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 supply-side 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 side (income levels and inequality).
  - Empirics: Measure 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.
      (Aguiar and Hurst 2007, Broda et al. 2009, Kaplan and Menzio 2015.)

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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. (2023), Menzio (2023), 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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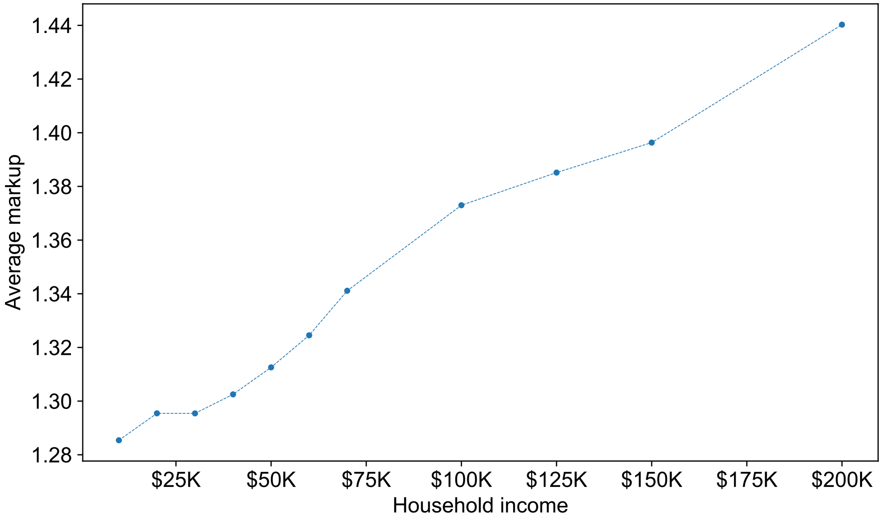
Descriptive evidence: Markup measure increases with household income

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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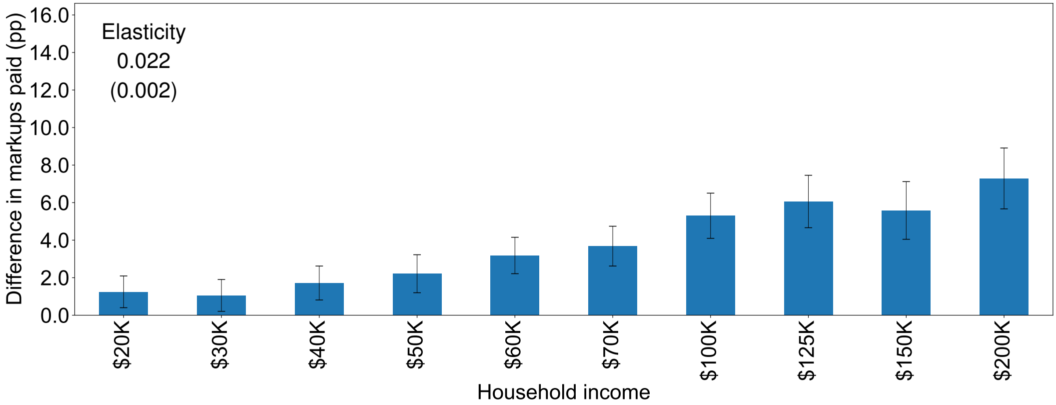

For household i, transaction k. FEs relative to group with $<$\$20K income. Std. errors two-way clustered by brand and county.

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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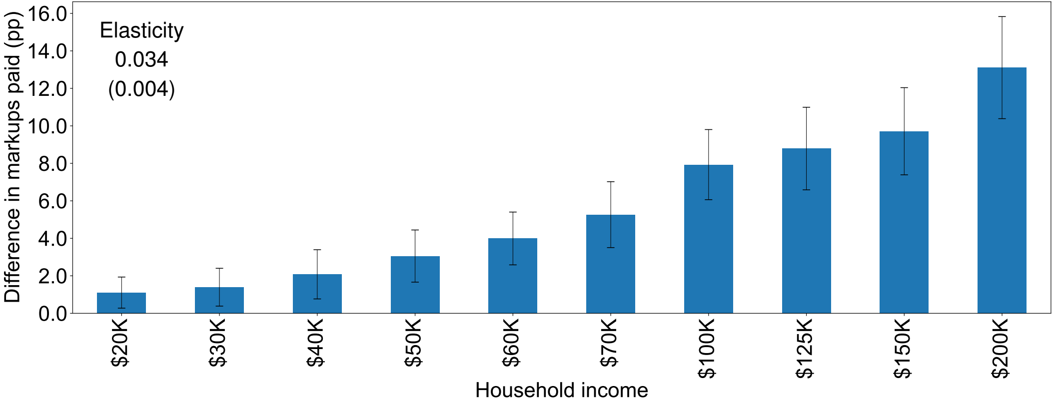

For household i, transaction k. FEs relative to group with <\$20K income. Std. errors two-way clustered by brand and county.

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...

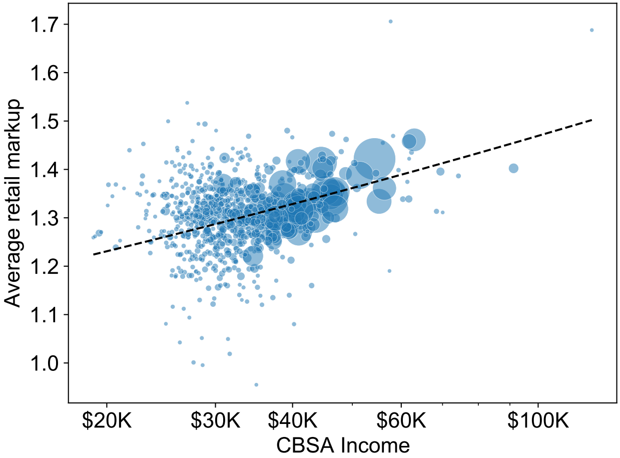
$$\frac{\partial \log \mu^{agg}}{\partial \log z} \approx \underbrace{\mathbb{E}_c\left[\frac{\partial \log \mu_i}{\partial \log z_i}\right]}_{\substack{\text{“Micro”} \\ \text{elasticity} \\ \text{(2-3\%)}}} + \underbrace{\mathbb{E}_c\left[\frac{\partial \log \mu_i}{\partial \log z_{-i}}\right]}_{\text{Spillovers}}.$$

- Classic "missing intercept" problem of going micro to macro.
    - In paper: Measure spillovers directly. (Identification controlling for local costs.)
    - For presentation today: "Macro elasticity" of markups to income across cities.

Micro to macro aggregation →

Estimated macro elasticity of 8–15%

Figure: CBSA average retail markup vs. income.



- Across CBSAs, "macro elasticity" of markups to income $\approx$ 11%.
- Identification of spillovers (controlling for local costs) yields estimates 8–15%.

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., 13pp 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.

Summary of Model Results

- 1. Differences in markups/prices paid for identical products.
    - Model can generate either "poverty premium," or higher markups for high-income.
    - Depends on race btwn household search technology and labor productivity (cost of time).
- 2. Macro elasticity $\neq$ micro elasticity.
    - Spillovers of others' incomes through price distributions and search choice.
- 3. Conditions under which rise in income levels / inequality raise aggregate markup.
    - FOSD shift in income distribution $\Rightarrow$ cost of search effort incr. in income.
    - Mean-preserving spread $\Rightarrow$ cost of search effort incr. and convex in income.

Comparison to related models of income and markups

Model	Comparison to data
Preferences:	
Non-homothetic CES e.g., Handbury (2021), Faber and Fally (2022)	Price dispersion within products.
Vertical & horizontal differentiation e.g., Fajgelbaum et al. (2011)	Income distribution affects markups only through composition of products.
Bounded marginal utility e.g., Simonovska (2015), Neiman and Vavra (2019)	Markups lowest for most commonly purchased products (rather than peripheral products).
Differentiation and finicky tastes e.g., Hummels and Lugovskyy (2009)	Limited relationship between markup and level of variety within product modules.
Search:	
Sales-based discrimination e.g., Varian (1980)	Positive spillovers of others' incomes for households at all income levels.
Representative agent:	
Oligopolistic competition e.g., Atkeson and Burstein (2008)	Sales shares and concentration do not explain link between income and retail markups.

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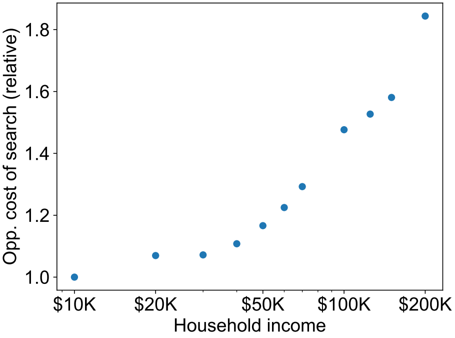
Calibration approach

- 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.

