Markups Across the Income Distribution: Measurement and Implications

Kunal Sangani

July 22, 2022

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.

The Law of Diminishing Elasticity of Demand: Micro Evidence, Macro Effects

- Harrod (1936) conjecture: as income rises, price sensitivity falls.
- **Micro evidence**:
  - Quantify using retail markups (price / wholesale cost) on 26M transactions.
  - High-income households pay 14pp higher markups on average.
    - Within county, high-income pay 12pp higher markups.
    - Within store, high-income pay 7pp higher markups.
    - Elasticity of markups to household income 2x prices of identical goods to income.
  - Across products, $\uparrow$ 10pp share of high-income customers $\Longrightarrow$ $\uparrow$ 4-8pp retail markup.

The Law of Diminishing Elasticity of Demand: Micro Evidence, Macro Effects

- **Micro-foundation**: A search model of income and markups.
  - Heterogeneous households with Burdett and Judd (1983) nonsequential search.
  - Markups rise with changes to income distribution...
    - a FOSD shift if opportunity cost of search rises with income.
    - a mean-preserving spread if opp. cost of search increasing and convex in income.

The Law of Diminishing Elasticity of Demand: Micro Evidence, Macro Effects

- **Micro-foundation**: A search model of income and markups.
  - Heterogeneous households with Burdett and Judd (1983) nonsequential search.
  - Markups rise with changes to income distribution...
    - a FOSD shift if opportunity cost of search rises with income.
    - a mean-preserving spread if opp. cost of search increasing and convex in income.
- **Calibration**:
  - Search spillovers: high-income shoppers increase markups paid by low-income by 9pp.
  - "Macro elasticity" of markups to income $>$ micro elasticity.
  - Income distribution 1950–2018 accounts for 14pp rise in retail markup.
    - Markup increase accelerates after 1980 due to $\uparrow$ income dispersion.
    - Increase due to within-product markups *and* reallocation to high-markup products.

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)
  - *Price elasticities over time or across groups*: Harrod (1936), Lach (2007), Anderson, Rebelo, and Wong (2018), Stroebel and Vavra (2019), DellaVigna and Gentzkow (2019), Faber and Fally (2017), Jaimovich, Rebelo, and Wong (2019), Argente and Lee (2021), Handbury (2021), Gupta (2020), Auer, Burstein, Lein, and Vogel (2022)
  - *Trade literature*: Alessandria and Kaboski (2011), Simonovska (2015).
- **Search in product markets**
  - Stigler (1961), Burdett and Judd (1983), Alessandria and Kaboski (2011), Kaplan and Menzio (2016), Pytka (2018), Kaplan, Menzio, Rudanko, and Trachter (2019), Albrecht, Menzio, and Vroman (2021), Menzio (2021)
- **Evolution of retail markups**
  - Neiman and Vavra (2019), Brand (2021), Döpper, MacKay, Miller, and Stiebale (2021).

Table of Contents

Data

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

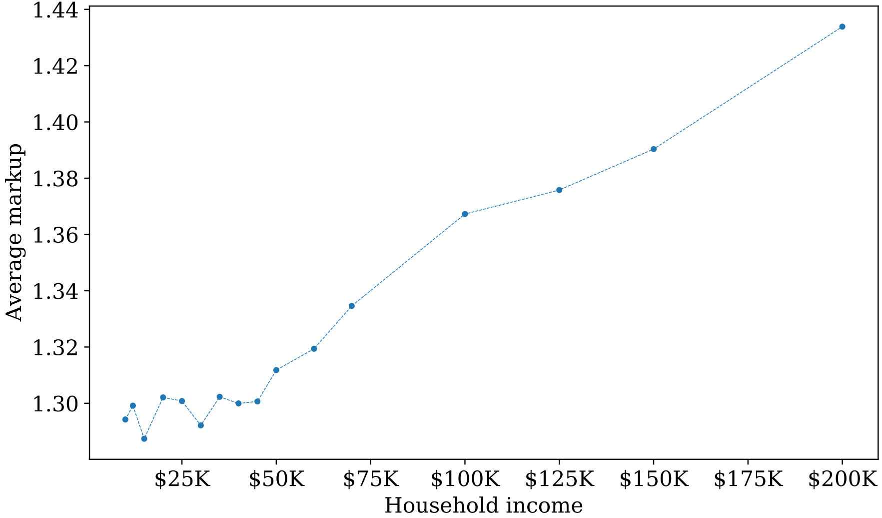
Coverage by income →

Retail markups calculated using wholesale cost

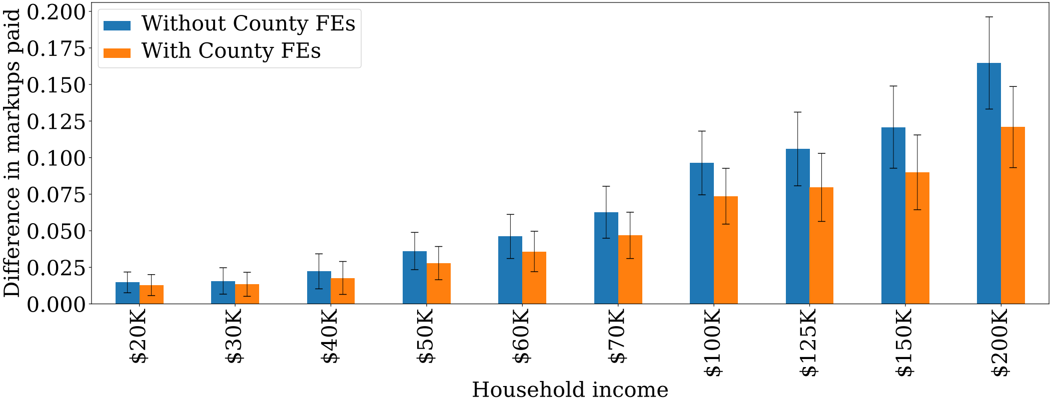
- Calculate Retail Markup $=$ Price$/$Wholesale Cost.
  - Replacement costs used by Gopinath et al. (2011), Anderson et al. (2018).
  - Differences in markups paid **within store** since wholesale costs, distribution costs, and overhead may differ across stores.
- Average (sales-weighted) markup is 32%.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

Average markup paid increases with household income

Figure: Sales-weighted average markup paid by income group.



