Markup Accounting

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Accounting for markup dispersion

- Markups are dispersed across firms, even within narrowly defined markets
  - Markup dispersion linked to misallocation and welfare losses

    (Baqaee, Farhi, Sangani, 2023; Edmond, Midrigan, Xu, 2023; Albrecht, Phelan, Pretnar, 2023; Dhingra, Morrow 2019; Zhelobodko, Kokovin, Parenti, and Thisse, 2012; Dixit, Stiglitz, 1977)

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1. New facts on markup dispersion and firm size

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3. How much of markup dispersion is accounted by firm size? (i.e. market power of large firms)
4. Efficiency losses from different sources of markup dispersion

Markup dispersion concentrated between firms of similar size

- Estimate markups for different countries and periods using different methodologies
  - Data on Indian, Colombian, and U.S. firms
  - Revenue and price based markup estimates
  - Industry and product level markups

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  - Within-size component: 57–74% with revenue-based markups
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- Accounting for markups requires high-markup small firms and low-markup large firms

Markups beyond firm size

- Model built to account for firm size–markup distribution
  - Large firms internalize market demand (Atkeson, Burstein, 2008)
  - Demand elasticity varies with firm size (Kimball, 1995)
  - Firm-specific demand elasticity elasticity shifters $\longrightarrow$ Deviations from size-based forces

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- Without elasticity shifters $\longrightarrow$ Miss 80% of markup dispersion
  - Generate a counterfactually strong markup-size relationship $\longrightarrow$ 2/3 between firm size
- Accounting for markups between similarly sized firms matters
  - Misallocation costs: *Distance to the frontier* 28% (Baqaee, Farhi, 2020)
  - Markup dispersion tied to dispersion in substitutability (Different from "*Darwinian*" logic)

Contributions

Sources of markup dispersion: Demand factors matter

Data: Blum, Claro, Horstmann, Rivers, 2024; Eslava, Haltiwanger, Urdaneta, 2023.

Models: Afrouzi, Drenik, Kim, 2025; Hubmer, Nord, 2025; Casal, 2026; Haddara, 2026.

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Efficiency costs of markup dispersion: Demand factors introduce new mechanism

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Modeling: Analytical framework that unifies two leading workhorse models

Frameworks: Kimball, 1995; Atkeson, Burstein 2008; Amiti, Itskhoki, Konings, 2019.

Applications: Edmond, Midrigan, Xu, 2015, 2023; Burstein, Carvalho, Grassi, 2025; Dotsey, King 2005; Barde, 2008; Behrens, Mion, Murata, Suedekum 2020; Baqaee, Farhi, Sangani 2023; Boar, Midrigan 2024; Afrouzi, Drenik, Kim 2025; Herreño, Pinardon-Touati, Thie, 2025.

Data and Markup Measurement

Data sources and definitions

Country	Source	Data	Period	Markup Estimates
India	Annual Survey of Industries	Price + Quantity	2001–2008	Raval 2023 DLGKP 2016 + ACF 2015
Colombia	Encuesta Anual Manufacturera	Revenue	1980–1989	Raval 2023
United States	Compustat	Revenue	1980–1989	DLEU 2020

Markets:

▸ examples

- Industry markets in Colombia and US; Product markets in India (Smith, Ocampo, 2025)
- Firm size is market revenue share, σ_i^m

Measuring markups from production functions

Cost minimization: Firm i in market m (independent of demand-side)

$$C_i^m(y) = \min_{\{x_n\}} \sum_{n=1}^{N} p_n x_n \qquad \text{s.t.} \qquad y \leq z_i^m F_m(x_1, \ldots, x_N, K_1, \ldots, K_H)$$

Markup formula

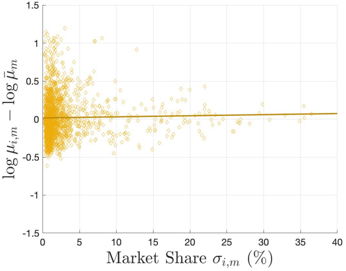
$$\mu_i \equiv \frac{p_i}{\lambda_i} = \frac{\epsilon_{x_n,i}}{\omega_{x_n,i}} \begin{array}{l} \rightarrow \text{Output elasticity to } x_n \\ \rightarrow \text{Revenue share of } x_n \end{array}$$