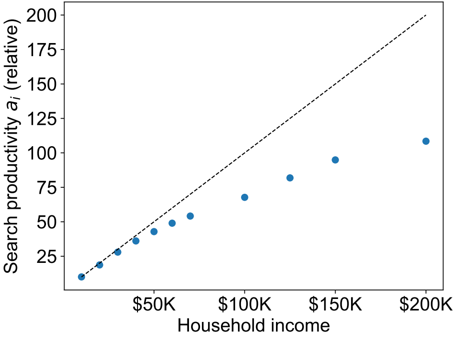
Parameter		Value	Source
Number of products	K	$10^{\dagger}$	Increasing $K > 10$ does not change results
Elasticity of substitution	σ	$1^{\dagger}$	Cobb-Douglas
Taste shifters	$\beta_k(z)$	-	Match spending shares exactly
Unit wage	w	1	Numeraire
Reservation price	R	$3.0^{\dagger}$	98th percentile of markups in the data
Search mapping	$\mathscr{S}$	Poisson	Albrecht et al. (2023), Menzio (2023)
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 results: Search parameters



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

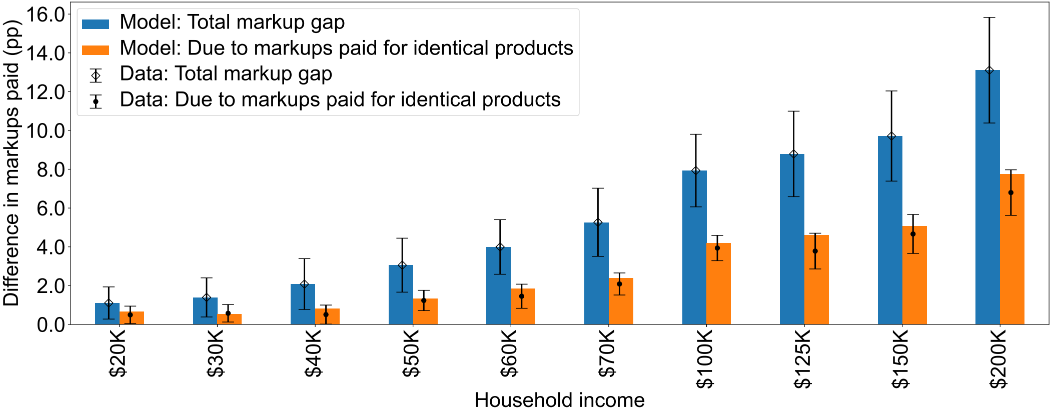


(b) Search productivity $a(z)$.

- 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: Micro elasticity and decomposition



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

Calibration fit: Strategic interactions and “macro elasticity”

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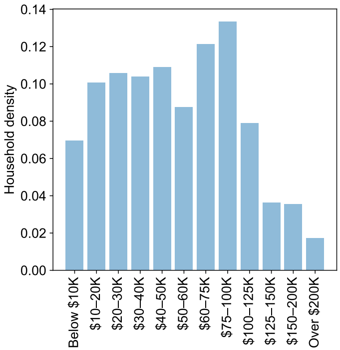
Markups across space: Predicting markups using income dist. of US cities

- 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

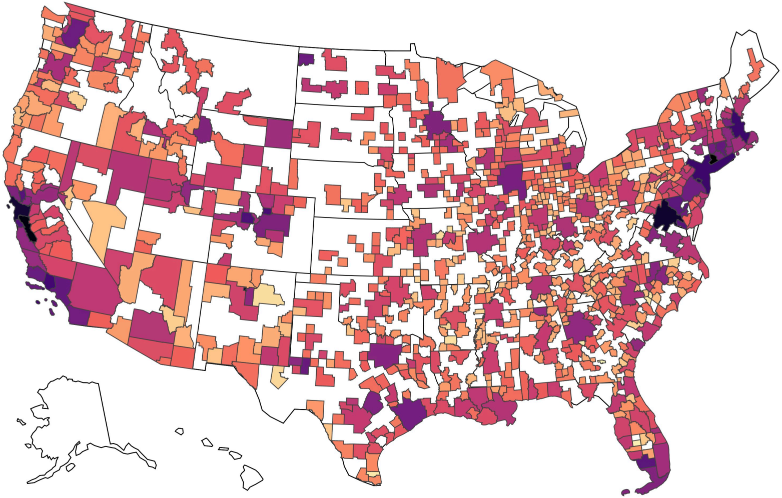


Figure: Predicted markups across CBSAs. 1.29 (yellow) to 1.45 (purple).

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 →

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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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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	

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- 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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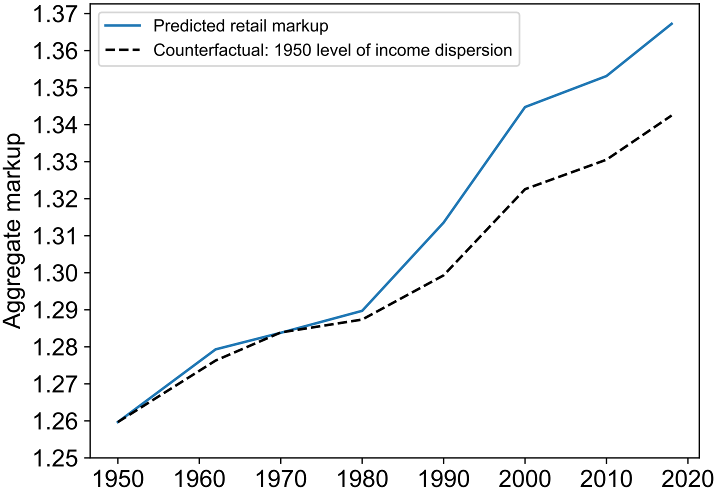
Markups over time: Model-based approach

- 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 →

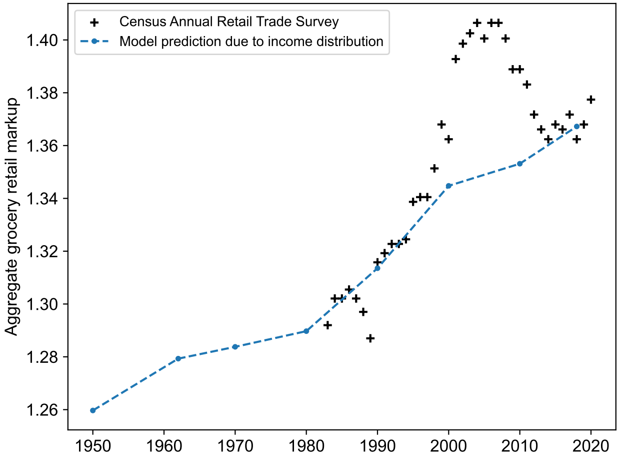
Markups over time: Income distribution from 1950–2018



- 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: 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 → Comparison to 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: Quantify how income matters for #2.
- Doubling income of households in an economy raises markups 8–15%.
- Income distribution can explain reallocations, $\uparrow$ markups without additional changes to nature of production or competition.

Extra Slides

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PromoData Price-Trak UPC data coverage by income level

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

	Percent matched to wholesale cost data		Average price index ($\hat{p}$)	
Income group	Transactions	Expenditures	Matched	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

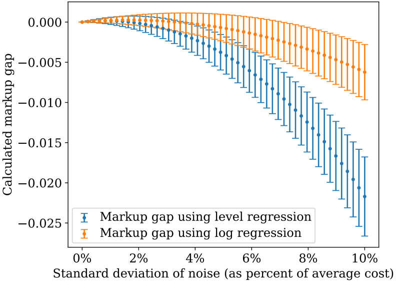
Table: Uniformity of wholesale prices across markets.