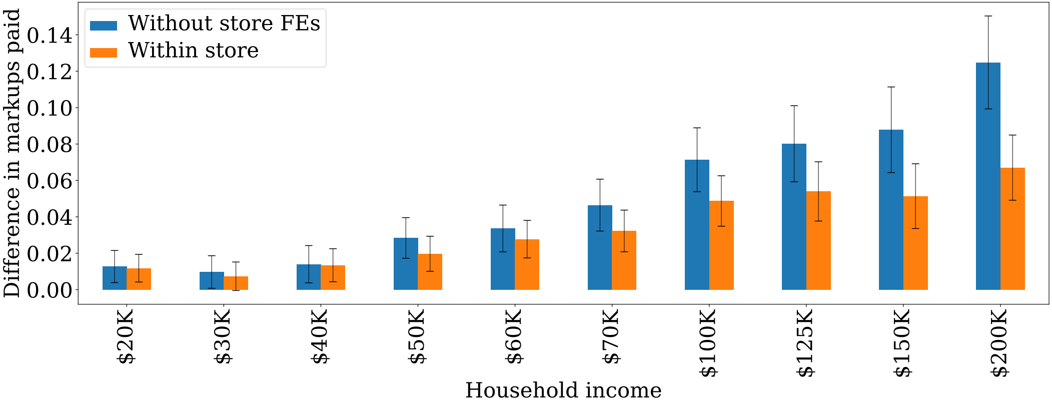
12pp gap in markups paid within county



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

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

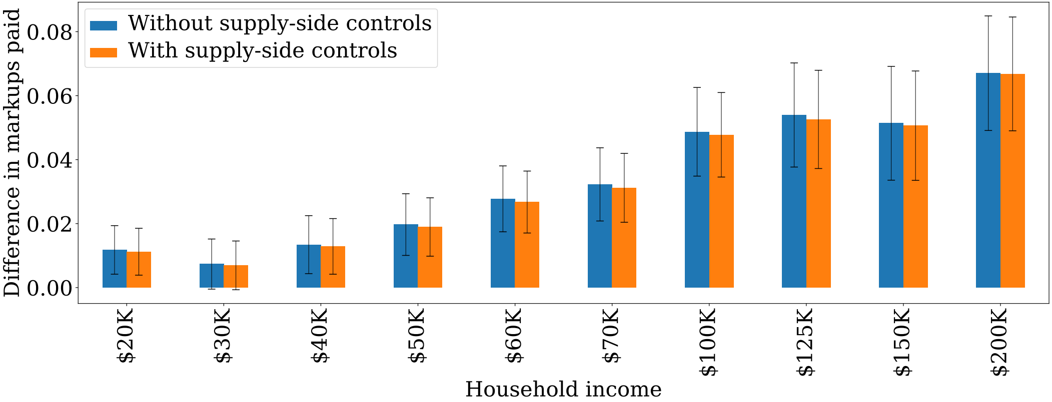
7pp gap in markups paid within store



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

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

Link between income and markups not explained by sales shares, HHI



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

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

Elasticity of markups to household income 2x prices of identical goods

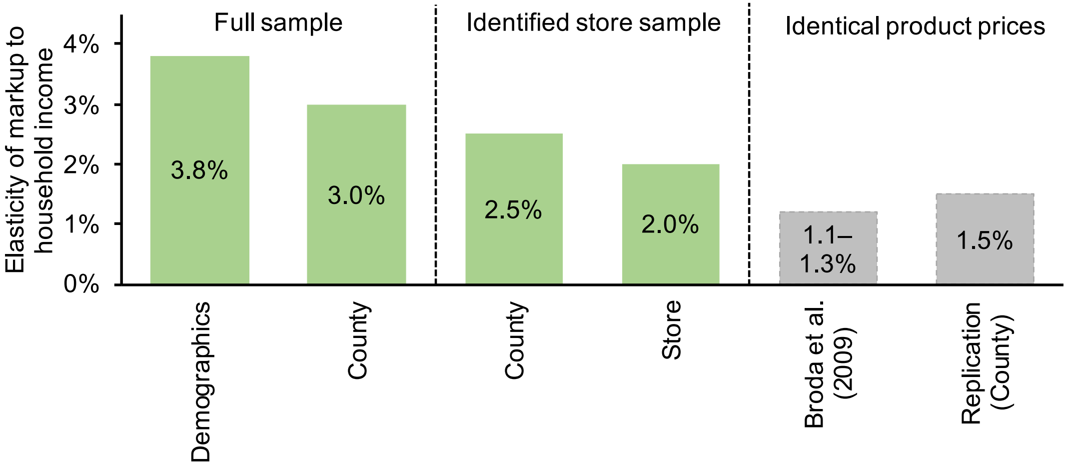
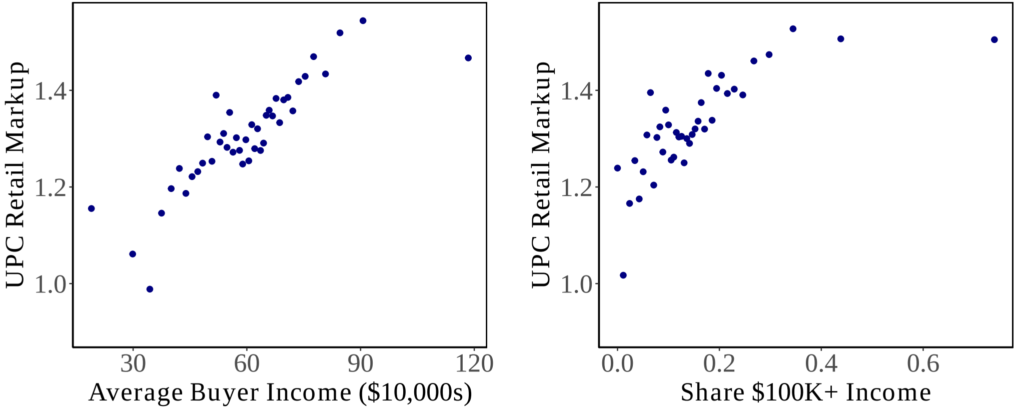


Table → Decomposition within store → Decomposition within group → Decomposition (FE) → Volume discounts →

UPC retail markups and buyer income



- ↑ 10pp share of buyers with $100K income associated with ↑ 4–8pp retail markup.

Table of Contents

Model Roadmap

Micro-foundation: Households exert search effort to find low prices.

Aguiar and Hurst (2007), Alessandria and Kaboski (2011), Kaplan and Menzio (2016), Pytka (2018).

1. Household search technology.
2. Household search effort decision.
3. Firm profit maximization.
4. Equilibrium.

Household Search Technology

- Households know the distribution of prices, but not which firms sell at which price.

- Household i has probability mass function over number of price quotes $\{q_{i,n}\}_{n=1}^{\infty}$,
  - Observes only one quote with probability $q_{i,1}$,
  - Observes two quotes with probability $q_{i,2}$, etc.

- For each purchase, households buy iff min price $p \leq$ reservation price R.
  Redraw n quotes costlessly if $p > R$.