- Input shares $\{\omega\}$ are observed from revenue data
- Output elasticities $\{\epsilon\}$ from production-function estimation
  (DLEU 2020; Raval 2023; DLGKP 2016; ACF 2015)

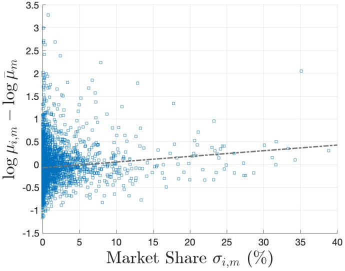
Details

Markup dispersion and firm size

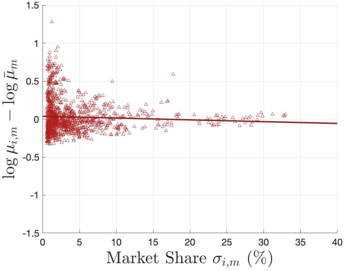
Colombia



India



United States



- Firm markups (μ_i^m) relative to market markup ($\bar{\mu}_m$) (revenue-based markups)
- Markup dispersion is large among small firms
- Large firms often have below-average markups

Variance decomposition: Dispersion between and within firm size

- Divide firms in each market by market share in 5pp bins
- Decompose market variance in markups $\longrightarrow$ Report average shares by country

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	Variance	Share within	Share between	Corr(log μ_i, σ_i)
Colombia	0.059	0.74	0.26	0.03
India	0.242	0.57	0.43	0.10
United States	0.024	0.68	0.32	-0.08

- Within-bin variation accounts for at least half of markup variance
- The markup-size correlation is weak

Price-based product markups

- Revenue-based markups are widely available but subject to output-price bias

  (Bond, Hashemi, Kaplan, Zoch, 2021)

- Quantity-based production functions estimated from price-quantity data address this

- Estimate for India at the 3-digit sector level using single-product firms

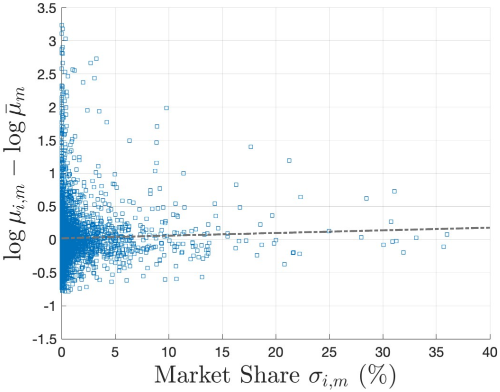
  - Bakery products; Soaps and detergents; Leather footwear; etc.

- Multi-product firm inputs allocated using within-firm revenue shares

  (results robust to single-product firms)

Details

Disperion of price-based markups



- **77%** of markup variance within 5pp market share bins (57% in 1pp bins)
- Variance of price-markups smaller than revenue-markups
- Robust to time aggregation, single product firms, and more

robustness

Oligopolistic Competition with Idiosyncratic Demands

Model objectives and overview

O1: Match distribution of markups and firm size

$\longrightarrow$ Small firms with high markups $+$ Large firms with low markups

O2: Disentangle role of heterogeneity in productivity, demand, and market concentration

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Model Ingredients

Oligopolistic Competition	+	Variable Elasticity of Demand	+	Productivity & Demand Shifters

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Model Ingredients

Oligopolistic Competition	+	Variable Elasticity of Demand	+	Productivity & Demand Shifters

- Demand for market's goods from CES aggregator: $\frac{P_m}{P} = \alpha_m \left(\frac{Y_m}{Y}\right)^{-\frac{1}{\gamma}}$
- Homothetic Direct Implicit Additivity Aggregator for market output (Matsuyama 2023)

