# Lecture 12:
# The Rise in Markups, contd.

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ECON 416-1

# Where we left off

- De Loecker et al. have been influential in shaping consensus on rising markups.
- Seems to accord with trends, e.g., falling labor share, labor market dynamism.
- Ratio estimator subject to many critiques and caveats (which we will now cover).
- Rest of class today: Alternative approaches to markup estimation.
    - Demand estimation.
    - Accounting / user cost approaches.
    - How well various approaches align.

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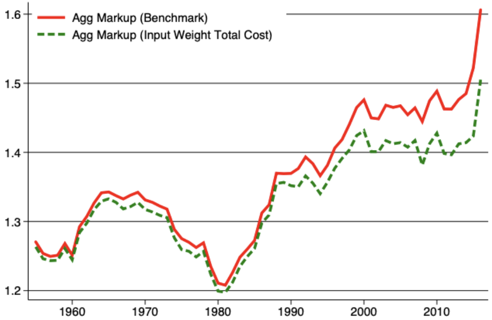
Critiques of the DLEU markups

Demand estimation

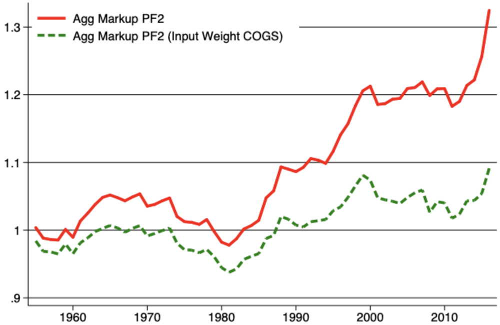
Accounting data and user cost approach

How well do approaches align?

# Sales- vs. cost-weighted markups (Edmond, Midrigan, and Xu 2015)




(B) Input weighted (total cost)




(B) COGS, PF2

- Edmond, Midrigan, and Xu (2015) calculate that cost-weighted average markup increases from 1.15 to 1.25 from 1950 to 2016.

- Why is cost-weighted markup the correct measure?

# Critiques of the DLEU markups: Traina (2018) on SG&A

Figure 4: COGS Share of OPEX

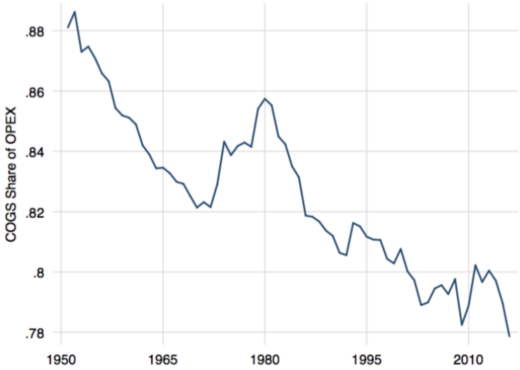
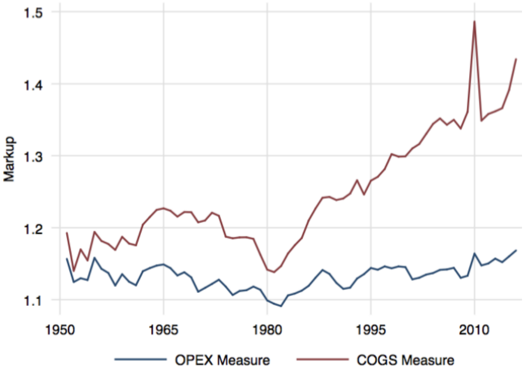



Figure 2: COGS vs. OPEX Markups




- Whether firms count expenses as costs of goods sold vs. sales, general, and administrative expenses depends more on accounting rules/practices and norms.

# Estimates of profit rate and returns to scale (Basu 2019)

- We can write profit rate as

$$\pi = \frac{py - C(y)}{py} = 1 - \frac{C(y)}{\mu \frac{\partial C}{\partial y} y} = 1 - \frac{1}{\mu} \frac{ac}{mc}.$$

- Basu (2019) critique: Most empirical evidence suggests roughly constant returns.

- If $ac/mc \approx 1$, then markup of $\mu = 1.61$ implies profit rate

$$\pi = 1 - \frac{1}{1.61} = 38\%.$$

  This is way higher than 8% profit rate DLEU find.

- In order to match profit rate of 8%, would need $ac/mc \approx 1.48$.

# Estimates of profit rate and returns to scale (Basu 2019)

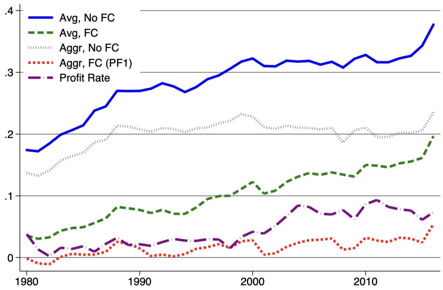
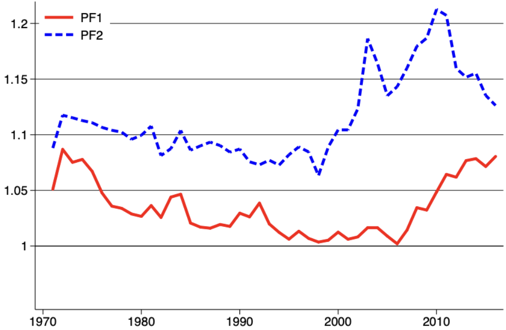



FIGURE XI

Decomposition of Equation (15) due to Overhead Costs and Aggregation




(A) Returns to scale (sum of output elasticities) of estimated PF1 and PF2; revenue weighted

- Combination of fixed costs and composition effects.
- Roughly constant returns to scale “on the margin.”