Household Search Technology

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

Conditions on $\mathscr{S}$ →

Household Problem

$$\max_{l_i, t_i} c_i \qquad \text{s.t.} \qquad \begin{cases} c_i t_i + l_i = 1 & \text{(Time constraint)} \\ \mathbb{E}[p_i] c_i = w z_i l_i. & \text{(Budget constraint)} \\ s_i = a_i t_i. & \text{(Search productivity)} \end{cases}$$

where

- c_i is units of good consumed,
- t_i is time spent shopping per unit,
- l_i is time spent working with labor productivity z_i,
- s_i is i's search intensity and a_i is i's search productivity.

- First order condition:

$$\underbrace{-\partial \mathbb{E}[p_i | s_i] / \partial s_i}_{\text{Marginal savings}} = \underbrace{\phi_i}_{\text{Opportunity cost}}$$

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

Returns to scale in search →

Aggregate Search Behavior

- Aggregate search behavior $\bar{q}$:

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

where $H(i)$ is CDF of types and $d\Lambda(i) = c_i dH(i) / \int_0^\infty c_i dH(i)$.

- Mass M of firms choose prices to maximize variable profits π:

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

where F is distribution of posted prices, marginal cost is w (one unit of labor), and total consumption is $C = \int_0^\infty c_i dH(i)$.

Dispersed Price Equilibrium (Burdett and Judd 1983)

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

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

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

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

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

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

- Mass of firms M adjusts to ensure $\pi = f_e \cdot w$.

Shifts in the Income Distribution

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

Proposition

Aggregate markup weakly increases if

- *First-order stochastic shift in $H(i)$ and opp. cost of search ϕ_i increasing in i.*
- *Mean-preserving spread in $H(i)$ and opp. cost of search ϕ_i increasing and convex in i.*

Functional forms → Intuition →

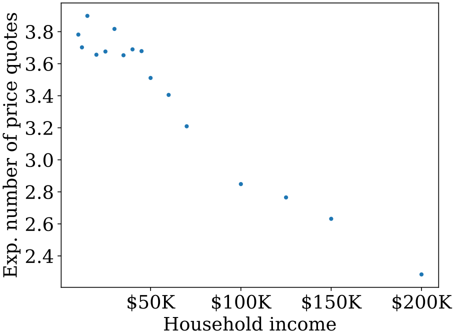
Table of Contents

Calibration: Price quotes received and search productivity

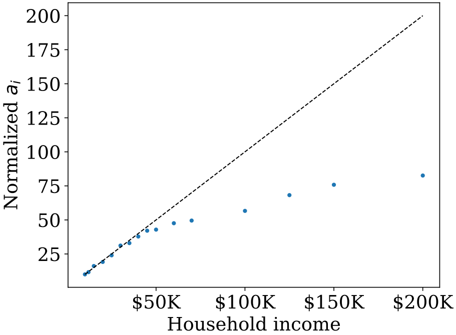
- Assume $\mathscr{S}$ is Poisson: $q_{i,n+1} = s_i^n \exp(-s_i)/n!$ (Albrecht et al. 2021, Menzio 2021.)
- Solve fixed point in $(F, \{s_i\})$ to match markups paid by income group.
- Assume households $>$\$200K income have identical behavior to those with \$200K.

Calibration: Price quotes received and search productivity

- Assume $\mathscr{S}$ is Poisson: $q_{i,n+1} = s_i^n \exp(-s_i)/n!$ (Albrecht et al. 2021, Menzio 2021.)



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

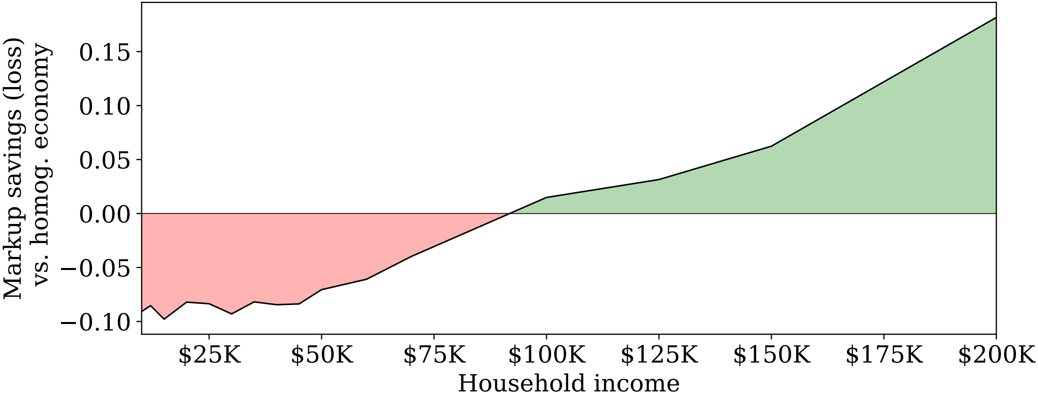


(b) Search productivity a_i.

- Doubling search time decreases prices paid 7–9%. (7–10% estimated by Aguiar and Hurst 2007.)

Search evidence → Comparison to Auer et al (2022) →

Spillovers from shopping behavior across households



- Macro elasticity of markups to income is 0.084.
  - Elasticity of markups to country per-capita income from Simonovska (2015) is 0.12–0.24.

Suggestive evidence: Macro > micro elasticity of markups to income

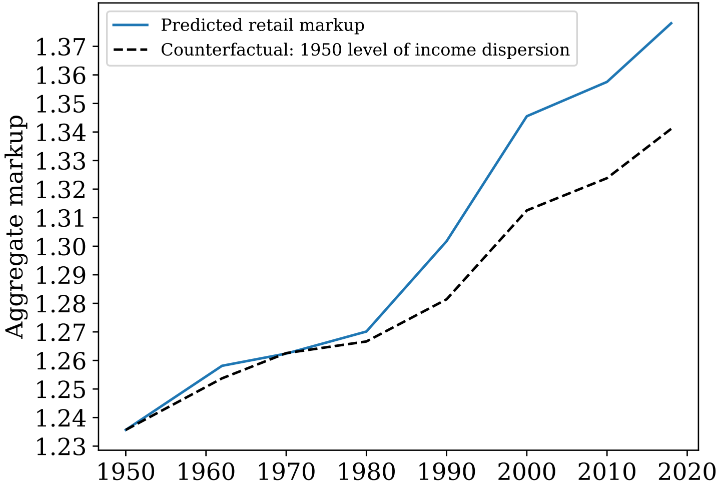
Log Retail Markup	(1)	(2)	(3)	(4)
Log Household Income	0.038**	0.033**	0.025**	0.022**
	(0.004)	(0.004)	(0.002)	(0.001)
Log Avg. CBSA Income		0.104**		
		(0.010)		
Log Avg. Income: Other UPC Buyers			0.291**	0.091**
			(0.066)	(0.039)
Demographic Controls	Yes	Yes	Yes	Yes
Product Module FEs				Yes
N (millions)	25.8	23.8	25.8	25.8
R^2	0.00	0.01	0.02	0.29

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

- Consistent with 0.084 macro elasticity of markups to income in model.

