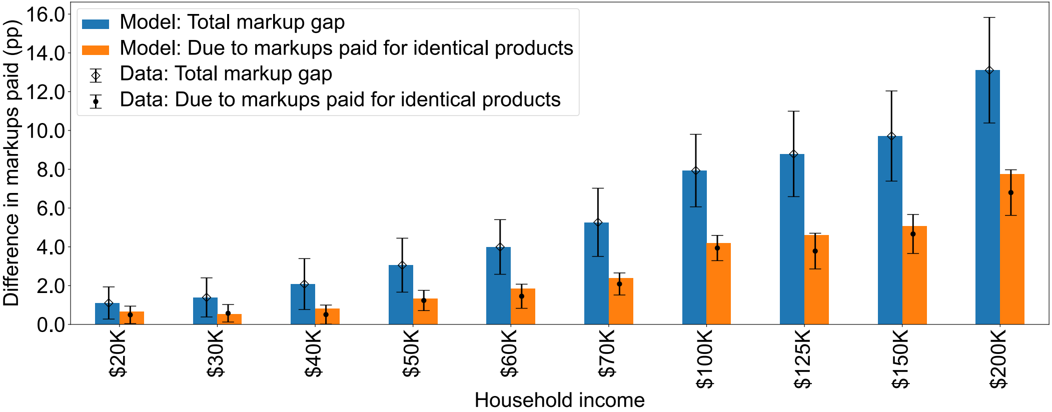


(b) Search productivity $a(z)$.

- 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) →

Calibration fit: Decomposition of markup gap across income groups



- Untargeted moment: Share of markup gap due to prices paid for identical products.

Calibration fit: Strategic interactions

- Simulate economies with income distributions of 881 CBSAs.
- Untargeted: "Macro elasticity" of 9% $=$ 2.8% (micro elasticity) $+$ 6.1% (spillovers).
- Untargeted: Search intensity (using various measures from Kaplan and Menzio 2015) falls with income, rises with others' income (strategic substitutes).

	Log markup		*Search intensity*	
	Data	Model	Data	Model
Log Own Income	0.038	0.028	-0.26	-0.11
Log Others' Income	0.083	0.061	0.03	0.03

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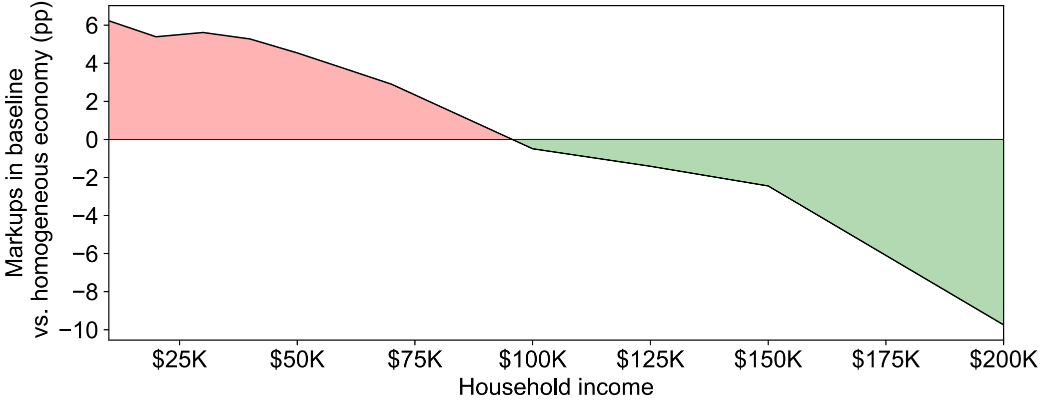
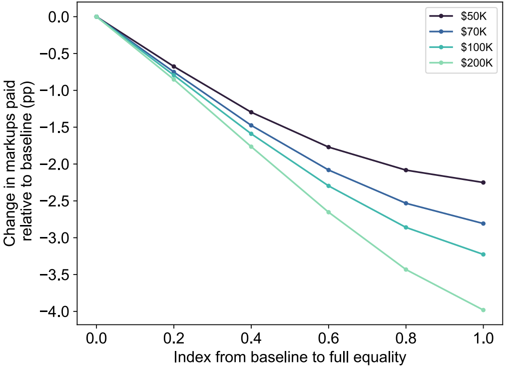
Spillovers: Effects of income level

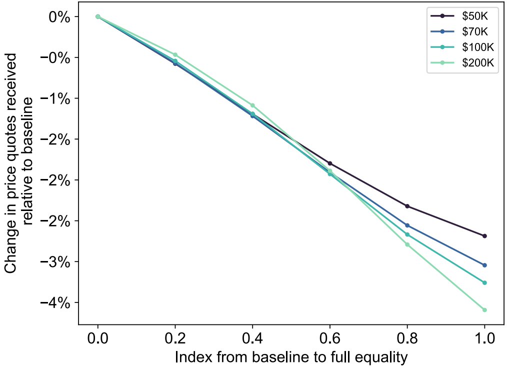


- Low-income pay 6pp higher markups due to presence of high-income shoppers.
- Moving to low-income area would save ≈$250/yr on $5K expenditures.