# Critiques of the DLEU markups: Benkard, Miller, Yurukoglu (2025)

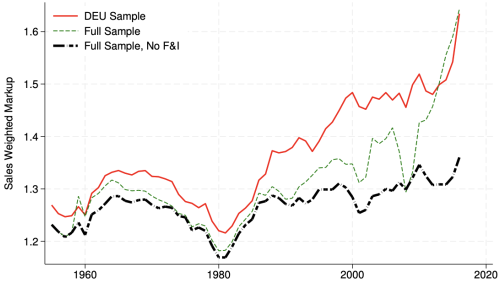



**Figure 1:** Markups Obtained with the DEU Sample and the Full Sample

*Notes:* The figure plots estimates of the sales-weighted average markup (the ratio of price to marginal cost) over time. The solid red line is a replication of Figure I of DEU, which uses a restricted sample. The dashed green line uses the full sample. The black dash - dot line uses the full sample except for the F&I sector.

Figure: Benkard, Miller, and Yurukoglu (2025).

- *"[Sample] restrictions excluded an additional 27% of the observations from the Compustat data used for the main results."*
- *"[...] Unlike the results in DEU, which are robust to the exclusion of individual sectors, in the full sample, the increase in markups at the end of the sample is driven almost entirely by a single sector: Finance and Insurance (F&I)."*

# Critiques of the DLEU markups: Benkard, Miller, Yurukoglu (2025)

- DLEU response: *"Here we show that the findings in BMY are entirely driven by outliers in one four-digit NAICS industry 3254 (Pharmaceutical and Medicine Manufacturing). BMY estimate output elasticities that are affected by the inclusion of extremely small firms that have negligible revenue because they produce no output. This severely impact the production function estimation and biases the estimates for the entire sample of firms in the broader industry (here NAICS 32)."*

- *"One key requirement of production function estimation is that there be production. [....] The key features of these small firms are: 1. They have very low sales, some costs, no SGA, and negative profits; 2. There is a substantial number of them; 3. There is a massive change over time, from virtually none in 1990 to more than half of the firms in this 4 digit industry; 4. These small firms jointly have a small market share in industry 3254, less than 3% of revenue."*

- *"By including firms that have revenue that is orders of magnitude smaller than their costs, the regression coefficients of the production function are unreliable. [...] These firms are negligible in sector 32, yet they have equal weight as large firms in the estimation because production function estimation typically does not weigh the observations. However, in the estimation, a small biotech startup for example has equal weight as Pfizer."*

# Alternatives to production function estimation

- Production function estimation powerful because of low informational requirements.
  - Data on variable input revenue share.
  - Elasticity of output w.r.t. variable input.
- Demand estimation:
  - Product-level prices and quantities.
  - Instruments for exogenous variation in costs.
- Accounting data, user cost estimation:
  - Data on costs (often highly sensitive).
  - How do marginal costs compare to accounting data?

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# Demand estimation: Elasticities and conduct

- Production function estimation exploits firm cost minimization.
- Demand estimation approach exploits firm profit maximization.
- If we know elasticities of residual demand curves firms face, and we know what they maximize (conduct), we can figure out what their optimal markups are.

# Demand estimation: Elasticities and conduct

- Production function estimation exploits firm cost minimization.
- Demand estimation approach exploits firm profit maximization.
- If we know elasticities of residual demand curves firms face, and we know what they maximize (conduct), we can figure out what their optimal markups are.
- One approach: Assume firms maximize markups for single products (ignore portfolio).
- Then, we just need elasticities of residual demand curves.

# Demand estimation: As-if single product firms

- What if we estimate residual elasticity of demand for product $i$ using:

$$\log y_{it} = -\sigma \log p_{it} + \alpha_i + \varepsilon_{it}.$$

# Demand estimation: As-if single product firms

- What if we estimate residual elasticity of demand for product $i$ using:

$$\log y_{it} = -\sigma \log p_{it} + \alpha_i + \varepsilon_{it}.$$

- Problems:
  1. Simultaneity: $p_{it}$ and $y_{it}$ both rise due to demand shock.
  2. Residual demand: We want to hold prices of other firms $p_{-it}$ fixed.

- Solutions:
  - 1a. Include seasonal fixed effects to absorb anticipated demand fluctuations.
  - 1b. Instrument for $p_{it}$ using $i$-specific cost shock or idiosyncratic pricing decision.
  - 2. Control directly for others' prices or assume $i$-specific shocks orthogonal to other firms.

# Demand estimation: As-if single product firms

- DellaVigna and Gentzkow (2019) estimate for each UPC $i$ in each store $s$:

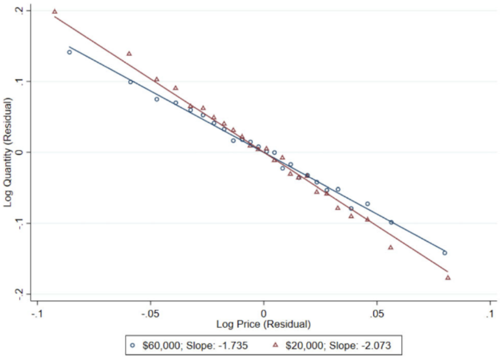
$$\log y_{sit} = -\sigma_{si} \log p_{sit} + \alpha_{siy} + \gamma_{siw} + \varepsilon_{sit},$$

  where $\alpha_{siy}$ are product-store-year FEs, and $\gamma_{siw}$ are product-store-week-of-year FEs.

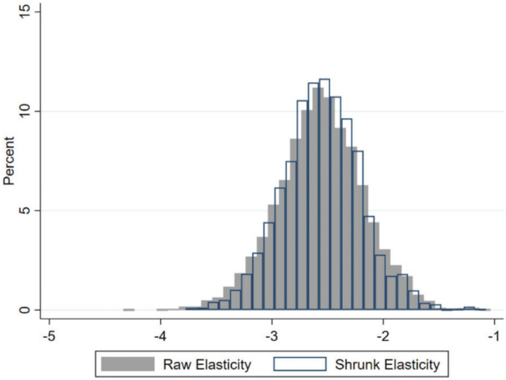
- Hausman (1996) instrument: price of same good in other markets.
  - Independent of local demand shocks? Independent of competitors' prices in market?