IV →

Counterfactual: Income distribution from 1950–2018

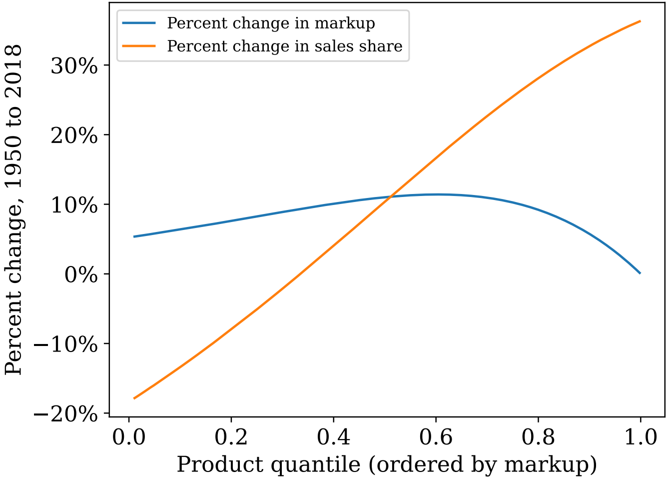


- 1950–2018 post-tax real income distribution from Saez and Zucman (2019).
- 14pp predicted increase in aggregate markup.
- Accelerates after 1980.
- After 1980, 30% due to ↑ income dispersion.

Table → Holding search fixed → Perfect price discrimination → Non-homothetic savings →

Reallocations across products vs. within-product changes

- Products at all quantiles increase markups.
- Reallocation of sales to high-markup products.
- 1/3 of rise due to cross-product reallocations.



Relative contributions →

Conclusion

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

Extra Slides

Table of Contents

PromoData Price-Trak UPC data coverage by income level

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

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

Uniformity of wholesale prices across markets

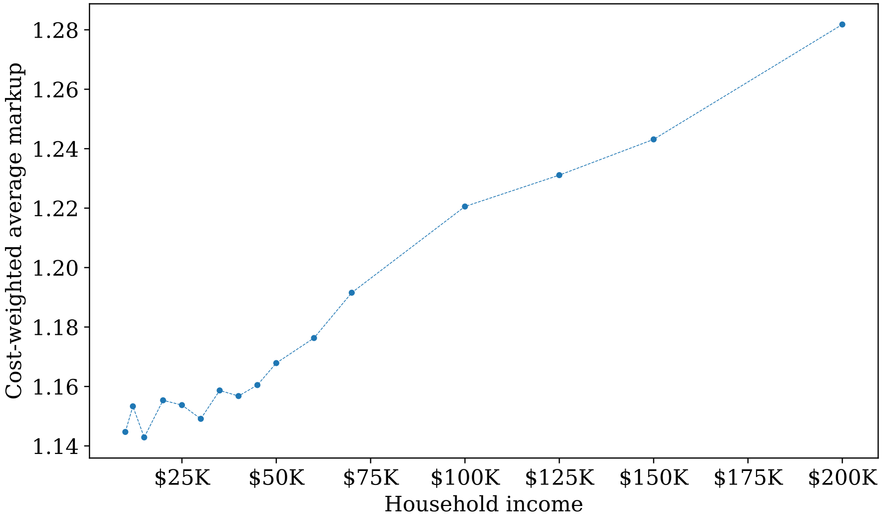
Table: Uniformity of wholesale prices across markets.

	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

Average cost-weighted markup paid increases with household income

Figure: Cost-weighted average markup paid by income group.



Share of sample used to estimate income FEs

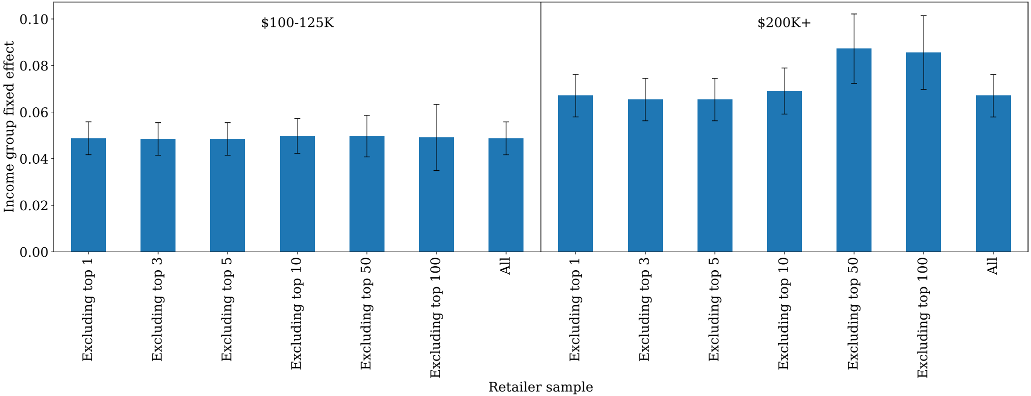
Table: Number of distinct income groups observed by split of data.

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

← Back

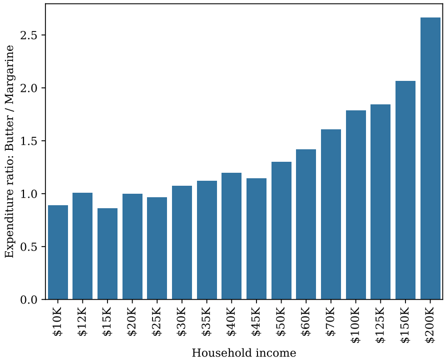
No decline in within-store income effect excluding largest retailers

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

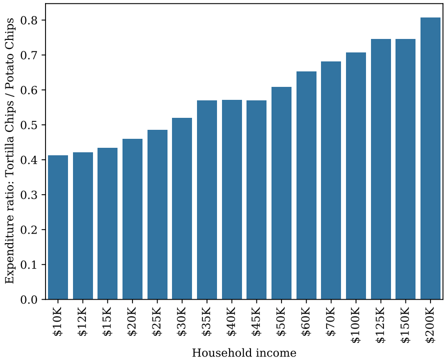


← Back

Example: Product modules consumed by rich have higher markups



(a) Expenditures on butter vs. margarine.