Spillovers: Gains from reducing income inequality



(a) Markups paid.



(b) Avg. price quotes received.

- Moving to full equality reduces markups paid 2–4pp and search time 2–4%.
- Note: One channel among several effects of inequality.

Differential effects due to segmentation →

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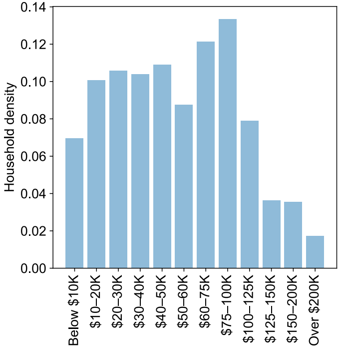
Markups across space: Predicting markups using income dist. of US cities

- Predict CBSA markups using income dist. from ACS.
- Compare predicted markups to retail markup data.
- Compare "supply-side" model of markups.
  - Macro literature inferring markups from market shares.
    (e.g., Atkeson and Burstein 2008, Smith and Ocampo 2023.)
  - Nested CES model using retailer market shares.



Example: Income dist. in Jefferson City, MO from ACS 5-year survey.

Markups across space: Model predictions

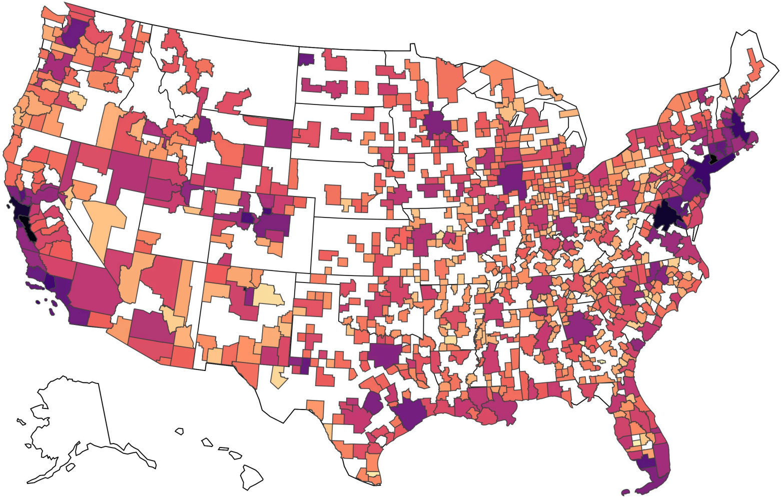


Figure: Predicted markups across CBSAs. 1.29 (yellow) to 1.45 (purple).

Data → Examples →

Markups across space: Explains 31% of variation in CBSA markups in data

- 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	0.086**	0.081**					
	(0.001)	(0.001)					
Gini Index		0.088**					
		(0.011)					
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 →

Markups across space: Explains 31% of variation in CBSA markups in data

- 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	0.086**	0.081**	0.110**	0.102**			
	(0.001)	(0.001)	(0.006)	(0.007)			
Gini Index		0.088**		0.153**			
		(0.011)		(0.057)			
Log Model-Predicted Markup							
Log Nested CES Markup							
N	881	881	881	881			
R^2	0.84	0.85	0.27	0.28			

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Gini Index		0.088**		0.153**			
		(0.011)		(0.057)			
Log Model-Predicted Markup					1.248**		
					(0.063)		
Log Nested CES Markup							
N	881	881	881	881	881		
R^2	0.84	0.85	0.27	0.28	0.31		

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Markups across space: Explains 31% of variation in CBSA markups in data

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

Log CBSA Markup	Model-Predicted (1)	(2)	Data (3)	(4)	(5)	(6)	(7)
Log CBSA Income	0.086**	0.081**	0.110**	0.102**			
	(0.001)	(0.001)	(0.006)	(0.007)			
Gini Index		0.088**		0.153**			
		(0.011)		(0.057)			
Log Model-Predicted Markup					1.248**		
					(0.063)		
Log Nested CES Markup						-0.720**	
						(0.072)	
N	881	881	881	881	881	881	
R^2	0.84	0.85	0.27	0.28	0.31	0.10	

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

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

Markups across space: Explains 31% of variation in CBSA markups in data

- 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	0.086**	0.081**	0.110**	0.102**			0.019
	(0.001)	(0.001)	(0.006)	(0.007)			(0.015)
Gini Index		0.088**		0.153**			0.075
		(0.011)		(0.057)			(0.058)
Log Model-Predicted Markup					1.248**		0.956**
					(0.063)		(0.169)
Log Nested CES Markup						-0.720**	-0.123*
						(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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Markups over time: Model-free estimates

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.