- DellaVigna and Gentzkow: use price of products at same retail chain outside market.
  - *"The first stages of our regressions are very strong, with coefficients close to 1. [....] The estimated elasticities with this IV procedure are highly correlated with elasticities estimated from specification (3) with OLS."*

# Demand estimation: As-if single product firms



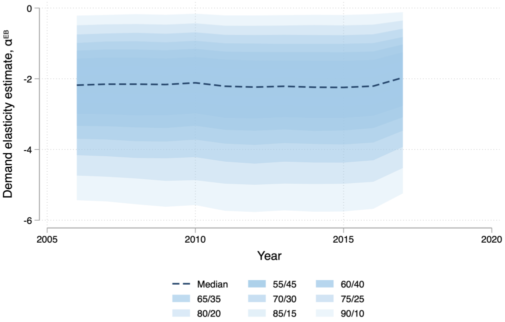

(a) Residualized price vs. quantity.




(b) Distribution of store-avg. elasticities.

Source: DellaVigna and Gentzkow (2019).

# Demand estimation: As-if single product firms

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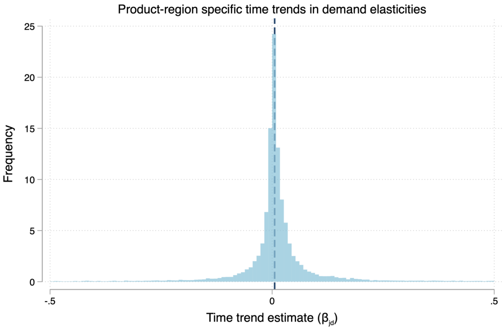


(b) Distribution of store-avg. elasticities.

Source: Rosenthal-Kay, Traina, and Tran (2021).

- In “Seven Million Demand Elasticities,” Rosenthal-Kay et al. apply approach at scale.
- Claim: Not much of a time trend.
- Aside: Low demand elasticities (median implies $\approx$ 100% markup). Why might this be?

# Demand estimation: Elasticities and characteristics space

- If we want markups for multi-product firms, we need cross-elasticities of demand.
- $N$ residual demand elasticities $\rightarrow N \times N$ elasticity matrix.

# Demand estimation: Elasticities and characteristics space

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- $N$ residual demand elasticities $\rightarrow N \times N$ elasticity matrix.
- Lancaster (1971): Instead of modeling demand for good, model demand for its characteristics.
  - $K$ characteristics, we now need to estimate tastes for $K$ characteristics.
  - Then can estimate cross-price elasticities for $N$ products no matter how large $N$ is.

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- Problem: One salient characteristic is brand. Back to $\approx N$ brand characteristics?
- Solution: Introduce unobserved characteristic. (Then deal with endogeneity.)

# Demand estimation: Berry, Levinsohn, and Pakes (1995)

- Workhorse model for demand estimation from BLP.
- Suppose utility of consumer $i$ for product $j$ is

$$u_{ij} = \boldsymbol{\beta}_i' \boldsymbol{x}_j - \alpha_i p_j + \xi_j + \varepsilon_{ij}.$$

  - $\boldsymbol{x}_j$ is vector of observed characteristics of product $j$.
  - $\boldsymbol{\beta}_i$ is vector of $i$'s taste for each characteristic.
  - $p_j$ is product $j$'s price.
  - $\alpha_i$ is $i$'s price sensitivity.
  - $\xi_j$ is unobserved product characteristic.
  - $\varepsilon_{ij}$ is $i$'s "taste shock" for $j$.

- Each consumer chooses one product, consumes one unit, $j = \arg\max_k \{u_{ik}\}$.

# Demand estimation: Berry, Levinsohn, and Pakes (1995)

- (With some abuse of notation), let's denote consumers that share same $\beta$ and $\alpha$ by $i$, but allow them to have different taste shocks (indexed by $t$):

$$u_{ijt} = \underbrace{\beta_i' \mathbf{x}_j - \alpha_i p_j + \xi_j}_{\delta_{ij}} + \varepsilon_{ijt}.$$

- Suppose $\varepsilon_{ijt}$ i.i.d., with $\Pr(\varepsilon_{ijt} \leq x) = e^{-e^{-x}}$.

- Gumbel, or Type 1 Extreme Value, distribution.

- Then, aggregating across $t$ and across $i$ gives us quantities sold:

$$q_{ij} = \frac{\exp(\delta_{ij})}{\sum_k \exp(\delta_{ik})}; \qquad q_j = \int_I \frac{\exp(\delta_{ij})}{\sum_k \exp(\delta_{ik})} di.$$

- Once we know $\beta$, $\alpha$, $\xi$, we can calculate $d \log q_j / d \log p_k \Rightarrow$ optimal markups.

# Demand estimation: Berry, Levinsohn, and Pakes (1995)

- If all consumers have same preferences (up to taste shocks), then logit demand:

$$q_j = \frac{\exp(\delta_j)}{\sum_k \exp(\delta_k)}.$$

$$\Rightarrow \log q_j = \text{const} + \delta_j = \text{const} + \beta' \boldsymbol{x}_j - \alpha p_j + \xi_j.$$

So we can estimate $\alpha$ by running this regression, using IV for $p_j$.

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  So we can estimate $\alpha$ by running this regression, using IV for $p_j$.

  - $\xi_j$ is unobserved and will generally be correlated with $p_j$, so simultaneity bias affects OLS.

- When consumers don't have the same preferences, then "mixed logit" demand (BLP):

$$q_j = \int_I \frac{\exp(\delta_{ij})}{\sum_k \exp(\delta_{ik})} di.$$

  Mixture allows for rich substitution patterns across goods.

  - Inner loop: Calculate unobserved $\xi_j$ to match market shares given guess of $\alpha$, $\beta$.
  - Outer loop: Choose $\alpha$, $\beta$, so $\xi_j$ uncorrelated with instruments.

# Aside: Why does this matter for macro (beyond markup estimation)?

- Notice that quantity shares under logit are:

$$\frac{q_j}{\sum_k q_k} = \frac{\exp(\delta_j)}{\sum_k \exp(\delta_k)} = \frac{\exp(\hat{\delta}_j - \alpha p_j)}{\sum_k \exp(\hat{\delta}_k - \alpha p_k)}$$

  where $\hat{\delta}_j = \beta' x_j + \xi_j$.

