Data and Markups: A Macro-Finance Perspective

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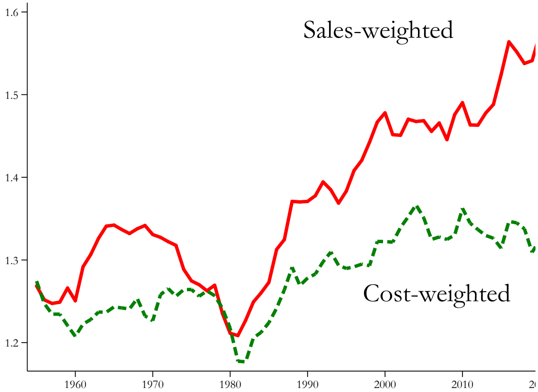
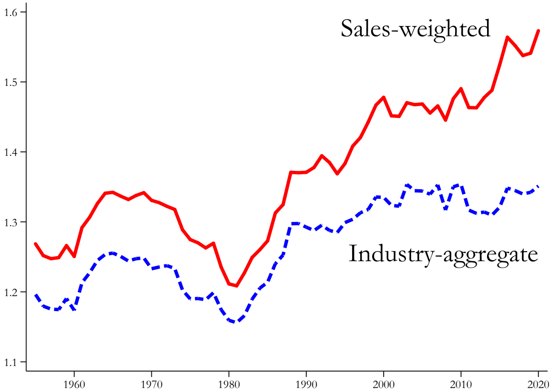
Main Idea: Data and Markups

- Modelling data
  - Data is information. Information improves predictions (e.g. uncertain consumer demand)
  - Firms choose an up-front investment and then choose how much to produce
  - Uncertain firms scale back (firms price risk)
- Data also affects competition: ambiguous effect
  - Data increases rent extraction
  - Data reduces risk
- Composition effects can measure data
  - Product $\rightarrow$ firm
  - Firm $\rightarrow$ industry (various)
  - Cyclical divergence
- A dynamic version of the model: Endogenous data adds 'data barter' to markups

Empirical Evidence: Firm/Industry Markup Divergence





Related Literature

- Model
  - Pelegrino (2024)
  - → Our model: risk aversion; investment in data
- Markup aggregation
  - Burstein, Carvalho, Grassi (2023) generate cyclical aggregation patterns with "shifters"
  - → Our model: data accumulation serves as the shifter
- Data Economy
  - Jones-Tonetti (2020), Farboodi-Veldkamp (2023): perfect or monopolistic competition
  - → Our model: oligopoly with strategic interaction
- Evidence:
  - Galdon-Gil-Uriz (2023)
  - → In progress: revenue forecasts

Model Setup: Firms

- n_F firms, indexed by i, produce multiple goods
- Firms:
  1. choose investment $g(\tilde{\boldsymbol{c}}_i)$ in lowering marginal cost $\tilde{\boldsymbol{c}}_i$ to maximize

$$\mathbf{E}\left[\pi_i|\mathcal{I}_i\right] - g(\tilde{\boldsymbol{c}}_i) - \rho_i \mathbf{Var}\left[\pi_i|\mathcal{I}_i\right]$$

  2. observe data, and choose a quantity to produce $\mathbf{q}_i$

$$\pi_i = \tilde{\boldsymbol{q}}_i'\left(\tilde{\boldsymbol{p}} - \tilde{\boldsymbol{c}}_i\right)$$

- ρ_i is firm i's price of risk

  Firms with less precise forecasts invest and produce less, Gorodnichenko-Coibon-Kumar (2023)

- $\mathcal{I}_i$ is the information set of firm i

Model Setup: Demand and Data

- Demand: Customers' willingness to pay decreases in the quantity that all firms produce

$$\mathbf{p_i} = \underline{p} - \frac{1}{\phi} \sum_{i'=1}^{N} \tilde{\mathbf{q}}_i + \mathbf{b}_i$$

  demand shock $\mathbf{b}_i \sim N(0, I)$, $\text{corr}(\mathbf{b}_i, \mathbf{b}_j) \in \{0, I\}$; goods are prefect subsitutes (common ϕ)

- n_{di}: # data points for firm i (exogenous for now)