Market *HDIA* aggregator

$$1 = \sum_{i=1}^{N_m} \Upsilon_i^m \left(\frac{y_i^m}{Y_m} \right) \qquad \text{CES: } \Upsilon \left(\frac{y_i^m}{Y_m} \right) = \left(\frac{y_i^m}{Y_m} \right)^{\frac{\nu-1}{\nu}}$$

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Inverse demand for firm *i*

$$\frac{p_i^m}{P_m} = \frac{\left(\Upsilon_i^m\right)' \left(\frac{y_i^m}{Y_m}\right)}{\sum_j \left(\Upsilon_j^m\right)' \left(\frac{y_j^m}{Y_m}\right) \frac{y_j^s}{Y_m}}$$

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Profit maximization

$$\max \quad p_i^m y_i^m - C_i(y_i^m) \quad \longrightarrow \quad p_i^m = \frac{1}{1 - \frac{1}{\eta_i^m}} C_i' \left(y_i^m\right) = \mu_i^m C_i' \left(y_i^m\right)$$

Equilibrium elasticity (Cournot)

$$\frac{1}{\eta_i^m} \equiv -\frac{\partial \log p_i^m}{\partial \log y_i^m}$$

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$$\frac{1}{\eta_i^m} = \underbrace{\left(- \frac{\partial \log \Upsilon_i'\left(\frac{y_i^m}{Y_m}\right)}{\partial \log y_i^m} \right)}_{\varepsilon_i^m\text{:Own-Demand Elasticity}}$$

Own elasticity: Captures elasticity over residual demand *all else equal*

$$\varepsilon_i^m = - \frac{\Upsilon_i'\left(\frac{y_i^m}{Y_m}\right)}{\frac{y_i^m}{Y_m}\Upsilon_i''\left(\frac{y_i^m}{Y_m}\right)}$$

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- **Key:** Demand elasticity depends only on own-elasticities and market shares $\{\varepsilon_i^m, \sigma_i^m\}$

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CES: $\varepsilon_i^m = \nu$

Equilibrium markups (Cournot)

▸ Bertrand ▸ Aggregation

$$\frac{1}{\mu_i^m} = \underbrace{\frac{\gamma - 1}{\gamma}}_{\text{Monopoly Markup}} + \underbrace{\left(\frac{1}{\gamma} - \frac{1}{\varepsilon_i^m}\right)\left(1 - \sigma_i^m\right)}_{\text{"}i\text{" vs Market}} + \underbrace{\left(\frac{1}{\varepsilon_i^m} - E_\sigma\left[\frac{1}{\varepsilon_j^m}\right]\right)\sigma_i^m}_{\text{"}i\text{" vs Competitors "}j\text{"}}$$

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Higher markup μ_i^m if

- “Own elasticity” $\left(\varepsilon_i^m\right)$ lower than market’s (γ)
- “Own variety” is elastic relative to market average (limiting substitution effects)

Limit cases: When $\varepsilon_i^m = \nu \longrightarrow$ Atkeson & Burstein; When $\sigma_i^m = 0 \longrightarrow$ Kimball

Estimation and Model Objects

Indian product markets with price-based markups

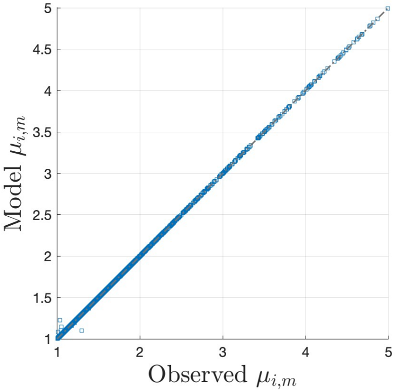
Recovering own elasticities $\{\varepsilon_i^m\}$