- Expenditure shares under CES are:

$$\frac{p_j q_j}{\sum_k p_k q_k} = \frac{\beta_j p_j^{1-\sigma}}{\sum_k \beta_k p_j^{1-\sigma}} = \frac{\exp(\log \beta_j - (\sigma - 1)\log p_j)}{\sum_k \exp(\log \beta_k - (\sigma - 1)\log p_k)}.$$

- Starting to look pretty similar...

# Aside: Why does this matter for macro (beyond markup estimation)?

- Consider the following discrete choice problem.
- Consumer has budget $E$. Gets utility $\beta_j \varepsilon_{ij}$ per unit of consumption of good $j$.

$$\arg\max_j u_{ij} = \beta_j \varepsilon_{ij} \frac{E}{p_j} = \arg\max_j \log \beta_j - \log p_j + \log \varepsilon_{ij}.$$

- Suppose $\Pr(\varepsilon_{ij} \leq x) = e^{-x^{-\theta}}$ (Frechet). Equivalent to $\log \varepsilon_{ij} \sim \text{Gumbel}(1/\theta)$.
- Sales of each product:

$$\frac{p_j q_j}{\sum_k p_k q_k} = \Pr(i \text{ chooses } j) = \frac{\exp(\theta(\log \beta_j - \log p_j))}{\sum_k \exp(\theta(\log \beta_k - \log p_k))}.$$

- So, CES $=$ discrete choice with unit elastic demand, $\varepsilon_{ij} \sim \text{Frechet}(\sigma - 1)$.

# Aside: Why does this matter for macro (beyond markup estimation)?

- Representative household preferences $\iff$ aggregation of discrete choices.
  - Anderson, de Palma, and Thisse (1992) is a useful reference.
- Consumer demand, firm input demand: all demand system problems.
- Demand estimation in IO has rich, flexible tools and results to apply.
- Recent example: Adao, Costinot, and Donaldson (2017).
  - Show that elasticities of substitution between different countries' factor supplies are sufficient statistics for counterfactuals in trade models.
  - So if we estimate this matrix of elasticities, we can estimate many counterfactuals.
  - Use "mixed CES," where CES : mixed CES :: logit : BLP.
  - Factor demand system used to evaluate e.g., effects of China's integration into WTO.

# Demand estimation: Markups over time

- Döpper, MacKay, Miller, and Stiebale (2024) use demand estimation approach to investigate whether markups are indeed rising over time.
- Estimate demand systems for $>$ 1000 products in 133 categories from 2006–2019.

# Demand estimation: Markups over time

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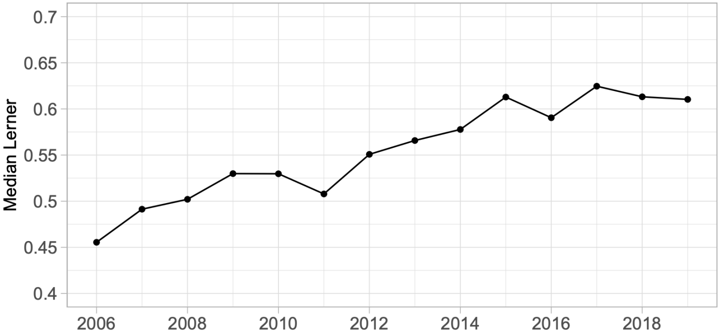
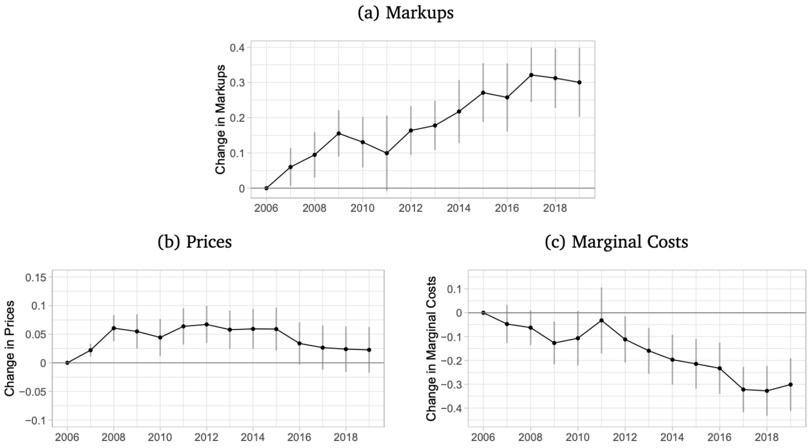
- Estimate demand systems for $>$ 1000 products in 133 categories from 2006–2019.

Figure 1: Markups Over Time Across Product Categories



# Demand estimation: Markups over time

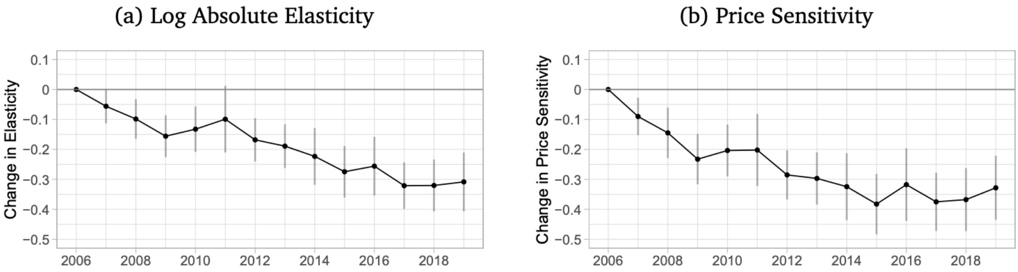



*Notes:* This figure shows coefficients and 95 percent confidence intervals of a regressions of the log of the Lerner index, real prices, and real marginal costs at the product-chain-DMA-quarter-year level on year dummies controlling for product-chain-DMA and quarter fixed effects. The year 2006 is the base category.

Source: Döpper, MacKay, Miller, and Stiebale (2024).