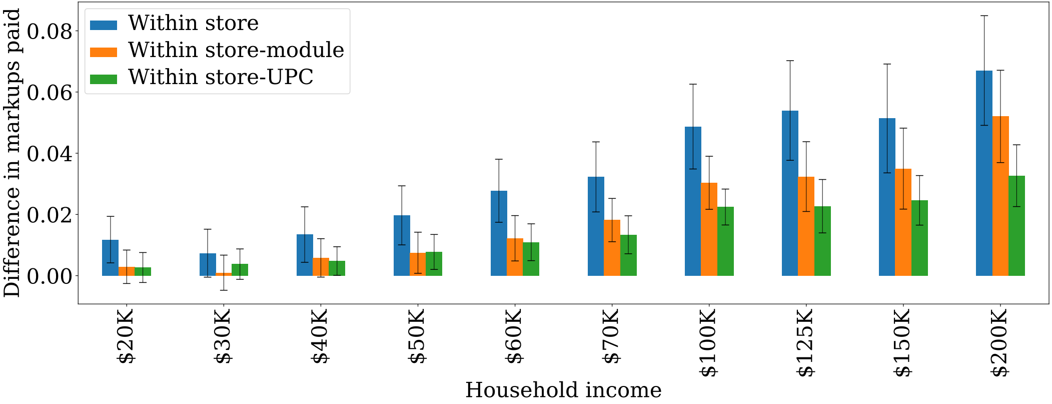


(b) Expenditures on tortilla chips vs. potato chips.

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

← Back

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.

Suggestive evidence: Macro > micro elasticity of markups to income (IV)

Log Retail Markup	(1)	(2)	(3)	(4)
Log Household Income (fit)	0.054**	0.051**	0.037**	0.032**
	(0.006)	(0.006)	(0.003)	(0.002)
Log Avg. CBSA Income		0.093**		
		(0.010)		
Log Avg. Income: Other UPC Buyers			0.282**	0.085**
			(0.066)	(0.039)
Demographic Controls	Yes	Yes	Yes	Yes
Product Module FEs				Yes
N (millions)	25.8	23.8	25.8	25.8
R^2	0.00	0.01	0.02	0.29

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

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

← Back

Elasticity of markups to household income: Decomposition

Product barcodes (UPCs) consumed by rich have higher markups

Table: Regression of UPC markup on consumer characteristics.

	(1)	(2)	(3)	(4)	(5)	(6)
Average Income (10,000s)	0.059**	0.027**				
	(0.013)	(0.009)				
Share $100K+ income			0.868**	0.423**		
			(0.176)	(0.110)		
Share $10-50K income					−0.435**	−0.149**
					(0.103)	(0.067)
Product Module FEs		Yes		Yes		Yes
N	67 161	67 161	67 161	67 161	67 161	67 161
R^2	0.01	0.42	0.01	0.42	0.01	0.42

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

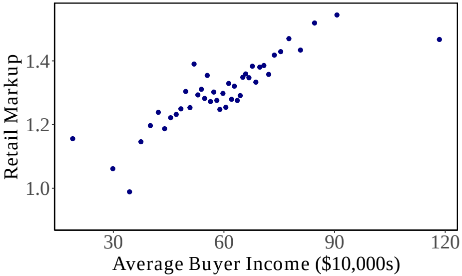
- 10pp increase in share of $100K+ customers increases markup 4–8pp.

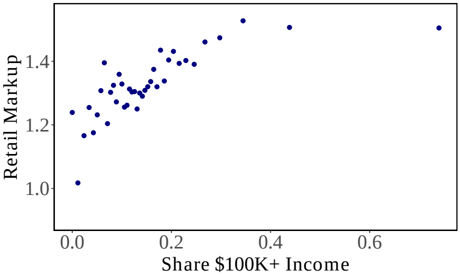
Link between income and markups not explained by sales shares, HHI

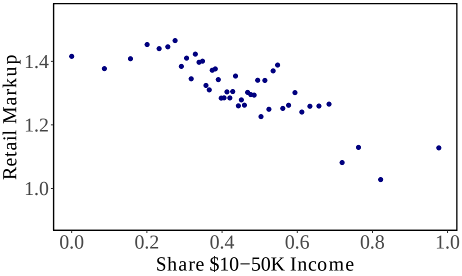
	(1)	(2)	(3)	(4)
Share $100K+ income	0.868**	0.866**	0.423**	0.424**
	(0.176)	(0.169)	(0.110)	(0.111)
UPC Sales Share		0.459		0.089
		(0.330)		(0.359)
Brand Sales Share		0.037		0.009
		(0.116)		(0.052)
Module HHI		0.206		
		(0.129)		
Product Module FEs			Yes	Yes
N	67 161	67 161	67 161	67 161
R^2	0.01	0.03	0.42	0.42

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

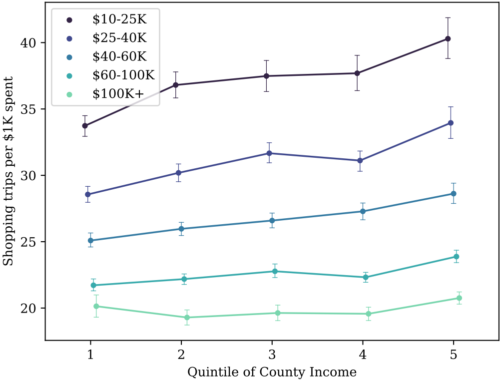
UPC retail markups and buyer income



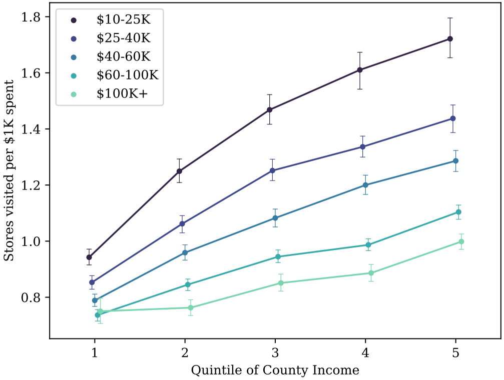




Search intensity decreasing in income, increasing in county income



(a) Shopping trips per $1K expenditures.