	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

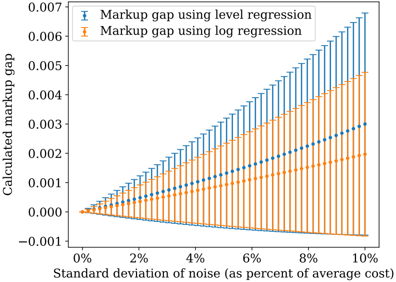
← Back

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

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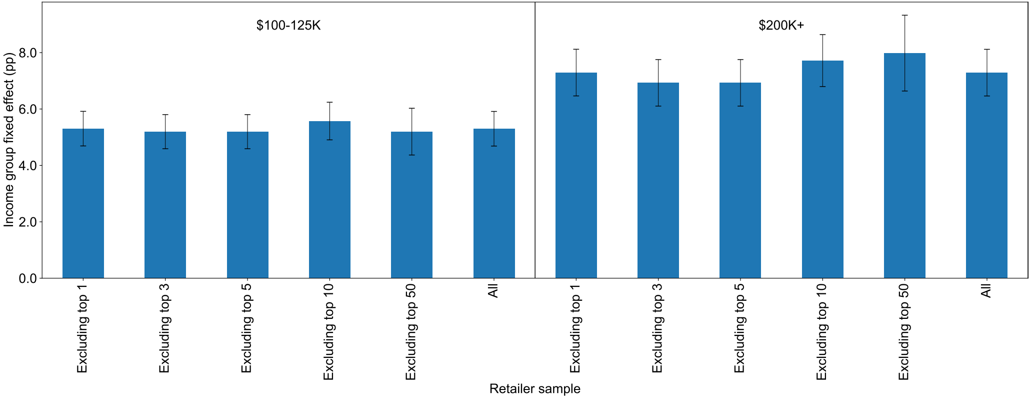
No decline in within-store income effect excluding largest retailers

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



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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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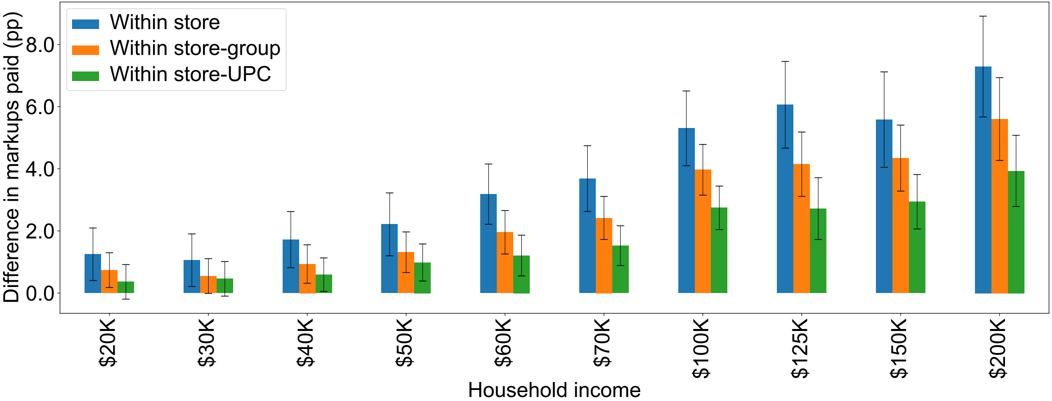
Understanding the gap in markups: Decomposition by module & UPC



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

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

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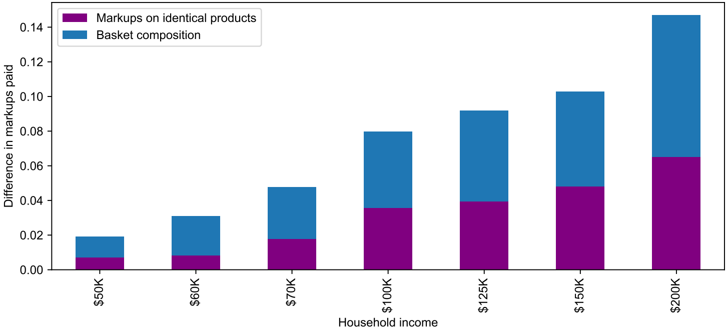
Markups across goods account for over 50% of markup gap

- 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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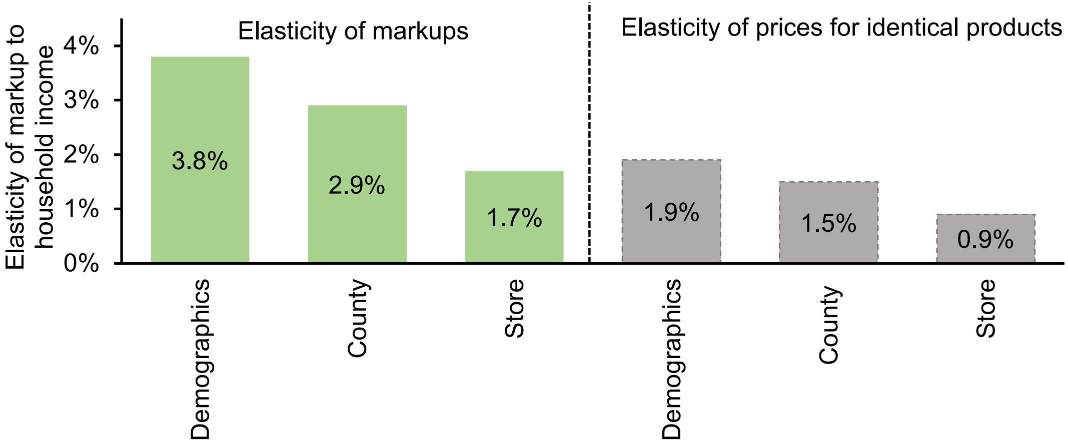
Why do high-income households pay higher markups?

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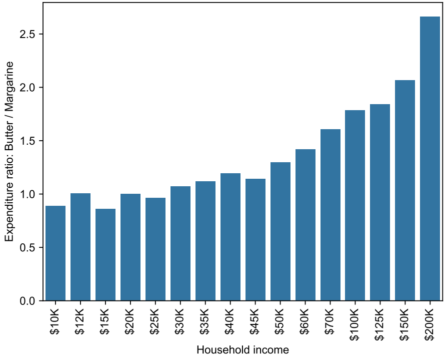
Within-household, over time elasticity of markups paid to income

- NielsenIQ 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%.

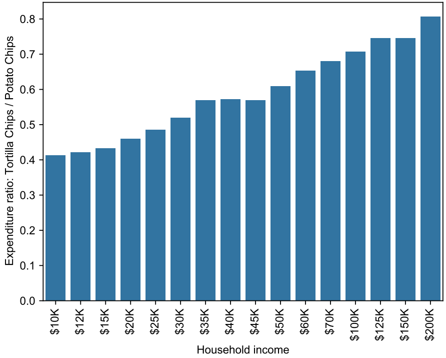
Log Retail Markup	(1)	(2)	(3)	(4)	(5)	(6)
Log Household Income	0.003**	0.001**	0.003**	0.001*	0.001	0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Household FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
County FEs			Yes	Yes		
Store FEs					Yes	Yes
UPC FEs		Yes		Yes		Yes
N (millions)	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.

Basket composition: Products bought by rich have higher markups



(a) Expenditures on butter vs. margarine.

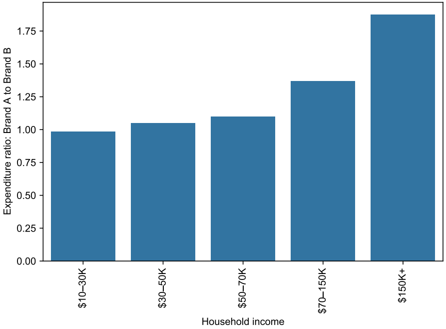


(b) Expenditures on tortilla chips vs. potato chips.

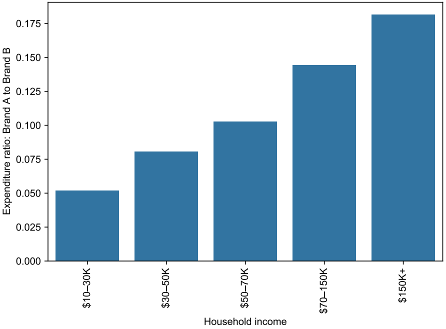
- Butter has higher markups than margarine (average 45% vs. 33%).
- Tortilla chips have higher markups than potato chips (average 50% vs. 19%).

Substitution across brands →

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%).

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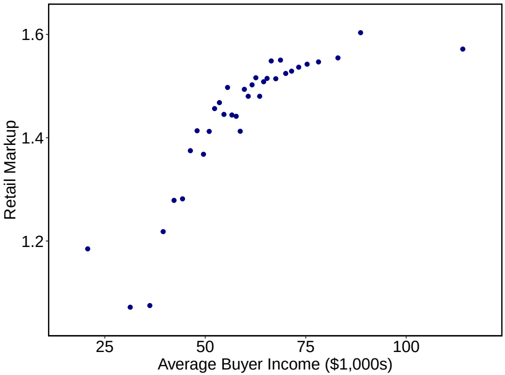
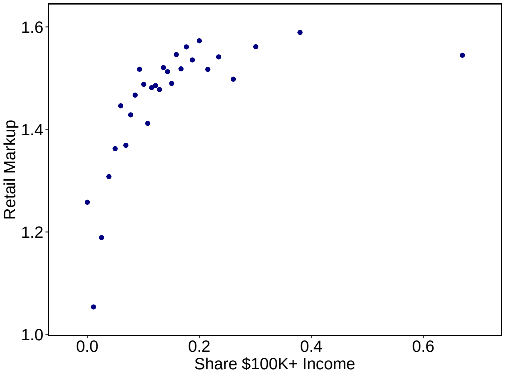
Basket composition: UPCs with high-income customers have high markups





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

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.