▸ ε distribution ▸ inversion

1. Observe markups and market shares $\{\mu_i^m, \sigma_i^m\}$
2. Set market elasticity $\gamma = 1.3$

   (Edmond, Midrigan, Xu, 2023)
3. Invert markups to recover $\{\varepsilon_i^m\}$

   This does not require parametric form for Υ_i



Estimating demand parameters: Elasticity shifters

Adopt parametric for Υ from from Klenow, Willis (2016)

$$\text{Elasticity:} \quad \varepsilon_i^m = \nu_i^m \left(\frac{y_i^m}{Y_m}\right)^{-\theta_m/\nu_i^m}, \qquad \text{Super-elasticity:} \quad \xi_i^m = \theta_m \left(\frac{y_i^m}{Y_m}\right)^{-\theta_m/\nu_i^m}$$

Elasticity shifters: ν_i^m Super-elasticity market parameter: θ_m

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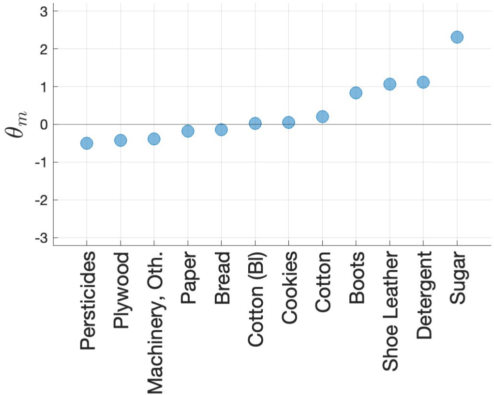
Changes in elasticity and market shares:

$$d\log\varepsilon_i^m = -\left(\frac{\xi_i^m}{\varepsilon_i^m}\right)\left(\frac{\varepsilon_i^m}{\varepsilon_i^m - 1}\right) d\log\sigma_i^m = -\left(\frac{\theta^m}{\nu_i^m}\right)\left(\frac{\varepsilon_i^m}{\varepsilon_i^m - 1}\right) d\log\sigma_i^m$$

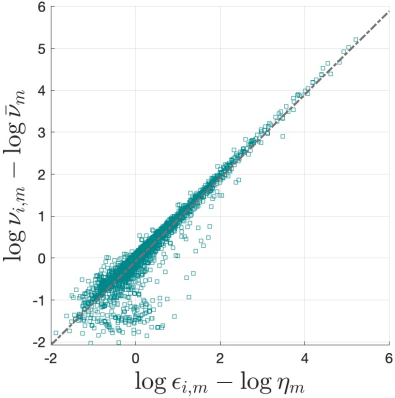
- Estimate θ_m and $\{\nu_i^m\}$ by method of moments

Super-elasticities and elasticity shifters

Demand curvature $\{\theta_m\}$



Shifters $\{\nu_i^m\}$ and own-elasticities $\{\varepsilon_i^m\}$

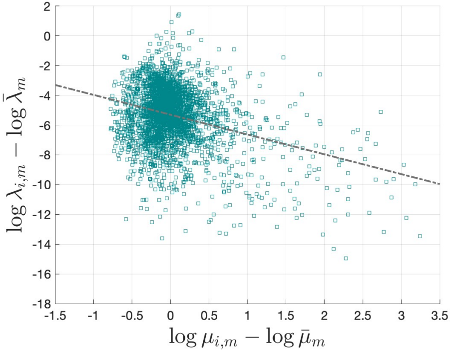


Much of variation in the own-elasticities $\{\varepsilon\}$ is not explained by firm size

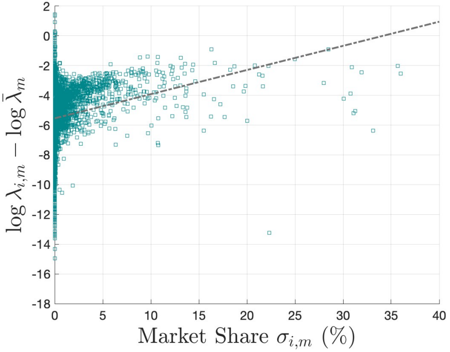
Marginal costs, markups, and firm size

‣ Recovering model objects

Marginal costs (λ) and markups (μ)



Marginal costs (λ) and market share (σ)