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

← Back

Conditional on income, households in rich counties search more

	Shopping trips per $1K			Unique stores visited per $1K		
	(1)	(2)	(3)	(4)	(5)	(6)
Income ($10,000s)	−1.36**	−1.39**	−1.40**	−0.05**	−0.05**	−0.05**
	(0.03)	(0.03)	(0.03)	(0.00)	(0.00)	(0.00)
Avg. County Income		0.95**	0.44*		0.11**	0.04*
		(0.16)	(0.23)		(0.03)	(0.02)
Log(Grocery Estabs.)			0.80**			0.12**
			(0.09)			(0.01)
State FEs		Yes	Yes		Yes	Yes
County FEs	Yes			Yes		
N	63 350	62 865	62 859	63 350	62 865	62 859
R^2	0.13	0.09	0.09	0.16	0.08	0.11

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

← Back

Robustness: Shopping behavior and income

	Shopping trips per 100 UPCs			Unique stores visited per 100 UPCs		
	(1)	(2)	(3)	(4)	(5)	(6)
Income ($10,000s)	−0.88**	−0.93**	−0.95**	−0.03**	−0.02**	−0.03**
	(0.09)	(0.09)	(0.09)	(0.00)	(0.00)	(0.00)
Avg. County Income		1.89**	1.04**		0.15**	0.06**
		(0.39)	(0.48)		(0.03)	(0.03)
Log(Grocery Estabs.)			1.34**			0.15**
			(0.27)			(0.01)
State FEs		Yes	Yes		Yes	Yes
County FEs	Yes			Yes		
N	63346	62861	62855	63346	62861	62855
R^2	0.05	0.01	0.01	0.06	0.01	0.02

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

← Back

Robustness: Shopping behavior and income

	Shopping trips per 100 brands			Unique stores visited per 100 brands		
	(1)	(2)	(3)	(4)	(5)	(6)
Income ($10,000s)	−1.18**	−1.24**	−1.27**	−0.03**	−0.03**	−0.03**
	(0.10)	(0.10)	(0.10)	(0.00)	(0.00)	(0.00)
Avg. County Income		2.52**	1.45**		0.20**	0.08**
		(0.49)	(0.64)		(0.04)	(0.03)
Log(Grocery Estabs.)			1.69**			0.19**
			(0.32)			(0.02)
State FEs		Yes	Yes		Yes	Yes
County FEs	Yes			Yes		
N	63 346	62 861	62 855	63 346	62 861	62 855
R^2	0.05	0.01	0.01	0.07	0.02	0.02

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

← Back

Robustness: Shopping behavior and income

	Shopping trips per 1k txns			Unique stores visited per 1k txns		
	(1)	(2)	(3)	(4)	(5)	(6)
Income ($10,000s)	−4.37**	−4.68**	−4.81**	−0.15**	−0.13**	−0.15**
	(0.77)	(0.79)	(0.80)	(0.03)	(0.04)	(0.04)
Avg. County Income		10.85**	5.78**		0.97**	0.37*
		(2.54)	(2.52)		(0.25)	(0.20)
Log(Grocery Estabs.)			8.04**			0.95**
			(2.06)			(0.12)
State FEs		Yes	Yes		Yes	Yes
County FEs	Yes			Yes		
N	63346	62861	62855	63346	62861	62855
R^2	0.05	0.00	0.00	0.05	0.01	0.01

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

← Back

Table of Contents

Conditions on Mapping $\mathscr{S}$

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

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

← Back

Two quote and Poisson mappings

- **Two quote**:

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

- **Poisson**:

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

← Back

Household Problem

$$\max_{l_i, s_i} c_i \qquad \text{s.t.} \qquad \begin{cases} t(c_i, s_i) + l_i = 1 & \text{(Time constraint)} \\ \mathbb{E}[p_i] c_i = z_i l_i. & \text{(Budget constraint)} \end{cases}$$

where

- c_i is units of good consumed,
- l_i is time spent working with labor productivity z_i.
- $t(c_i, s_i)$ is the time it takes to shop for c_i units with search intensity s_i.

- First order condition:

$$\underbrace{-\partial \mathbb{E}[p_i | s_i] / \partial s_i}_{\text{Marginal savings}} = \underbrace{\phi_i}_{\text{Opportunity cost}}$$

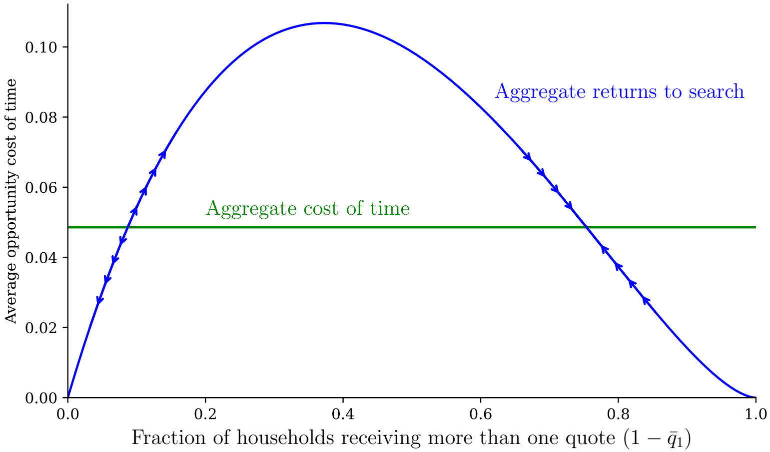
where opportunity cost of increasing search intensity $\phi_i = z_i \cdot \frac{1}{c_i} \frac{\partial t(c_i, s_i)}{\partial s_i}$.

- If $t(c_i, s_i) = s_i c_i^{\alpha}$ ($\alpha < 1$: returns to scale in search), $\phi_i = z_i / c_i^{1-\alpha}$.

← Back

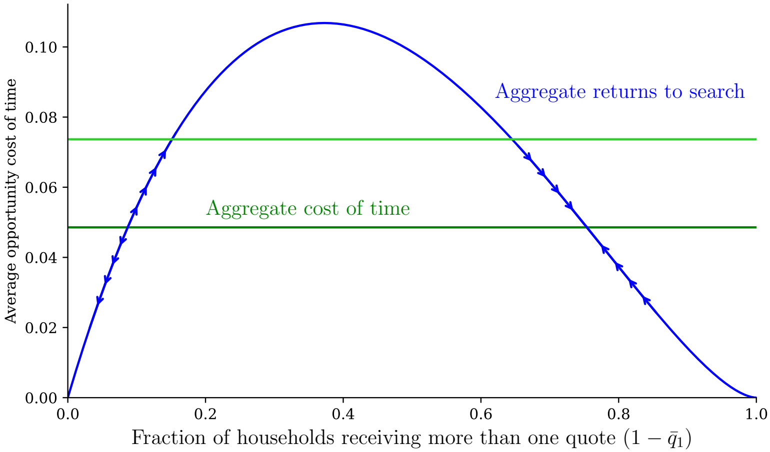
Stable Dispersed-Price Equilibrium

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



Stable Dispersed-Price Equilibrium: Comparative Statics

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



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

Lemma

In equilibrium, the aggregate markup is

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

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

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

- Aggregate markup is

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

← Back

Comparison of markup distribution in data to model

Percentile of	\$20–\$25K		\$50–\$60K		\$100–\$125K		Over \$200K	
markup distribution	Data	Model	Data	Model	Data	Model	Data	Model
10	0.83	1.13	0.84	1.13	0.88	1.13	0.93	1.13
25	1.01	1.15	1.02	1.15	1.06	1.16	1.10	1.17
50	1.21	1.20	1.22	1.20	1.27	1.23	1.33	1.26
75	1.45	1.32	1.46	1.33	1.52	1.41	1.60	1.51
90	1.76	1.58	1.77	1.61	1.85	1.78	1.94	2.00