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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 (NAICS 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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Decomposition of macro elasticity

- Let $\mu_i(z_i, z_{-i})$ be the markup paid by household i.
- Household i's shares of expenditures is λ_i, share of costs of goods sold is c_i.
- Aggregate markup is cost-weighted average: $\mu^{\text{agg}} = \sum_i c_i \mu_i$.
- To a first order, changing everyone's income by $d \log z$ leads to:

$$\frac{d \log \mu^{\text{agg}}}{d \log z} = \underbrace{\sum_i c_i \frac{\partial \log \mu_i}{\partial \log z_i}}_{\text{Elasticity to own inc.}} + \underbrace{\sum_i c_i \frac{\partial \log \mu_i}{\partial \log z_{-i}}}_{\text{Spillovers of others' inc.}} - \underbrace{\sum_i c_i d \log \lambda_i}_{\substack{\text{Changes in exp. shares} \\ \text{(Disappears if exp.} \\ \text{scales 1-for-1 with inc.)}}}$$

$\Rightarrow$ Elasticity of agg. markup is cost-weighted avg. of own-income effect $+$ spillovers.

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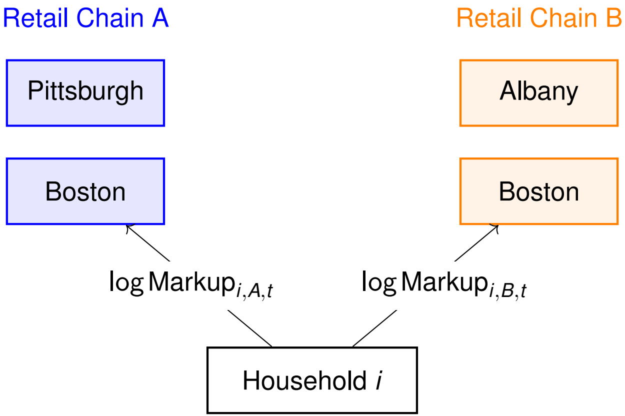
Identifying spillovers: Example

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



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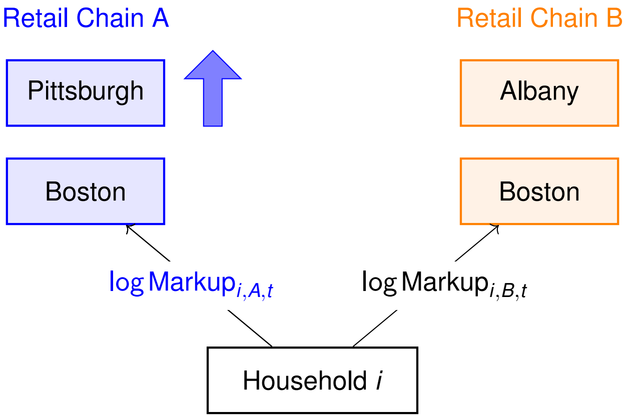
Identifying spillovers: Example

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



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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.

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Robustness for spillovers over time, 2006–2012

- Alternate specifications yield spillovers of 6–14%.

Log Retail Markup	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log Avg. CBSA Income	0.082**	0.071**								
	(0.016)	(0.013)								
Log Income at Retailer's Locations			0.088**	0.087**	0.087**	0.076**	0.068**			
			(0.031)	(0.017)	(0.037)	(0.029)	(0.030)			
Log Income of Other UPC Buyers								0.154**	0.145**	0.142**
								(0.041)	(0.038)	(0.038)
Household-Income Level FEs	Yes	Yes	Yes	Yes	Yes	Yes		Yes	Yes	
Year FEs	Yes	Yes	Yes	Yes				Yes		
Household-Year FEs							Yes			Yes
Household County FEs	Yes									
Store County FEs			Yes							
Store FEs		Yes		Yes		Yes	Yes	Yes		
Store County-Year FEs					Yes	Yes	Yes			
Store-Year FEs									Yes	Yes
N (millions)	133	91.9	50.8	50.8	50.8	50.8	50.8	97.0	97.0	97.0
R^2	0.17	0.19	0.17	0.19	0.17	0.19	0.21	0.19	0.21	0.21

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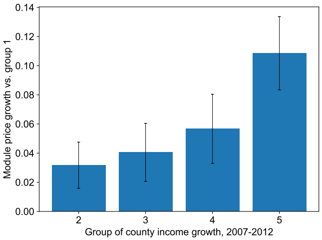
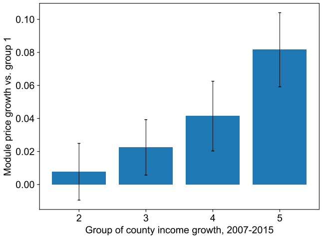
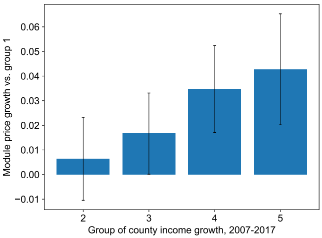
Time series evidence consistent with macro elasticity in cross-section

- 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.

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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)	(5)	Cost-weighted markup (6)	(7)	(8)	(9)	(10)
Log CBSA Income	0.131**	0.118**	0.105**	0.106**	0.115**	0.110**	0.102**	0.092**	0.094**	0.100**
	(0.006)	(0.007)	(0.007)	(0.008)	(0.008)	(0.006)	(0.007)	(0.007)	(0.008)	(0.008)
Gini Index		0.267**					0.153**			
		(0.060)					(0.057)			
Top 10% Income Share			0.156**					0.104**		
			(0.024)					(0.023)		
Top 5% Income Share				0.121**					0.078**	
				(0.025)					(0.024)	
Top 1% Income Share					0.091**					0.059**
					(0.030)					(0.029)
N	881	881	881	881	881	881	881	881	881	881
R^2	0.33	0.34	0.36	0.34	0.33	0.27	0.28	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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Bias due to local costs

- Let variable costs include COGS, wages, and rents: $VC(Y) = cY + wL(Y) + rA(Y)$.
- Let $\mu^{\text{COGS}} = pY/cY$, $\mu^{\text{true}} = pY/VC(Y)$.
- Assuming Leontief production, we get:

$$\frac{d\log\mu^{\text{COGS}}}{d\log z} \approx \underbrace{\frac{d\log\mu^{\text{true}}}{d\log z}}_{\text{True elasticity}} + \underbrace{\frac{wL}{VC}\frac{d\log w}{d\log z} + \frac{rA}{VC}\frac{d\log r}{d\log z}}_{\text{Bias from local costs}}.$$

- Using estimates from 2007 Census Annual Retail Trade Survey, $\frac{wL}{VC} < 17\%$, $\frac{rA}{VC} < 4\%$.
- Using data from OEWS and REIS, $\frac{d\log w}{d\log z} \approx 0.27$ and $\frac{d\log r}{d\log z} \approx 1.2$.
- Using estimates of variable labor from Kesavan et al. (2014), bias is 0.8%.

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Robustness: Search decreasing in own income, increasing in county income

Dependent variable (Measure of search intensity)	Log Own Income (IV) Coefficient	SE	Log County Income Coefficient	SE
Log Shopping trips per $1K spent	-0.40**	(0.01)	0.09**	(0.02)
Log Shopping trips per transaction	-0.30**	(0.01)	0.19**	(0.03)
Log Shopping trips per brand bought	-0.27**	(0.01)	0.16**	(0.03)
Log Shopping trips per UPC bought	-0.29**	(0.01)	0.18**	(0.03)
Log Unique stores visited per $1K spent	-0.34**	(0.01)	0.26**	(0.07)
Log Unique stores visited per transaction	-0.24**	(0.01)	0.36**	(0.06)
Log Unique stores visited per brand bought	-0.21**	(0.01)	0.33**	(0.06)
Log Unique stores visited per UPC bought	-0.23**	(0.01)	0.34**	(0.06)
Log Unique retailers visited per $1K spent	-0.26**	(0.01)	0.11**	(0.02)
Log Unique retailers visited per transaction	-0.15**	(0.01)	0.21**	(0.03)
Log Unique retailers visited per brand bought	-0.12**	(0.01)	0.18**	(0.02)
Log Unique retailers visited per UPC bought	-0.14**	(0.01)	0.19**	(0.03)

* is significant at 10%, ** at 5%. Standard errors clustered by county.

$$\text{SearchIntensity}_{i,c} = \beta \text{Log Income}_i + \gamma \text{Log County Income}_c + \delta \text{Log Grocery Estabs}_c + \kappa_{\text{State}(c)} + \varepsilon_{i,c}.$$

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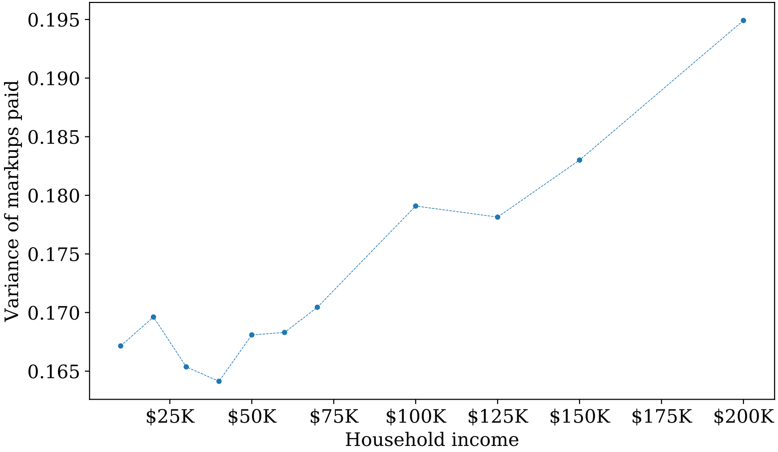
Variance of markups paid rises with income, consistent with search

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



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Model prediction: Returns to scale from ticket size

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

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 $s_i \geq 0$.