- Data is information about demand shocks. Each data point:

$$\tilde{\boldsymbol{s}}_{i,z} = \boldsymbol{b}_i + \tilde{\varepsilon}_{i,z}, \quad \text{where} \quad \tilde{\varepsilon}_{i,z} \sim N(\mathbf{0}, \Sigma)$$

- Information set:

$$\mathcal{I}_i := \{\tilde{\boldsymbol{s}}_{i,z}\}_{z=1}^{n_{di}} \qquad \text{(data is private information)}$$

$$\mathcal{I}_i := \{\{\tilde{\boldsymbol{s}}_{i,z}\}_{z=1}^{n_{di}}\}_{i=1}^{n_F} \quad \text{(data is public information)}$$

Production – Stage 2

- FOC: Production depends on risk and price impact (denominator) and expected profit (numerator) Kyle (1989) or Back-Zender (1993)

$$\tilde{\boldsymbol{q}}_i = \boldsymbol{H}_i(\mathbf{E}[\tilde{\boldsymbol{p}}_i|\mathcal{I}_i] - \boldsymbol{c}_i)$$

$$\text{where} \quad \boldsymbol{H}_i = \left(\rho_i \mathbf{Var}[\tilde{\boldsymbol{p}}_i|\mathcal{I}_i] + \frac{\partial \mathbf{E}[\tilde{\boldsymbol{p}}_i|\mathcal{I}_i]}{\partial \tilde{\boldsymbol{q}}_i}\right)^{-1}$$

  - Data lowers *Var*, raises $\mathbf{H}_i$
  - $\mathbf{H}_i$ governs the $cov(q_i, p_i)$
- Data allows a firm to choose quantities that covary with prices

  Evidence: Galdon-Gil-Uriz (2023)

Bertrand

Investment and Product Markups – Stage 1

- **Data-investment complementarity.** Firms with more data invests more (lower c_i)
  - Optimal choice of cost (firm size):

$$\frac{\partial \mathbf{E}[U_i]}{\partial \tilde{\boldsymbol{c}}_{ij}} = \frac{1}{2} \underbrace{\frac{\partial \mathbf{E}[\tilde{\boldsymbol{p}} - \tilde{\boldsymbol{c}}_i]' \boldsymbol{H}_i \mathbf{E}[\tilde{\boldsymbol{p}} - \tilde{\boldsymbol{c}}_i]}{\partial \tilde{\boldsymbol{c}}_{ij}}}_{marginal\ \ benefit} - \underbrace{\frac{\partial g(\chi_c, \tilde{\boldsymbol{c}}_i)}{\partial \tilde{\boldsymbol{c}}_{ij}}}_{marginal\ \ cost} = 0 \ \ \forall j$$

  - Product-level markup for good k produced by firm i:

$$M_{ik}^{p} := \mathbf{E}[\boldsymbol{p}_i(k)]/\boldsymbol{c}_i(k)$$

- **Higher investment raises product markups.** More investment (lower c_{ik}) increases the markup of good k

Product Markups: Could Increase or Decrease

Data reduces markup risk premium *Holding firm size fixed, more data reduces the firm-product markup.*

Why? If $\rho > 0$, data $\uparrow$ average quantity, $\downarrow$ prices.

Proposition

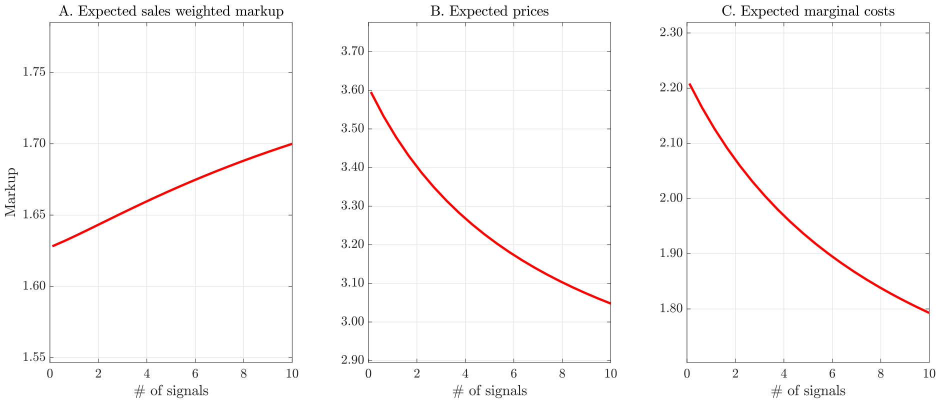
Net effect*: Data in(de)creases product markups when risk price or marginal cost of investment is sufficiently low (high)*