# Demand estimation: Markups over time

Figure 3: Changes in Demand




*Notes:* This figure shows coefficients and 95 percent confidence intervals of a regression of log absolute elasticity and price sensitivity at the product-chain-DMA-quarter-year level on year dummies controlling for product-chain-DMA and quarter fixed effects. The year 2006 is the base category.

Source: Döpper, MacKay, Miller, and Stiebale (2024).

# Demand estimation: Markups over time

Table 2: Factors Predicting Cross-Category Variation in Markup Trends

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Marginal Cost (Standardized) | $-0.585^{***}$ | | | | | $-0.461^{***}$ |
| | (0.020) | | | | | (0.021) |
| Price Sensitivity | | $-0.728^{***}$ | | | | $-0.397^{***}$ |
| | | (0.025) | | | | (0.022) |
| Quality (Standardized) | | | $-0.137^{***}$ | | | 0.002 |
| | | | (0.021) | | | (0.006) |
| Income (Log) | | | | $0.101^{***}$ | | $0.061^{***}$ |
| | | | | (0.029) | | (0.013) |
| Children at Home | | | | $-0.114^{*}$ | | $-0.017$ |
| | | | | (0.065) | | (0.049) |
| Parent HHI | | | | | 0.323 | $0.221^{***}$ |
| | | | | | (0.206) | (0.060) |
| Brand HHI | | | | | $-0.004$ | $-0.102^{**}$ |
| | | | | | (0.186) | (0.051) |
| Retailer HHI | | | | | $0.192^{***}$ | $0.069^{**}$ |
| | | | | | (0.068) | (0.027) |
| Brand-Category-DMA-Retailer FEs | X | X | X | X | X | X |
| Time Period FEs | X | X | X | X | X | X |
| Observations | 14,406,731 | 14,406,731 | 14,406,731 | 14,406,731 | 14,406,674 | 14,406,674 |
| $R^2$ (Within) | 0.715 | 0.476 | 0.045 | 0.000 | 0.003 | 0.825 |

*Notes:* This table reports regression results where the dependent variable is log markups. Observations are at the brand-category-DMA-retailer-year-quarter level, and brand-category-DMA-retailer and year-quarter fixed effects are included in each specification. Standard errors are clustered at the category level and are reported in parentheses.

# Aside: Demand estimation and price rigidity

- With demand estimation, we recover markups by assuming profit maximization.
- Price rigidity creates gap between realized and desired markups.
- One example: Nakamura and Zerom (2010) estimate demand system and then solve numerically for Markov perfect Nash equilibrium given menu cost.

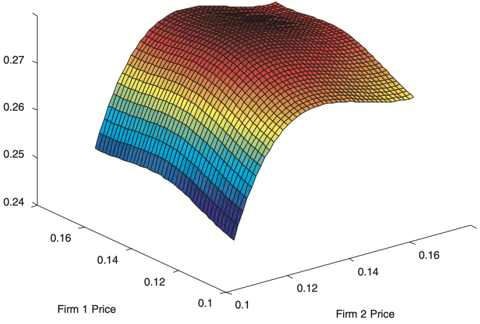



FIGURE 6

Probability of adjustment as a function of competitors' prices

This figure plots the probability of adjustment as a function of competitors' prices for a particular firm and state vector, based on the menu cost oligopoly model.

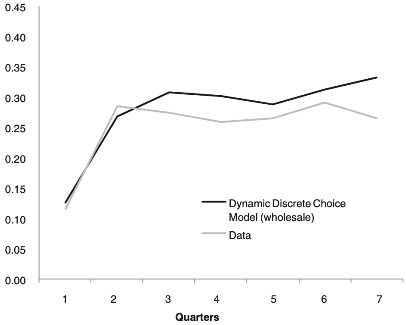



FIGURE 9

Impulse response to a cost shock

The figure plots the impulse response of wholesale prices to a permanent 1% cost shock implied by the model (based on 10000 simulated price series) and the corresponding statistics in the data.

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# User cost approach: Gutierrez and Philippon (2016), Gutierrez (2017)

- Gutierrez (2017) studies profits net of both costs of goods sold and capital costs.

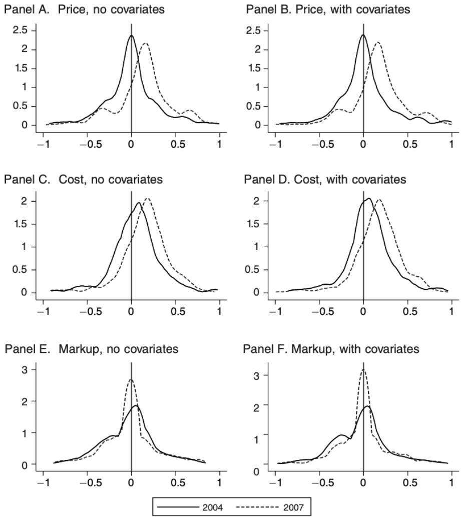
- This approach, also used by Gutierrez and Philippon (2016) and Baqaee and Farhi (2020) referred to as "user cost" approach.

- Difference vs. DLEU net profit rates is to measure required rate of return on capital.

- Suppose investor indifferent between buying unit of capital at investment price $\zeta_t$, collecting rental fee $r_t^K$, and selling depreciated capital tomorrow for $\zeta_{t+1}(1-\delta)$ vs. earning nominal rate of return $i_t$.

$$
\begin{aligned}
r_t^K &= \zeta_{t-1}(1+i_t) + \zeta_t(1-\delta_t) \\
&= \zeta_{t-1}(1+\underbrace{r_t^f + ERP_t}_{\text{risk-free rate + equity risk premium}}) + \zeta_t(1-\delta_t).
\end{aligned}
$$

# Accounting data: Gopinath et al. (2011)




- A number of papers also study markups at retail level using accounting data.
- Gopinath et al. (2011) argue that retailers' other expenses (rent/labor) fixed at horizon of price spell, so marginal cost $\approx$ replacement cost of merchandise.
- Use markups estimated with retailers' replacement costs to estimate whether comovement between real and nominal exchange rates due to markup adjustment.