Moreover, we will require:

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

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

for any non-degenerate distribution F, where $\mathbb{E}[p|n;F]$ is the expected value of the minimum of n draws from F.

← Back

Micro- and Macro-Elasticities: Intuition

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

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

where the (strictly positive) κ coefficients are given by

$$\kappa_1 = \frac{1}{a}\frac{-p_s}{p_{ss}}, \qquad \kappa_2 = \frac{1}{a}\frac{-p_{s_{-i}}}{p_{ss}+p_{s,s_{-i}}}, \qquad \kappa_3 = \frac{1}{a}\frac{-p_s}{p_{ss}+p_{s,s_{-i}}}.$$

  - $-p_s > 0$ (i.e., price falls with search) since $\uparrow s_i$ leads to FOSD shift in $\{q_{i,n}\}_{n=1}^{\infty}$.
  - $p_{ss} > 0$ (i.e., the price function convex) guaranteed by Assumption 1.
  - $p_{ss} + p_{s,s_{-i}} > 0$ guaranteed by stability of equilibrium.

← Back

Two quote and Poisson mappings

- **Two quote**:

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

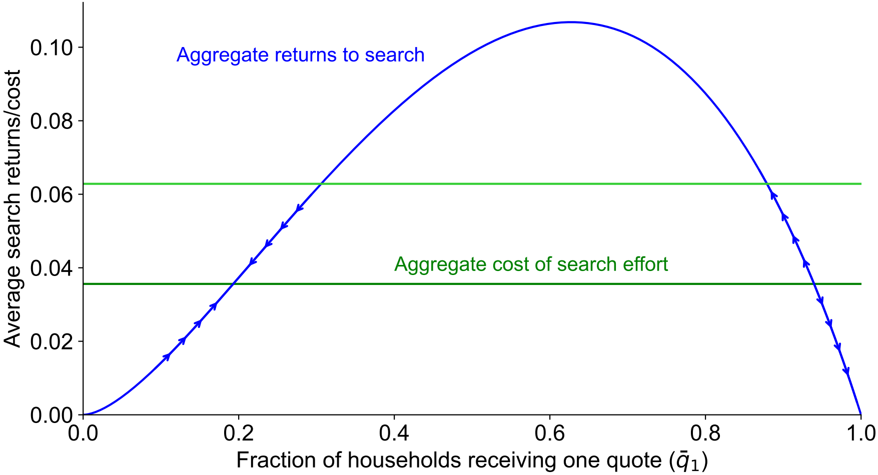
- **Poisson**:

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

← Back

Comparative Statics: Intuition

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



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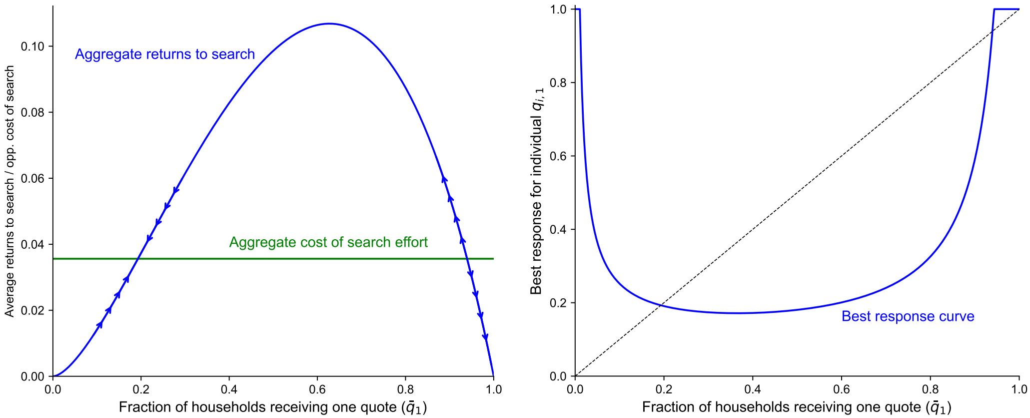
Stable Dispersed-Price Equilibrium: Strategic Interactions



(a) Aggregate equilibrium condition.

(b) Individual best response curve.

← Back

Balanced Growth?

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

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.

← Back to macro elast. ← Back to proposition ← Back to markups over time

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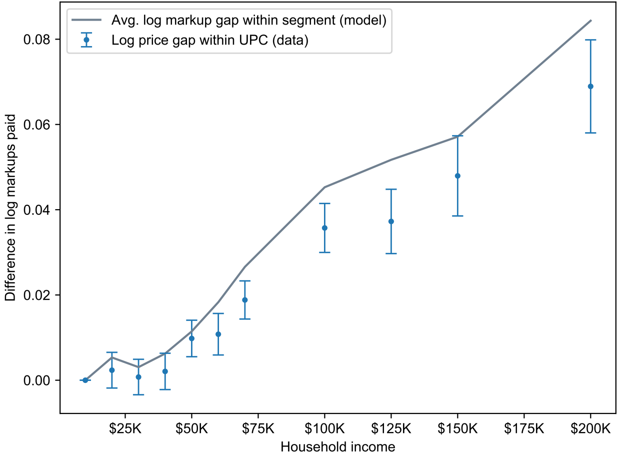
Within-segment markup gap $\approx$ gap in prices paid for identical products

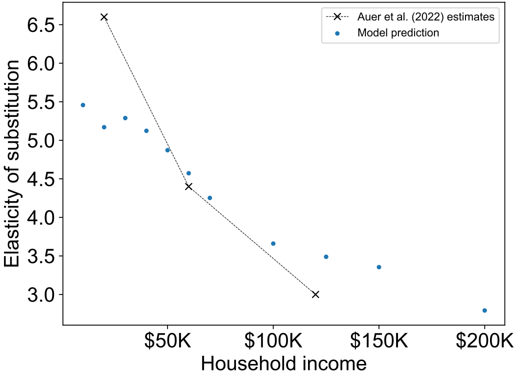


- Untargeted moment: differences in prices paid for identical products.
- Overall markup gap $=$ within-segment price gap $+$ cross-segment markup gap.

← Back

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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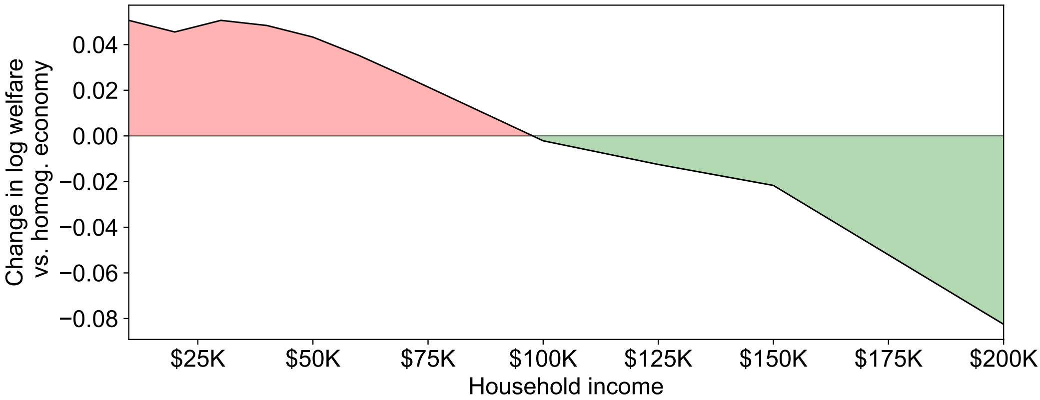
Magnitude of markup spillovers across households

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

Income level	Markup savings (pp)	(%)	Average NielsenIQ 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

← Back

Change in welfare relative to homog. economy



- Welfare for low-income 4% lower, for high-income 8% higher, in baseline.