- High-markup firms tend to have lower marginal costs
- Larger firms tend to have higher marginal costs on average

Market Structure, Firm Scale, and Demand Factors

Alternative models of variable markups

Objective: Disentangle role of concentration, firm size, and demand factors

- Construct counterfactual markups under alternative models

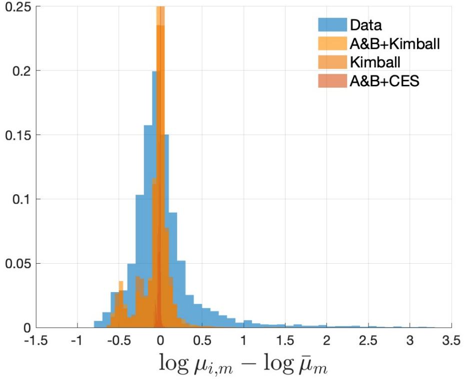
Model	Strategic interaction	Variable elasticity	Firm-specific shifter
Atkeson-Burstein	Yes	No	No
Kimball	No	Yes	No
A&B + Kimball	Yes	Yes	No
Full model	Yes	Yes	Yes

- All alternatives match market shares and average market markups
- We look at the dispersion of markups and their distribution over firm size

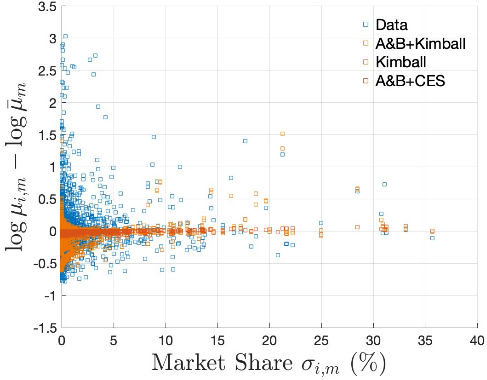
Markup distributions across models

▸ Col/US

Markup distribution



Markup and market share



Models without elasticity shifters miss small high-markup firms and large low-markup firms

Variance decomposition across models

▸ Col/US

	Variance	Share within	Share between	Corr(log μ_i, σ_i)
Data	0.196	0.77	0.23	0.06
Full model	0.195	0.77	0.23	0.06
A&B + Kimball	0.047	0.39	0.61	0.21
Kimball	0.048	0.34	0.66	0.22
Atkeson-Burstein	0.001	0.18	0.82	0.34

- Alternative models generate too little dispersion
- They also assign too much variation to differences across firm sizes

Markups and misallocation

- Compute distance to the efficient frontier $\left(\frac{Y}{Y^{\star}}\right)$ following Baqaee & Farhi (2020)
  - Incorporate non-CES into allocation patterns

$$\varphi_{ij}^{m} \equiv \frac{1}{\sigma_j^m} \frac{\partial \log y_j^m}{\partial \log p_i^m}\bigg|_{Y_m} = \begin{cases} \frac{\varepsilon_i^m \varepsilon_j^m}{E_\sigma[\varepsilon_h]} & \text{if } j \neq i \\ -\frac{\varepsilon_i^m}{\sigma_i^m}\left(1 - \frac{\sigma_i^m \varepsilon_i^m}{E_\sigma[\varepsilon_h]}\right) & \text{if } j = i \end{cases}$$

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- Compute distance to the efficient frontier $\left(\frac{Y}{Y^{\star}}\right)$ following Baqaee & Farhi (2020)
  - Incorporate non-CES into allocation patterns

$$\varphi_{ij}^{m} \equiv \frac{1}{\sigma_j^m} \frac{\partial \log y_j^m}{\partial \log p_i^m}\bigg|_{Y_m} = \begin{cases} \frac{\varepsilon_i^m \varepsilon_j^m}{E_\sigma[\varepsilon_h]} & \text{if } j \neq i \\ -\frac{\varepsilon_i^m}{\sigma_i^m}\left(1 - \frac{\sigma_i^m \varepsilon_i^m}{E_\sigma[\varepsilon_h]}\right) & \text{if } j = i \end{cases}$$