# Accounting data: Anderson, Rebelo, and Wong (2023)

- Anderson, Rebelo, & Wong (2023) use cost data from two retailers to study cyclicality.
- Markups are either acyclical or procyclical, at odds with NK model.

Table 17: Cyclicality of Store-Item Variables: U.S. Retailer Margins and Markups

| | Elasticity with respect to local UR | | Elasticity with respect to local house prices | |
|---|---|---|---|---|
| Gross margin | -0.003*** | (0.001) | -0.0029 | (0.015) |
| Markups | -0.003*** | (0.000) | -0.0004 | (0.001) |

Table 18: Cyclicality of Store-Item Variables: Canadian Retailer Margins and Markups

| | Elasticity with respect to local UR | | Elasticity with respect to change in oil prices | |
|---|---|---|---|---|
| Gross margin | 0.0001 | (0.002) | -0.086 | (0.057) |
| Markup | 0.0004 | (0.002) | -0.040 | (0.028) |

# Accounting data: Anderson, Rebelo, and Wong (2023)

- Across cities, markups also strongly correlated with income and housing value.
- Consistent w/ Stroebel & Vavra (2019) on effect of housing wealth on prices / markups.
- Aside: Is this inconsistent with uniform retail pricing?

Table 16: Cross-sectional Variation in Margins and Regional Characteristics

| | U.S. Retailer | | Canadian Retailer | |
|---|---|---|---|---|
| | Estimate | Std error | Estimate | Std error |
| Log household income | 0.17*** | (0.06) | 0.10** | (0.04) |
| Log median house value | 0.16*** | (0.05) | 0.01 | (0.01) |
| Herfindahl index | -0.01 | (0.05) | n.a. | n.a. |
| Rural county | 0.02 | (0.01) | n.a. | n.a. |

# Accounting data: Bias from unobserved costs

- Suppose we are interested in the empirical behavior of markups over time, over the business cycle, or across cities of different sizes.

- Estimate gap between markup estimated with accounting data and true markup.

- E.g., suppose true costs are Leontief in merchandise, labor, and real estate:

$$C(Y) = cY + wL(Y) + rA(Y),$$

  where $L(Y)$ and $A(Y)$ are linear functions.

- Suppose we observe $cY$. Construct $\mu^{\text{acct}} = pY/cY$ as proxy for $\mu^{\text{true}} = pY/C(Y)$.

$$\frac{d\log\mu^{\text{acct}}}{d\log t} = \underbrace{\frac{d\log\mu^{\text{true}}}{d\log t}}_{\text{True elasticity}} + \underbrace{\frac{wL(Y)}{C(Y)}\frac{d\log w}{d\log t} + \frac{rA(Y)}{C(Y)}\frac{d\log r}{d\log t}}_{\text{Bias}}.$$

- In Stroebel and Vavra, $t$ is housing wealth; in Anderson, Rebelo, Wong, $t$ is business cycle; in Sangani (2023), $t$ is income.

# Accounting data: Bias from unobserved costs

$$\frac{d\log\mu^{\text{acct}}}{d\log t} = \underbrace{\frac{d\log\mu^{\text{true}}}{d\log t}}_{\text{True elasticity}} + \underbrace{\frac{wL(Y)}{C(Y)}\frac{d\log w}{d\log t} + \frac{rA(Y)}{C(Y)}\frac{d\log r}{d\log t}}_{\text{Bias}}.$$

- Bias depends on two sets of statistics: (1) shares of wages/rents in total variable costs, and (2) elasticities of wages/rents w.r.t. driver variable $t$.
- E.g., from 2007 Census Retail Trade Survey of Detailed Operating Expenses:
  - In 2007, grocery stores had \$491B sales, \$350B merchandise costs, \$68B labor expenses, \$9.8B rent expenses.
  - Labor cost / (Labor + Rent + Merchandise) = 14.7%.
  - Rent cost / (Labor + Rent + Merchandise) = 2.1%.

# Accounting data: Bias from unobserved costs

**Table D2:** Elasticities of retail wages and rents to CBSA income.

| Variable: | *Log Retail Wages (OEWS)* Cashiers (1) | Retail Salespersons (2) | *Log Retail Rents (REIS)* Asking Rent (3) | Effective Rent (4) |
|---|---|---|---|---|
| Log Avg. CBSA Income | 0.285** | 0.265** | 1.226** | 1.265** |
| | (0.040) | (0.027) | (0.203) | (0.208) |
| $N$ | 330 | 330 | 68 | 68 |
| $R^2$ | 0.19 | 0.23 | 0.42 | 0.43 |

- $d \log \mu^{\text{acct}} / d \log I \approx 11.0\%$.
- If 15% of labor/rent costs are variable (estimates from Kesavan et al. 2014),

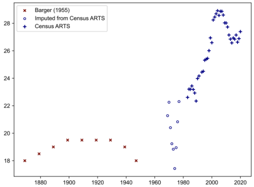
$$\frac{d \log \mu^{\text{true}}}{d \log I} = \frac{d \log \mu^{\text{acct}}}{d \log I} - 0.15[(0.147)(0.285) - (0.028)(1.265)] = 0.10$$

- Even if all labor/rent costs are variable, $d \log \mu^{\text{true}} / d \log I \approx 4.2\%$.
- Could use exercise to bound elasticity of markups to biz cycle, housing wealth, or time.

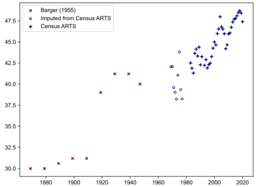
# Accounting data: Markups over time

- Markups from user cost approach for Compustat firms similar to “profit rates” in DLEU.
- Accounting data for retail also shows clear patterns, consistent with Döpper et al.

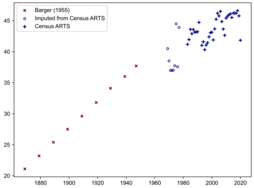
**Figure B13:** Data on retail gross margins over time by subsector.