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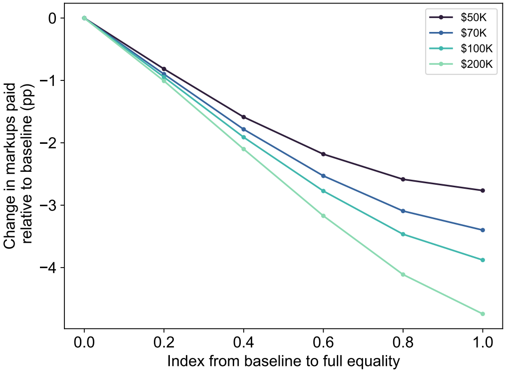
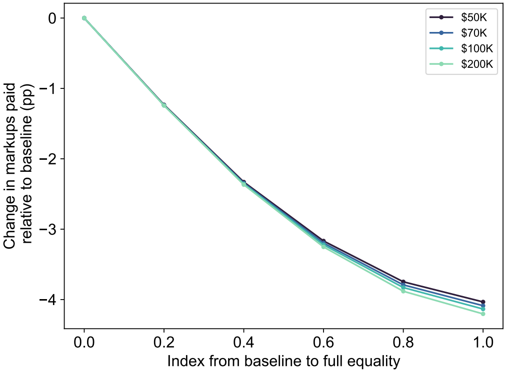
Differential costs for high-income households due to segmentation



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



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

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

← Back

Markups across space: Data

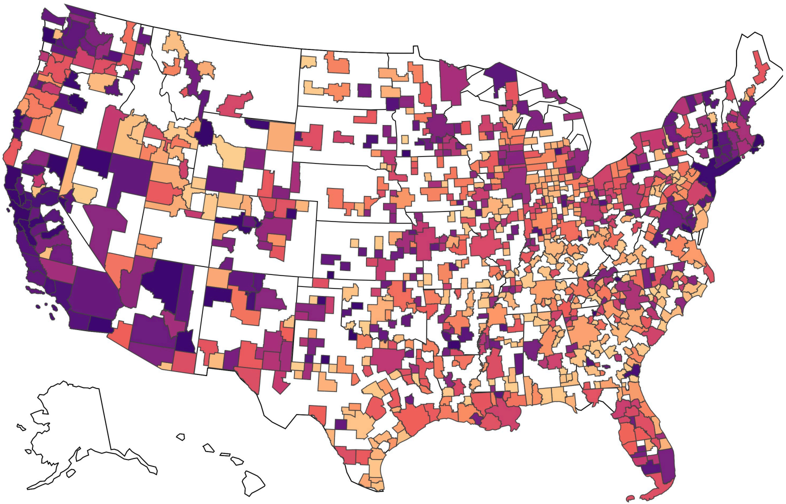
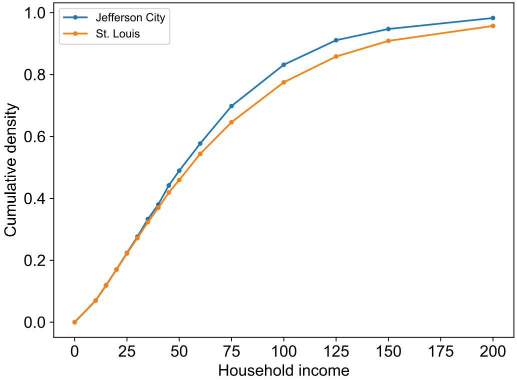
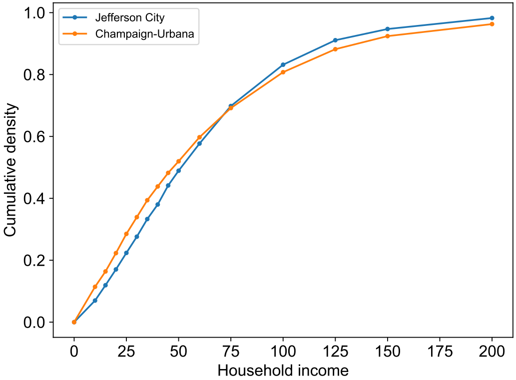


Figure: Aggregate (cost-weighted average) markups across CBSAs.

← Back

Model predicts that markups increase with income level and dispersion



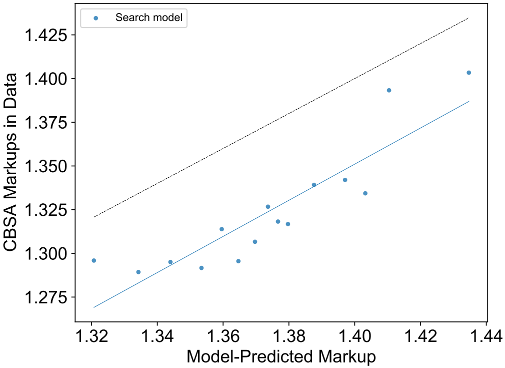


CBSA	Average Income	Gini Index	Predicted Markup
Jefferson City	$33.3K	0.41	34%
St. Louis	$41.0K	0.46	38%

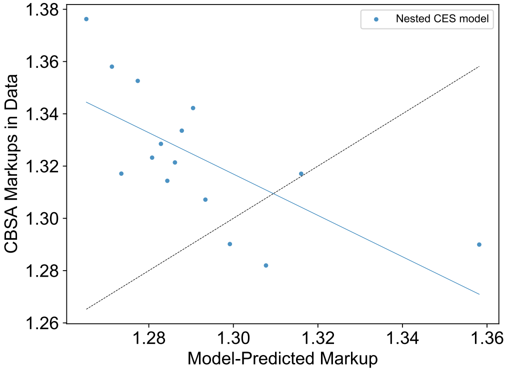
CBSA	Average Income	Gini Index	Predicted Markup
Jefferson City	$33.3K	0.41	34%
Champaign-Urbana	$33.7K	0.48	37%

← Back

CBSA markups predicted by model vs. data: Binscatters



(a) Search model.

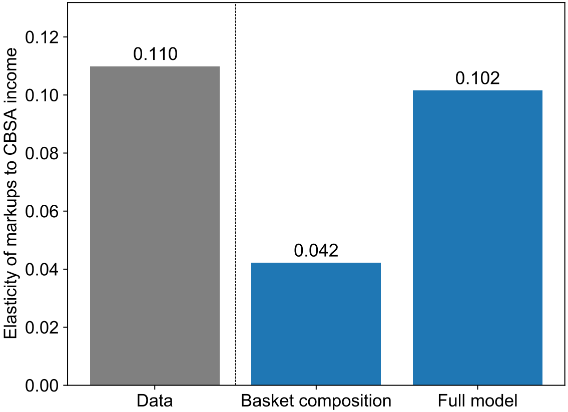


(b) Nested CES model.

← Back

40% of markup differences across CBSAs due to basket composition

- Markups across CBSAs differ due to basket composition + markup differences.
- In model, basket composition explains 40 percent of cross-CBSA markup differences.



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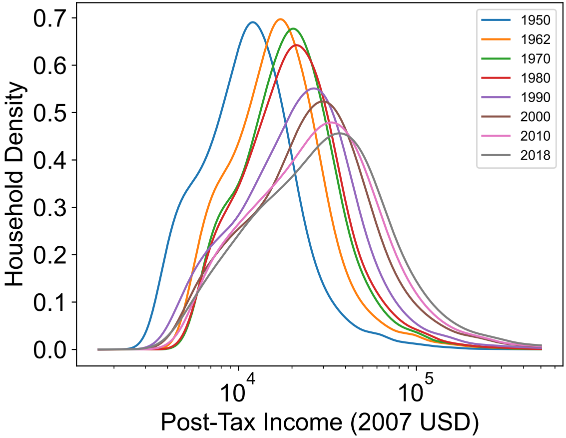
Income distribution from 1950–2018

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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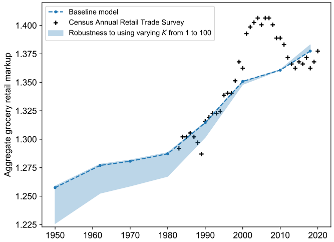
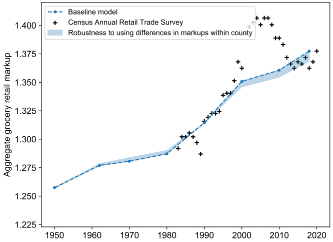
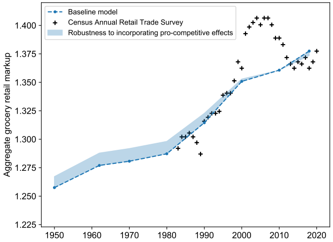
Markups over time: Robustness to calibration choices



(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.