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

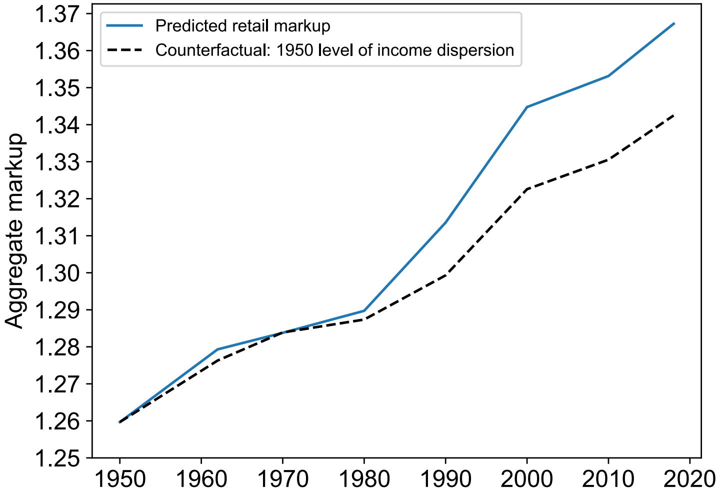
   - Does not account for rising income dispersion ($\uparrow$).

Markups over time: Model-based approach

- 1950–2018 post-tax real income distribution from Saez and Zucman (2019).
- How does search productivity evolve over time?
  - Baseline assumption: $\phi(z)$ fixed over time.
  - Search productivity is growing with z at same rate as in cross-section.
  - Robustness: Secular growth in search productivity to match elasticity of markups to income over time in the data. (Very similar.)

Similar elasticities over time vs. across space →

Markups over time: Income distribution from 1950–2018

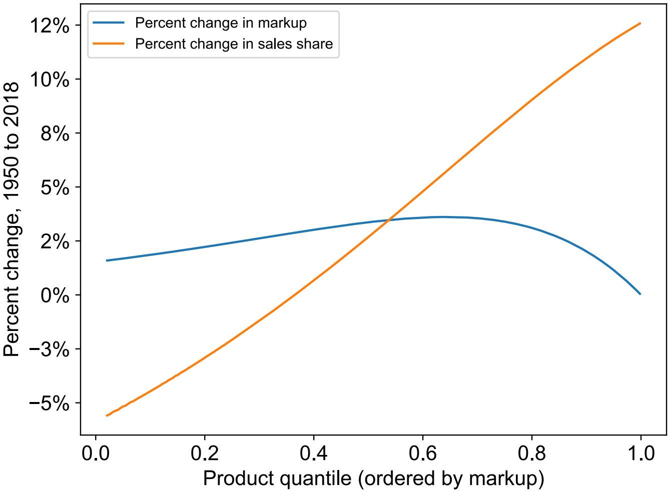


- Post-tax real income from Saez and Zucman (2019).
- 11pp predicted increase in aggregate markup.
- After 1980, 30% due to ↑ income dispersion.

Table → Holding search fixed → Perfect price discrimination →

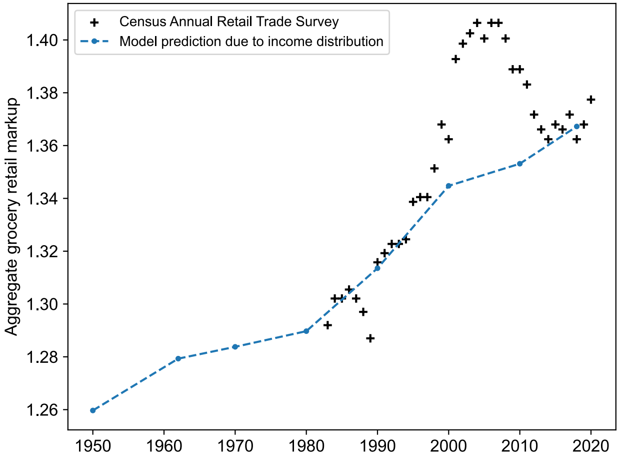
Markups over time: Role of reallocations

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



Relative contributions →

Markups over time: Comparison to data



- 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 →

Markups over time: Taking stock

1. 11pp rise in aggregate retail markup, consistent with rise in the data.
2. Income inequality responsible for 25% of increase and acceleration in 1980.
3. Reallocations account for 40% of the rise in markups.

Robustness to calibration choices $\rightarrow$ Comparison to non-homothetic preferences $\rightarrow$ Evolution of consumption inequality $\rightarrow$ Spatial spillovers NY $\rightarrow$ SF $\rightarrow$

Broader questions

- **Does the rise in retail markups extend back before 1980?**
  - Digitize Census Annual Retail Trade Surveys (1969–1977), NBER reports (Barger 1955).
  - Suggest rise in retail markups extends further back before 1980.

Broader questions

- **Does the rise in retail markups extend back before 1980?**
  - Digitize Census Annual Retail Trade Surveys (1969–1977), NBER reports (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 $\uparrow$ markups upstream (Tirole 1988; Wu 2022).
  - Using supplier-retailer pairs from Compustat Customer Segments, I find De Loecker et al. (2020) markups of suppliers increase with income downstream.

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

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: Quantify how income matters for #2.
- Quantitatively important link between income and markups (8–15% macro elasticity).
- Income distribution can explain reallocations, $\uparrow$ markups without additional changes to nature of production or competition.