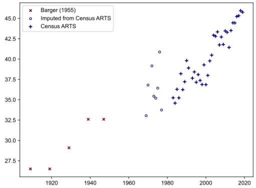

**(a)** Grocery stores




**(b)** Furniture stores




**(c)** Apparel stores




**(d)** Automobile accessory stores

# Table of Contents

Critiques of the DLEU markups

Demand estimation

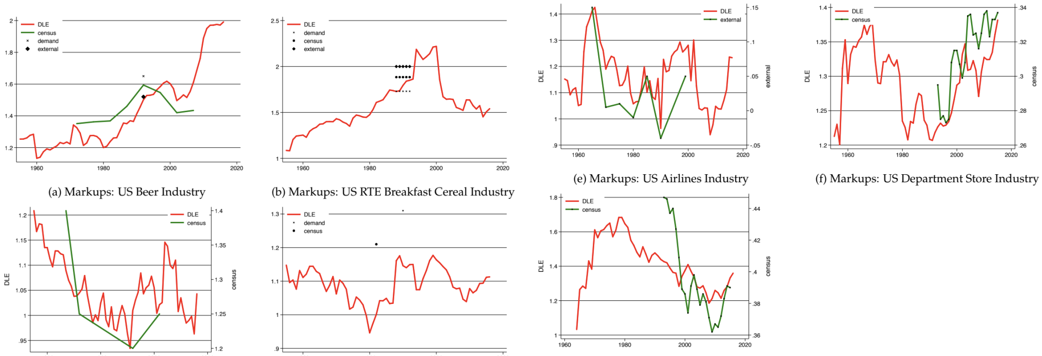
Accounting data and user cost approach

How well do approaches align?

# Different approaches, same results?

- How closely do different approaches align for markup estimates?
- For markups over time,
  - Production function estimation approach said markups $\uparrow$.
  - As-if single-product firms Hausman instrument approach said $\rightarrow$.
  - Demand estimation approach said $\uparrow$ for fast-moving consumer goods.
  - User cost approach said $\uparrow$.
  - Census / accounting data in retail says retail markups $\uparrow$.
- But can we say anything about accuracy of various approaches at more granular level?

# DLEU markups vs. other estimates




(a) Markups: US Beer Industry

(b) Markups: US RTE Breakfast Cereal Industry

(c) Markups: US Steel Industry

(d) Markups: US Automobile Industry

(e) Markups: US Airlines Industry

(f) Markups: US Department Store Industry

(g) Markups: US Electronic Shopping and Mail-[13] Order Houses Industry

- *"Whenever there is overlap, the patterns of markups obtained with the demand approach closely follow those obtained with our cost-based approach. This is remarkable because not only are the methods different, they rely on different data. This is testament to the fact that the estimates we obtain are robust across different methods and data sources."*

# Retail markups (accounting approach) vs. demand estimation

**Table F4:** Relationship between estimated marginal costs and wholesale costs.

| *Panel A. Correlation coefficients.* | Log unit wholesale cost | | Log retail markup | |
|---|---|---|---|---|
| Using PromoData price: | Base | Deal | Base | Deal |
| Log unit marginal cost (demand est.) | 0.92 | 0.90 | | |
| Log markup (demand est.) | | | 0.54 | 0.62 |
| *Panel B. Marginal costs.* | Unit marginal cost ($/lb.) (demand est.) | | | |
| | (1) | (2) | (3) | (4) |
| PromoData unit wholesale cost (base) | 1.224** | 0.248* | | |
| | (0.091) | (0.139) | | |
| PromoData unit wholesale cost (deal) | | | 1.183** | 0.303** |
| | | | (0.085) | (0.067) |
| Constant | -0.338** | | -0.092 | |
| | (0.106) | | (0.092) | |
| UPC FEs | | Yes | | Yes |
| *N* | 261552 | 261552 | 261552 | 261552 |
| $R^2$ | 0.92 | 0.99 | 0.87 | 0.99 |
| *Panel C. Markups.* | Log markup (demand est.) | | | |
| | (1) | (2) | (3) | (4) |
| Log retail markup (using base wholesale cost) | 0.743** | 0.970** | | |
| | (0.111) | (0.015) | | |
| Log retail markup (using deal wholesale cost) | | | 0.794** | 0.960** |
| | | | (0.112) | (0.016) |
| Constant | 0.327** | | 0.134 | |
| | (0.121) | | (0.110) | |
| UPC FEs | | Yes | | Yes |
| *N* | 261552 | 261552 | 261552 | 261552 |
| $R^2$ | 0.29 | 0.90 | 0.38 | 0.90 |

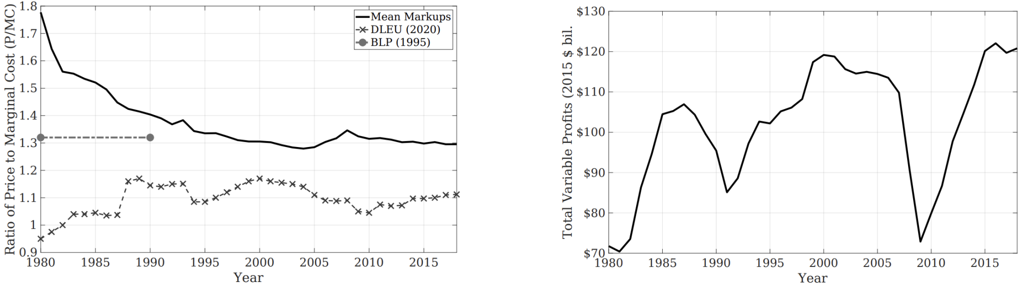
Source: Sangani (2023).

- For a specific category, seem to match.
- Difficult to check if cross-category markup differences are consistent across approaches.
- Whose markups are these?

# DLEU vs. demand estimation: Grieco, Murry, Yurukoglu (2024)

- Grieco, Murry, and Yurukoglu (2024) estimate markups for the U.S. automobile industry from 1980–2018.
- Data on car models and characteristics from Ward's, CEX data on purchases.