- Dispersion in own-elasticities (and elasticity shifters) affects reallocation in two ways:

  (i) Reflect substitutability **(i)** Generate productive small firms

Markups and misallocation

- Compute distance to the efficient frontier $\left(\frac{Y}{Y^\star}\right)$ following Baqaee & Farhi (2020)
  - Incorporate non-CES into allocation patterns

$$\varphi_{ij}^m \equiv \frac{1}{\sigma_j^m} \frac{\partial \log y_j^m}{\partial \log p_i^m}\bigg|_{Y_m} = \begin{cases} \frac{\varepsilon_i^m \varepsilon_j^m}{E_\sigma[\varepsilon_h]} & \text{if } j \neq i \\ -\frac{\varepsilon_i^m}{\sigma_i^m}\left(1 - \frac{\sigma_i^m \varepsilon_i^m}{E_\sigma[\varepsilon_h]}\right) & \text{if } j = i \end{cases}$$

- Dispersion in own-elasticities (and elasticity shifters) affects reallocation in two ways:

(i) Reflect substitutability **(i)** Generate productive small firms

	$\log(Y^\star/Y)$
Full model	0.25
A&B + Kimball	0.06
Kimball	0.06
Atkeson-Burstein	0.03

- Output loss of 28%

  (comparable with EMX)

- 5 times larger than loss without elasticity shifters

Conclusions

- Most markup dispersion is concentrated in firms of similar size
- Accounting for markups (and firm size!) reveals role of **demand factors**
  - Active literature on this front:

    Blum, Claro, Horstmann, Rivers, 2024; Eslava, Haltiwanger, Urdaneta, 2023; Afrouzi, Drenik, Kim, 2025; Hubmer, Nord, 2025; Casal, 2026; Haddara, 2026; and more!
- Demand factors weaken link between firm size, productivity, and market power
- Ignoring demand heterogeneity understates the efficiency cost of markup dispersion

Appendix

Appendix: firms, sectors, and products

◂ back

Indian ASI product markets

Sector	Example products	Product revenue share in sector
Bakery products	Biscuits & cookies; bread, buns & croissants	0.83; 0.10
Pesticides & insecticides	Pesticides; insecticides	0.59; 0.23
Soaps & detergents	Detergent powder; toilet soap	0.20; 0.34
Leather footwear	Boots; leather shoe uppers	0.50; 0.25
Audio/video apparatus	Printed circuit boards; color TV sets	0.06; 0.61

- India: product-year markets; production functions estimated at the 3-digit sector level.
- Colombia and U.S.: industry-year markets; prices and quantities are not separately observed.
- Multi-product establishments are assigned product-line inputs using within-firm revenue shares.

Appendix: revenue-based production-function approach

back

Cost-share approach

- Used for Colombia, U.S., and revenue-based Indian robustness.
- Relies on cost minimization and constant returns to scale in observed flexible inputs.
- Recovers output elasticities from average input cost shares.

$$E[P_n X_{n,i}] = \epsilon_n E[\lambda_i Y_i], \qquad \epsilon_n = \frac{E[P_n X_{n,i}]}{E[\sum_{k=1}^{N} P_k X_{k,i}]}$$

Appendix: quantity-based production-function approach

Indian ASI price and quantity data

$$q_{ijt} = f(m_{ijt}, l_{ijt}, k_{ijt}) + \omega_{ijt} + \zeta_{ijt}$$

- Quantity production functions remove output-price bias.
- Estimated at the 3-digit sector level.
- Single-product firms identify production parameters without product-level input allocation.
- Multi-product firms receive sector elasticities and product-level input allocations.
- Implemented with Wooldridge's control-function estimator; first-order lags instrument materials, output prices, and market shares.

Appendix: details on quantity-production estimation

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- Product-level input allocations are unobserved for multi-product firms.
- Estimation uses single-product firms, so $\rho_{x,ijt} = 1$.
- Output prices help proxy for unobserved input quality.
- State fixed effects absorb geographic input-price differences.
- Baseline assumes capital and labor are predetermined, materials are flexible.