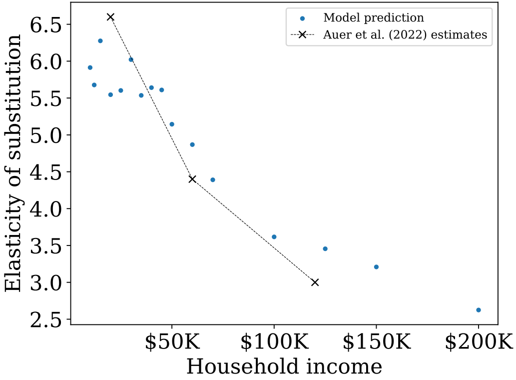
← Back

Comparison to estimates from Auer et al. (2022)

- Construct equivalent of elasticity of substitution for household type i,

$$\sigma_i = \frac{\mu_i}{\mu_i - 1},$$

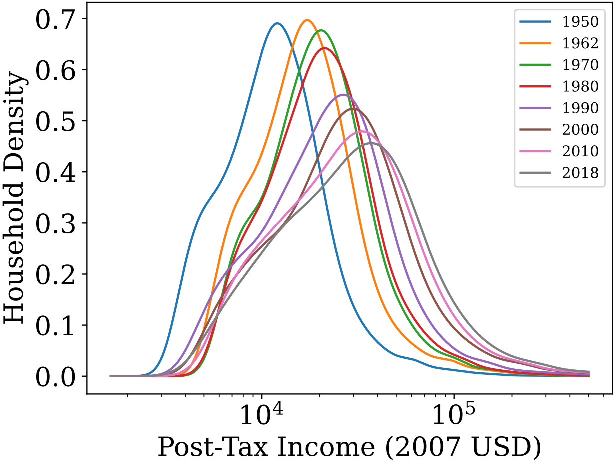
where μ_i is aggregate markup in an economy with only households of type i.



← Back

Income distribution from 1950–2018

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



← Back

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	14.2pp	10.5pp	3.7pp	10.1pp	4.2pp
1950–1980	3.4pp	3.1pp	0.3pp	2.5pp	1.0pp
1980–2018	10.8pp	7.4pp	3.3pp	7.7pp	3.1pp

← Back

Robustness: Non-homotheticity in savings rate

- Baseline: Assume households spend all post-tax income on consumption.
- Alternative: Rich spend lower share of income (Dynan et al. 2004, Straub 2019).
  - Use elasticity of consumption expenditures to post-tax income of 0.7 (Straub 2019).
- Result: *Larger* results because greater differences in ϕ_i needed to match baseline.

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	15.1pp	11.2pp	3.9pp	10.9pp	4.3pp
1950–1980	3.6pp	3.3pp	0.4pp	2.6pp	1.0pp
1980–2018	11.5pp	7.9pp	3.6pp	8.3pp	3.2pp

← Back

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	5.7pp	4.4pp	1.4pp
1950–1980	1.5pp	1.4pp	0.1pp
1980–2018	4.2pp	3.0pp	1.2pp

← Back

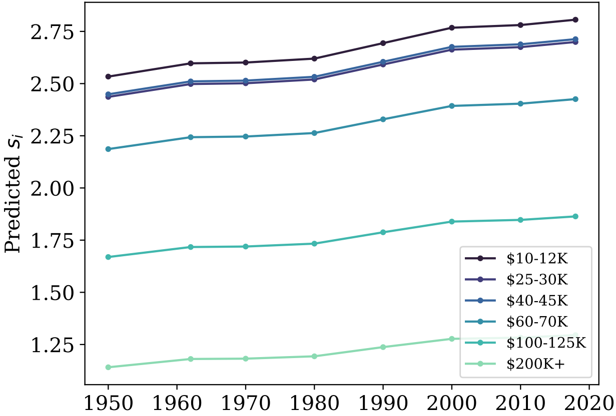
Predicted change in aggregate markup, holding search constant

- 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	19.4pp	14.0pp	5.4pp
1950–1980	4.8pp	4.3pp	0.5pp
1980–2018	14.6pp	9.7pp	5.0pp

← Back

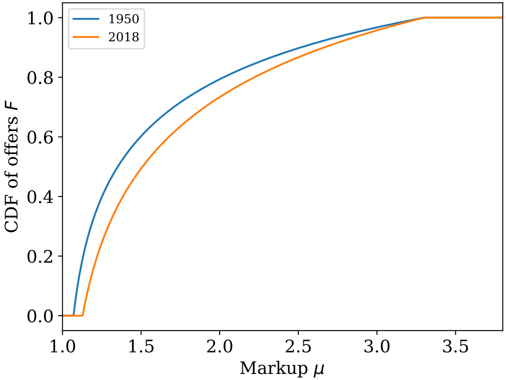
Predicted search intensities over time



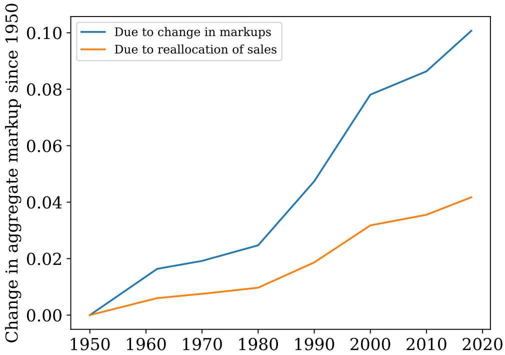
- Since household search decisions are strategic substitutes, households' search intensity (conditional on income) rises as economy gets richer.

← Back

Within-firm markup changes and reallocations



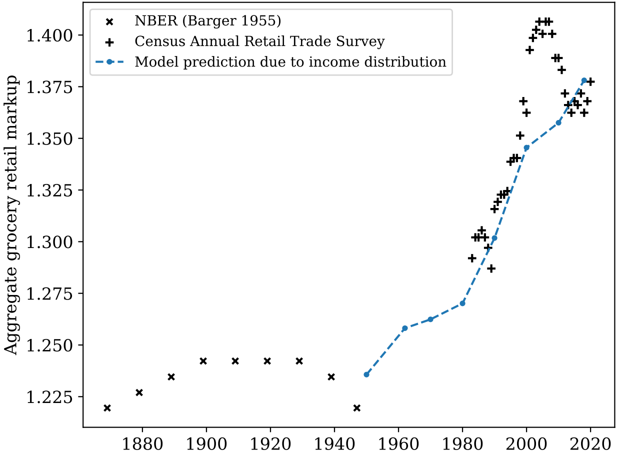
(a) Predicted offer F in 1950 and 2018.