Figure XI: Comparison to De Loecker et al. (2020)




(a) Price over Marginal Cost

(b) Total Variable Profits

# DLEU vs. demand estimation: Grieco, Murry, Yurukoglu (2024)

- Since we only observe national prices and market shares each year, estimate

$$q_j = \int \frac{\exp(\beta_i' x_j - \alpha_i p_j + \delta_j)}{\sum_k \exp(\beta_i' x_k - \alpha_i p_k + \delta_k)} di,$$

  using variation across years.

- Clever approach to deal with unobserved quality changes within car model over time.

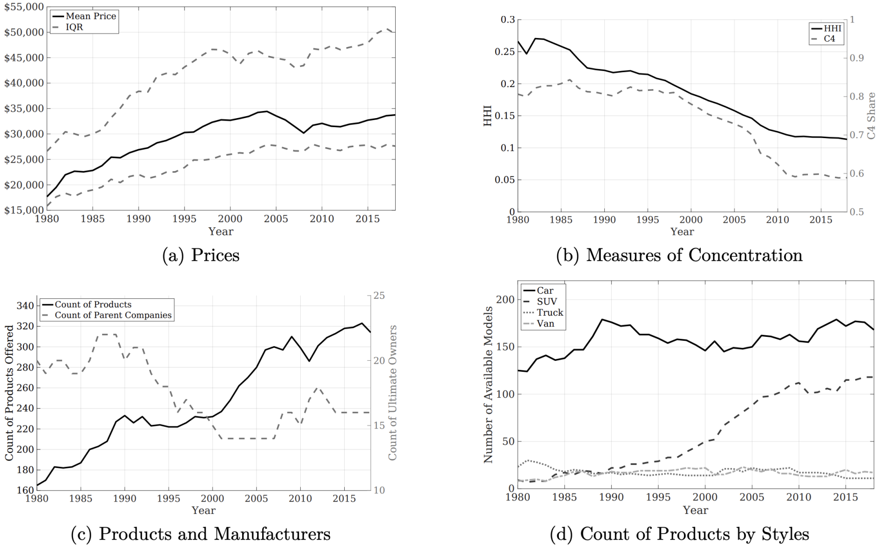
- For any consumer $i$, price elasticity is

$$\frac{d \log q_{ij}}{d \log p_j} = -\alpha_i p_j (1 - q_{ij}).$$

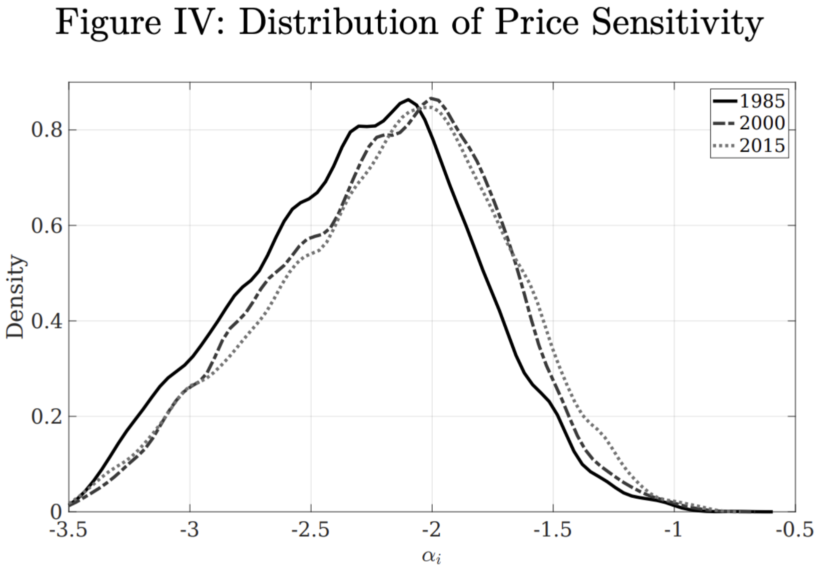
- Holding fixed $\alpha_i$ across time, changes in (observed) market shares and prices will drive markups implied by model.

# DLEU vs. demand estimation: Grieco, Murry, Yurukoglu (2024)

Figure II: Prices and Market Structure, 1980-2018

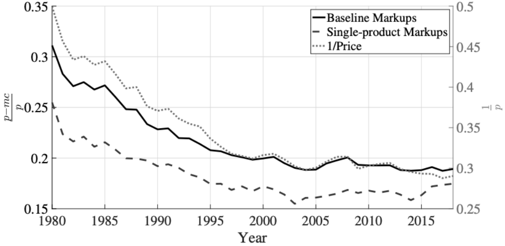


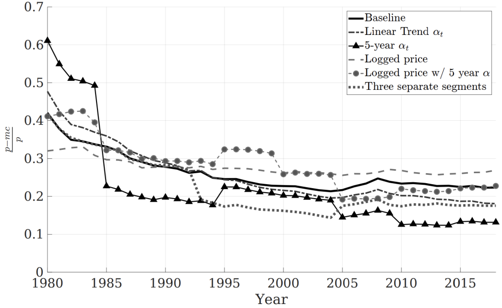
# DLEU vs. demand estimation: Grieco, Murry, Yurukoglu (2024)



# DLEU vs. demand estimation: Grieco, Murry, Yurukoglu (2024)

Figure 7: Markups and Prices




(b) Average Markups, Additional Specifications

- How does relationship between demand elasticity and price relate to pass-through?
- What is the elasticity of demand if I instead use formulation, $\delta_{ij} = \beta_i' x_j - \alpha_i \log p_j + \xi_j$?

# Recap

*"Markups are notoriously difficult to measure because marginal costs are generally unobservable. Most empirical studies use structural approaches that rely on assumptions about production functions and market structure to infer marginal costs. This literature, reviewed in depth by Nekarda and Ramey (2020), is divided in its conclusions about the cyclical properties of markups, in part because different studies rely on different structural assumptions."*
*—Anderson, Rebelo, Wong, 2023.*

- There was a growing consensus that markups are rising.
- Critiques to DLEU methodology and studies of individual industries have alternatively confirmed or rejected this view.
- Markup trend may be as contested as markups over cycle.
- But microdata spawned the field and has moved the debate forward (or backward).