Markup at product level

$$\mu_{ijt} = \epsilon_{x,ijt} \frac{P_{ijt} Q_{ijt}}{\rho_{x,ijt} R_{x,it}}$$

Appendix: price-based markup robustness

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Observed price-based markup variance: India, 2001–2008

	Baseline	Avg. across years	At least 2	At least 3	At least 4
Variance	0.196	0.232	0.178	0.169	0.115
% Within (1pp)	0.564	0.833	0.704	0.550	0.400
% Within (5pp)	0.770	0.961	0.860	0.783	0.692
Avg. number firms	386	386	142	66	32

- Columns restrict to firms observed producing the same product for more years.
- Within-size dispersion remains large in the more persistent-product samples.

Single product firms

	Variance	Share within	Share between	Corr(log μ_i, σ_i)
All firms	0.196	0.770	0.230	0.061
Single product	0.184	0.549	0.451	0.076

Appendix: Bertrand markups

◂ back

$$\frac{1}{\mu_i^m} = 1 - \frac{1}{\gamma\sigma_i^m + \varepsilon_i^m\left[1 - \left(\frac{\varepsilon_i^m}{E_\sigma[\varepsilon_j^m]}\right)\sigma_i^m\right]}$$

- Strategic interaction enters through market share σ_i^m.
- The substitution term depends on own elasticity relative to the market's sales-weighted elasticity.
- This is the baseline formula used for the price-based model exercises.

Appendix: Aggregate markups

◂ back

Market marginal cost

$$\lambda_m = \sum_{i=1}^{N_m} \lambda_i^m \frac{y_i^m}{Y_m}$$

Market markup

$$\mu_m = \frac{P_m}{\lambda_m} = \left[\sum_{i=1}^{N_m} \frac{1}{\mu_i^m} \sigma_i^m \right]^{-1}$$

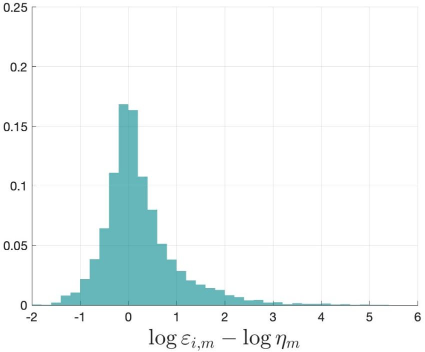
Cournot aggregate expression

$$\frac{1}{\mu_m} = \left(1 - \frac{1}{\gamma}\right) + \left(\frac{1}{\gamma} - E_\sigma \left[\frac{1}{\varepsilon_i^m}\right]\right)(1 - \mathrm{HHI}_m) + 2\,\mathrm{Cov}_\sigma \left(\sigma_i^m, \frac{1}{\varepsilon_i^m}\right)$$

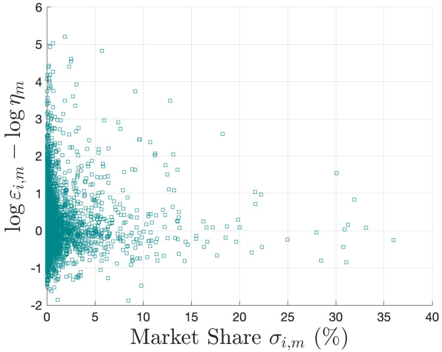
Appendix: Recovered own elasticities

back

Distribution of ε_i^m



ε_i^m and market share



- Own-elasticity dispersion is large, especially among small product lines.
- This is the input into the demand-shifter and model-object recovery steps.