(b) Decomposition of change in agg. markup.

← Back

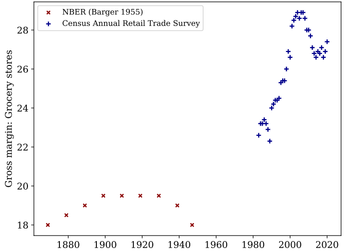
Comparison to data on retail grocery stores gross margins



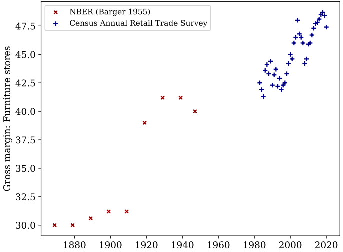
Notes: Gross margins for retail grocery stores are available for selected years from 1869 to 1947 from Barger (1955), and annually from the Census Annual Retail Trade Survey from 1983 to 2020. Both sources report gross margins as total sales less total costs of goods sold as a percent of total sales. The relationship between the aggregate markup and gross margin is Agg. Markup $=$ Sales$/$Costs $= 1/(1 -$ Gross Margin$)$.

← Back

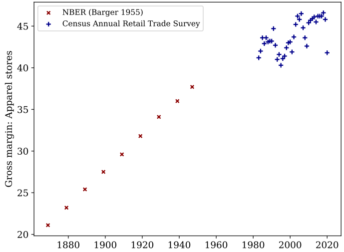
Data on U.S. retail gross margins over time



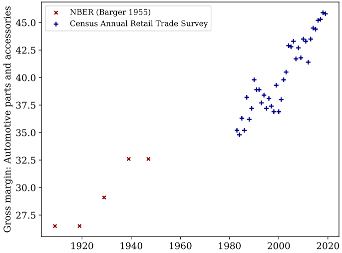
(a) Grocery stores



(b) Furniture stores



(c) Apparel stores



(d) Automobile accessory stores

Aguiar, M. and E. Hurst (2007). Life-cycle prices and production. *American Economic Review 97*(5), 1533–1559.

Albrecht, J., G. Menzio, and S. Vroman (2021). Vertical differentiation in frictional product markets. ‘ 29618, National Bureau of Economic Research.

Alessandria, G. and J. P. Kaboski (2011). Pricing-to-market and the failure of absolute ppp. *American Economic Journal: Macroeconomics 3*(1), 91–127.

Anderson, E., S. Rebelo, and A. Wong (2018). Markups across space and time. Technical Report 24434, National Bureau of Economic Research.

Argente, D. and M. Lee (2021). Cost of living inequality during the great recession. *Journal of the European Economic Association 19*(2), 913–952.

Auer, R. A., A. Burstein, S. Lein, and J. Vogel (2022). Unequal expenditure switching: Evidence from switzerland. Technical Report 29757, National Bureau of Economic Research.

Barger, H. (1955). *Distribution's Place in the American Economy Since 1869*, Chapter ”Trends in Margins”, pp. 80–90. NBER.

Brand, J. (2021). Differences in differentiation: Rising variety and markups in retail food stores. Working Paper.

Broda, C., E. Leibtag, and D. E. Weinstein (2009). The role of prices in measuring the poor's living standards. *Journal of Economic Perspectives 23*(2), 77–97.

Burdett, K. and K. L. Judd (1983). Equilibrium price dispersion. *Econometrica 51*(4), 955–969.

DellaVigna, S. and M. Gentzkow (2019). Uniform pricing in us retail chains. *The Quarterly Journal of Economics 134*(4), 2011–2084.

Döpper, H., A. MacKay, N. H. Miller, and J. Stiebale (2021). Rising markups and the role of consumer preferences. Technical report, Working Paper.

Dynan, K. E., J. Skinner, and S. P. Zeldes (2004). Do the rich save more? *Journal of Political Economy 112*(2), 397–444.

Faber, B. and T. Fally (2017). Firm heterogeneity in consumption baskets: Evidence from home and store scanner data. Technical Report 23101, National Bureau of Economic Research.

Gopinath, G., P.-O. Gourinchas, C.-T. Hsieh, and N. Li (2011). International prices, costs, and markup differences. *American Economic Review 101*(6), 2450–86.

Gupta, A. (2020). Demand for quality, variable markups and misallocation: Evidence from india. Working paper.

Handbury, J. (2021). Are poor cities cheap for everyone? non-homotheticity and the cost of living across u.s. cities. *Econometrica 89*(6), 2679–2715.

Harrod, R. F. (1936). *Trade Cycle. An essay.* London: Oxford University Press.

Jaimovich, N., S. Rebelo, and A. Wong (2019). Trading down and the business cycle. *Journal of Monetary Economics 102*, 96–121.

Kaplan, G. and G. Menzio (2015). The morphology of price dispersion. *International Economic Review 56*(4), 1165–1206.

Kaplan, G. and G. Menzio (2016). Shopping externalities and self-fulfilling employment fluctuations. *Journal of Political Economy 124*(3), 771–825.

Kaplan, G., G. Menzio, L. Rudanko, and N. Trachter (2019). Relative price dispersion. *American Economic Journal: Microeconomics 11*(3), 68–124.

Lach, S. (2007). Immigration and prices. *Journal of Political Economy 115*(4), 548–587.

Menzio, G. (2021). Optimal product design: Implications for competition and growth under declining search frictions. Technical Report 28638, National Bureau of Economic Research.

Neiman, B. and J. Vavra (2019). The rise of niche consumption. Technical Report No. 26134, National Bureau of Economic Research.

Pytka, K. (2018). Shopping effort in self-insurance economies. Working Paper.

Saez, E. and G. Zucman (2019). *The triumph of injustice: How the rich dodge taxes and how to make them pay*. WW Norton and Company.

Simonovska, I. (2015). Income differences and prices of tradables: Insights from an online retailer. *The Review of Economic Studies 82*(4), 1612–1656.

Stigler, G. J. (1961). The economics of information. *Journal of Political Economy 69*(3), 213–225.

Straub, L. (2019). Consumption, savings, and the distribution of permanent income. Technical report, Working Paper.

Stroebel, J. and J. Vavra (2019). House prices, local demand, and retail prices. *Journal of Political Economy 127*(3), 1391–1436.