← Back Varying K and ζ → Varying σ →

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

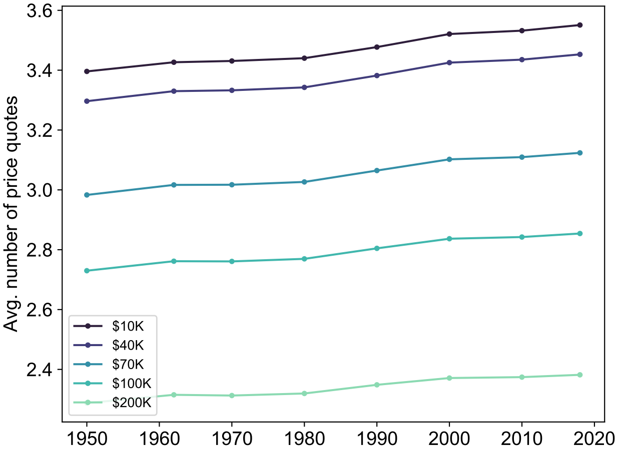
Predicted change in aggregate markup, holding search constant

- 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

← Back

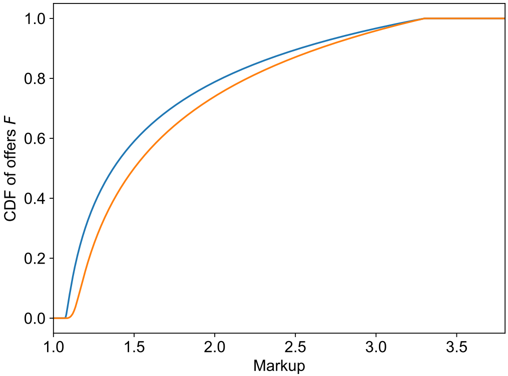
Predicted search intensities over time



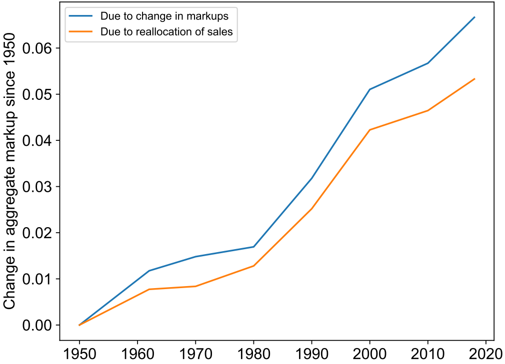
- Since household search decisions are strategic substitutes, households' search intensity (conditional on income) rises as economy gets richer.

← Back

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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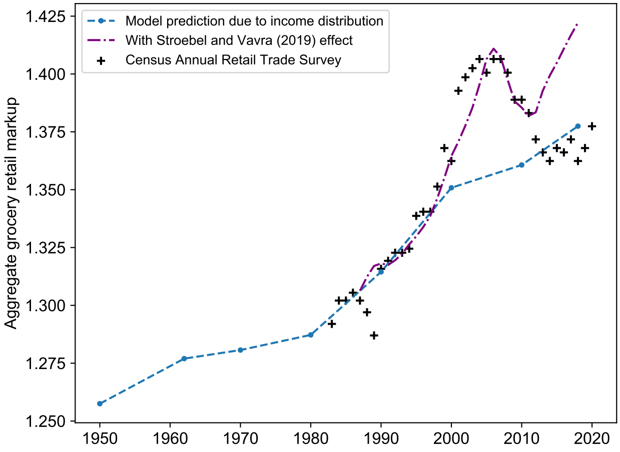
Including house price effect from Stroebel and Vavra (2019)



- Census Annual Retail Trade gross margins for retail grocery.
- Adding median OLS estimates from Stroebel and Vavra (2019).

← Back

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.

← Back

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**	0.073**	0.065**
	(0.011)	(0.018)	(0.016)
Log Avg. CBSA Income $\times$ Mid-Income Group	0.016*	0.021**	0.006
	(0.008)	(0.008)	(0.005)
Log Avg. CBSA Income $\times$ High-Income Group	0.030**	0.034**	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

← Back

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

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

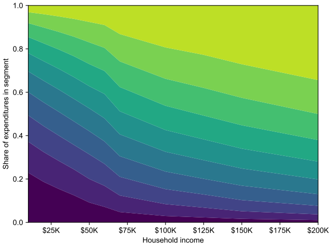
No. segments (K)	Predicted Δ markup 1950–2018		Markup externality low-income		Markup externality high-income	
	$\zeta = 0$	$\zeta = 0.3$	$\zeta = 0$	$\zeta = 0.3$	$\zeta = 0$	$\zeta = 0.3$
1	15.7pp	12.8pp	+10pp	+8pp	-19pp	-11pp
3	12.6pp	10.9pp	+7pp	+6pp	-13pp	-6pp
5	12.2pp	10.7pp	+6pp	+6pp	-12pp	-6pp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

← Back

Robustness to elasticity of substitution across segments

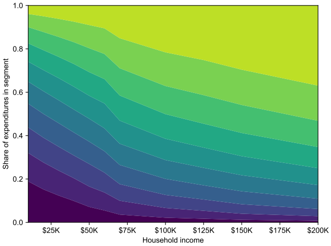
- Relative prices of different goods do not change enough to trigger large endogenous changes in spending shares, even with $\sigma \gg 1$.
- Result: Changing σ does not materially affect results.

Figure: Model predicted spending shares in 1950.



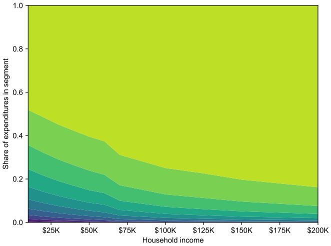
(a) $\sigma = 0.01$.

$\Delta\bar{\mu}_{1950-2018} = 11.995$.



(b) $\sigma = 10$.

$\Delta\bar{\mu}_{1950-2018} = 11.998$.



(c) $\sigma = 100$.

$\Delta\bar{\mu}_{1950-2018} = 12.026$.

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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 →

Non-homothetic CES model

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

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

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

		Portion due to	
Period	Predicted Δ agg. markup	Δ Income level	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

Non-homothetic CES model produces counterfactual macro elasticity

- Elasticity of markups to income across cities is more than 2x the data.

	CES Model-Predicted		Data	
Log CBSA Markup	(1)	(2)	(3)	(4)
Log CBSA Income	0.297**	0.278**	0.110**	0.102**
	(0.005)	(0.005)	(0.006)	(0.007)
Gini Index		0.369**		0.153**
		(0.042)		(0.057)
N	881	881	881	881
R^2	0.82	0.84	0.27	0.28

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

← Back

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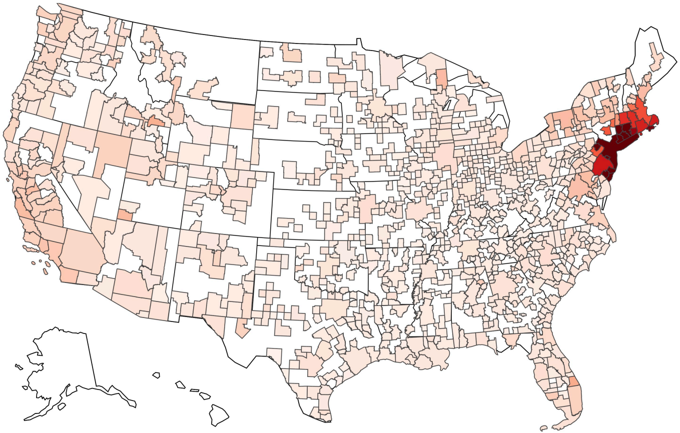
Spatial spillovers: Effects of higher incomes among rich in New York

- 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

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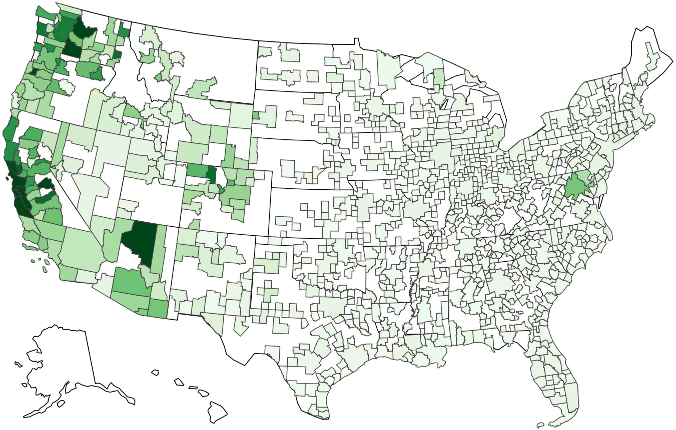
Spatial spillovers: Effects of "Tech Recession"

- #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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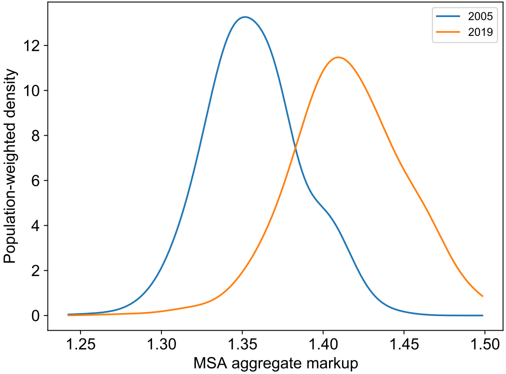
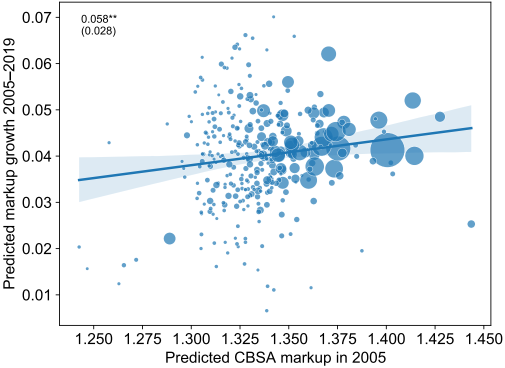
Predicting markups across cities and over time from 2005–2019

- Predict markups for 349 MSAs using inc. dists. from ACS 1-year surveys (2005–2019).
- Markup dist. shifts to the right and widens + Divergence in markups across cities.