Appendix: Recovering model objects

back

Recovering relative output

$$\varepsilon_i^m = \nu_i^m \left(\frac{y_i^m}{Y_m}\right)^{-\theta_m/\nu_i^m} \quad \Rightarrow \quad \frac{y_i^m}{Y_m} = \left(\frac{\varepsilon_i^m}{\nu_i^m}\right)^{-\nu_i^m/\theta_m}$$

Recovering relative prices

$$\sigma_i^m = \frac{p_i^m y_i^m}{P_m Y_m} \quad \Rightarrow \quad \frac{p_i^m}{P_m} = \sigma_i^m \frac{Y_m}{y_i^m}$$

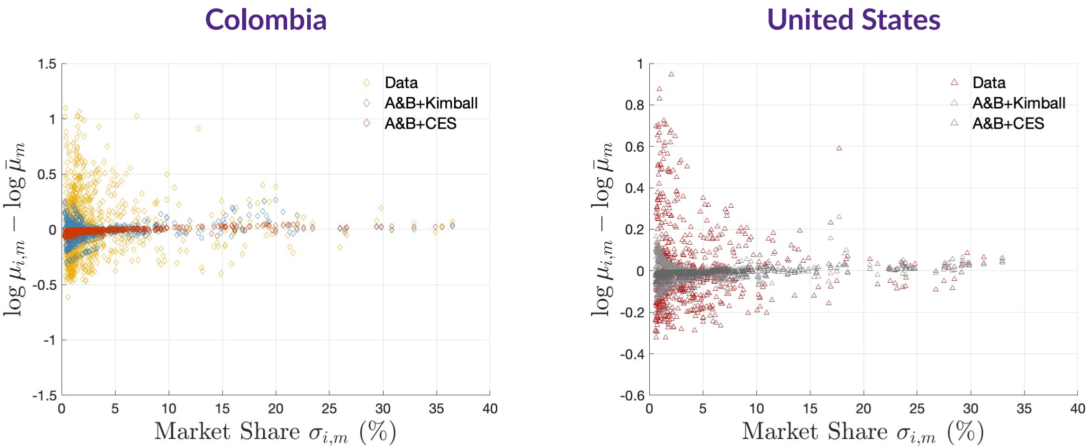
- These objects are relative to market-level price and quantity indexes.
- Levels are not needed for the decomposition exercises.

Recovering marginal costs

$$\frac{\lambda_i^m}{\lambda_m} = \frac{\frac{\sigma_i^m}{\mu_i^m}}{\sum_j \frac{\sigma_j^m}{\mu_j^m}} \left(\frac{y_i^m}{Y_m}\right)^{-1}$$

Appendix: markup distributions, Colombia and U.S.

back



Model variants shown against the measured markup-size relationship.

Appendix: variance decomposition, Colombia and U.S.

back

Colombia

	Var.	Within	Between	Corr.
Data	0.059	0.524	0.476	0.029
Full model	0.059	0.525	0.475	0.030
Atkeson-Burstein	0.001	0.001	0.999	0.608
Kimball	0.006	0.012	0.988	0.213
A&B + Kimball	0.006	0.021	0.979	0.183

United States

	Var.	Within	Between	Corr.
Data	0.024	0.386	0.614	-0.075
Full model	0.024	0.386	0.614	-0.074
Atkeson-Burstein	0.000	0.001	0.999	0.628
Kimball	0.002	0.008	0.992	-0.018
A&B + Kimball	0.002	0.014	0.986	-0.061

1 percentage point market-share bins. Corr. is Corr($\log \mu_i, \sigma_i$).

Appendix: own-elasticity inversion

back

Cournot inversion is linear in reciprocal elasticities

$$\frac{1}{\varepsilon_i^m}(1-\sigma_i^m) + \sum_{j \neq i} \frac{1}{\varepsilon_j^m} \sigma_j^m \frac{\sigma_i^m}{1-\sigma_i^m} = \frac{1 - \frac{1}{\gamma}\sigma_i^m}{1-\sigma_i^m} - \frac{1}{\mu_i^m(1-\sigma_i^m)}$$

Bertrand inversion is nonlinear

$$\frac{\mu_i}{\mu_i - 1} = \gamma\sigma_i + \varepsilon_i \left[1 - \frac{\varepsilon_i \sigma_i}{E_\sigma[\varepsilon]}\right]$$

- Appendix proves uniqueness under the Bertrand markup equation.