(a) Density of MSA markups in 2005 vs. 2019.



(b) Divergence in MSA markups.

Model markups predict changes in unit prices within cities over time

- Use average unit prices for product modules to validate markup predictions:

$$\text{Log AvgUnitPrice}_{c,g,t} = \beta \, \text{Log Markup}_{c,t} + \alpha_c + \delta_{g,t} + \varepsilon_{c,g,t}.$$

- Result: Markups predict unit prices across MSAs and within MSA over time.

Log Avg. Unit Price (deflated)	(1)	(2)	(3)
Log Model-Predicted Markup	1.860**	2.018**	0.596**
	(0.266)	(0.276)	(0.269)
Product Module FEs	Yes		
Year-Product Module FEs		Yes	Yes
CBSA FEs			Yes
N (millions)	12.5	12.5	12.5
R^2	0.99	0.99	0.99

Standard errors two-way clustered by CBSA and year. Regressions weighted by deflated sales. * is significant at 10%, ** at 5%.

MSA markup growth, divergence patterns in unit price data

- Predictions for which MSAs have greatest markup growth replicated in price data.
- Pattern of markup diverge replicated in data.

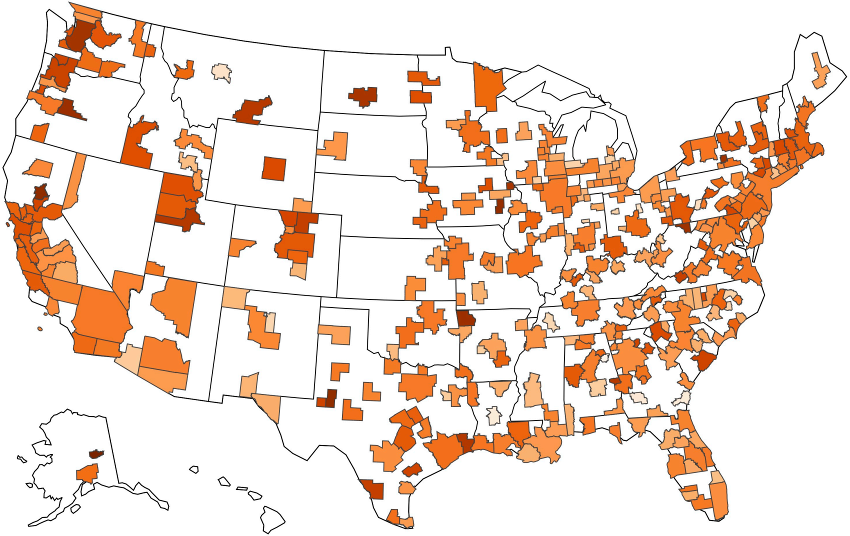
Table: Quartile of markup growth.

	μ^{pred}	p^{data}
Year × Markup Growth Q2	0.001**	0.001
	(0.000)	(0.001)
Year × Markup Growth Q3	0.002**	0.002*
	(0.000)	(0.001)
Year × Markup Growth Q4	0.001**	0.002**
	(0.000)	(0.001)
Year-Product Module FEs	Yes	Yes
N (millions)	12.3	12.3
R^2	0.99	0.99

Table: Quartile of 2005 markup.

	μ^{pred}	p^{data}
Year × Initial Markup Q2	0.001**	0.000
	(0.000)	(0.000)
Year × Initial Markup Q3	0.001**	0.001**
	(0.000)	(0.000)
Year × Initial Markup Q4	0.002**	0.003**
	(0.000)	(0.001)
Year-Product Module FEs	Yes	Yes
N (millions)	12.3	12.3
R^2	0.99	0.99

Predicted growth in markups from 2005–2019 across MSAs



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Shopping time increases with basket size: Cross section

- Larger basket requires more shopping time (conditional on income, demographics, and markups paid).
- Use household size (conditional on demographics, etc.) 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 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	63314	63314	63314	63314	63314	63314
R^2	0.39	0.39	0.38	0.36	0.33	0.25

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

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Shopping time increases with basket size: Time series

- Within-household, larger basket size leads to more shopping time.
- Use income as 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	0.745**	0.143**	0.527**	0.203**	0.193**	0.115**
	(0.010)	(0.029)	(0.006)	(0.032)	(0.002)	(0.029)
Household FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
N	917692	917692	917692	917692	917692	917692
R^2	0.92	0.87	0.87	0.85	0.77	0.77

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

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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. (2023).

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

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Country-level markups exhibit similar relationship with income

- Country-level markups est. by De Loecker and Eeckhout (2018) from 1980–2016.
- Markups rise with per-capita income and inequality for 32 matched countries.

Log Country Markup (1980–2016)	Full Panel (1)	Within-Country Over Time (2)	Within-Year Across Countries (3)
Log Per-Capita Income	0.073**	0.214**	0.062*
	(0.035)	(0.088)	(0.031)
Gini Index	1.015**	1.991**	0.993**
	(0.220)	(0.657)	(0.197)
Country FEs		Yes	
Year FEs			Yes
N	642	642	642
R^2	0.15	0.64	0.30

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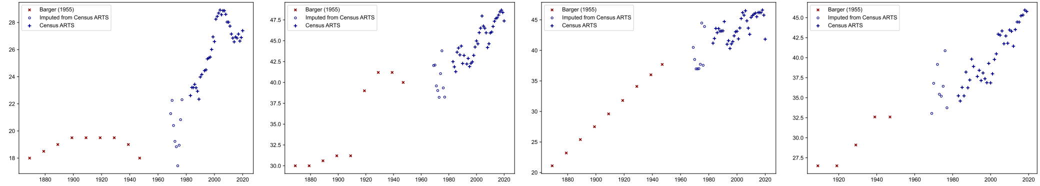
Were markups rising before 1980?

- Newly digitized Census Annual Retail Trade Surveys from 1969–1977 and historical data from NBER report by Barger (1955).



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

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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.

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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%.

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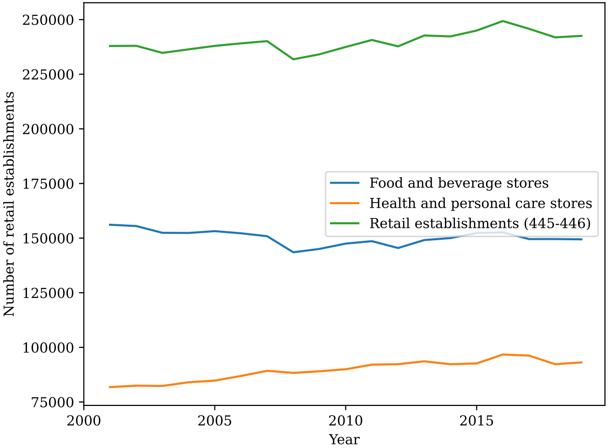
Total number of retail establishments

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



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Related models of income and markups: Comparison

Model	Comparison to data
Preferences:	
Non-homothetic CES e.g., Handbury (2021), Faber and Fally (2022)	Price dispersion within products.
Vertical & horizontal differentiation e.g., Fajgelbaum et al. (2011)	Income distribution affects markups only through composition of products.
Bounded marginal utility e.g., Simonovska (2015), Neiman and Vavra (2019)	Markup decreasing in share of households purchasing product.
Differentiation and finicky tastes e.g., Hummels and Lugovskyy (2009), Brand (2021)	No relationship between markup and measures of module differentiation.
Search:	
Sales-based discrimination e.g., Varian (1980)	Positive spillovers of others' incomes for households at all income levels.
Representative agent:	
Oligopolistic competition e.g., Atkeson and Burstein (2008)	Sales shares and concentration do not explain link between income and retail markups.

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