Markups capture market power and risk

Data affects both, in opposite ways

Product Markups: Could Increase or Decrease

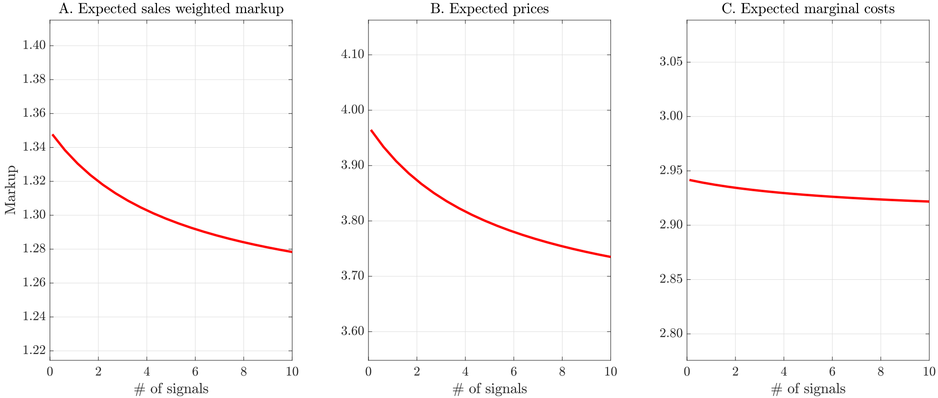
Low Investment Cost/price of risk



Notes: This comparative static exercise is constructed over a single-good duopoly example. The x-axis is the number of data points that both firms have. The investment cost function is assumed as $g(\chi_c, c_i) = \chi_c \left(\bar{c} - c_i\right)^2 / 2$ with $\chi_c = 1$ and $\bar{c} = 3$. Other parameters are: $\bar{p} = 5$, $\phi = 1$, $\sigma_b = 1$, $\mu_b = 0$, $\sigma_e = 2$,

Product Markups: Could Increase or Decrease

High Investment Cost/price of risk



Notes: This comparative static exercise is constructed over a single-good duopoly example. The x-axis is the number of data points that both firms have. The investment cost function is assumed as $g(\chi_c, c_i) = \chi_c (\overline{c} - c_i)^2 / 2$ with $\chi_c = 10$ and $\overline{c} = 3$. Other parameters are: $\overline{p} = 5$, $\phi = 1$, $\sigma_b = 1$, $\mu_b = 0$,

Aggregation Effects: Data and Firm Markups

- **Definition**: Firm-level markup is total revenue, divided by variable cost

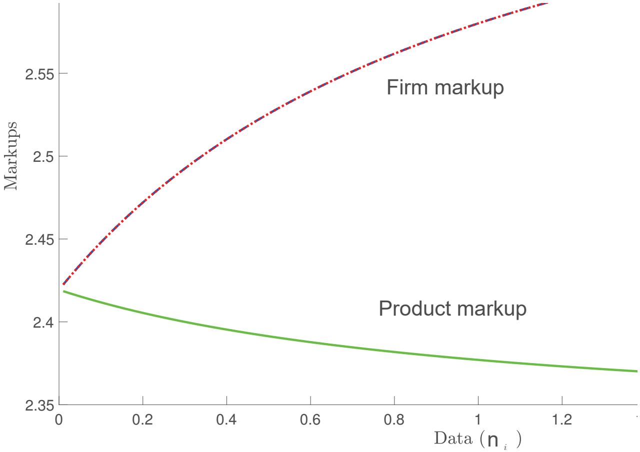
$$M_i^f := \frac{\mathbf{E}[\boldsymbol{q}_i' \boldsymbol{p}_i]}{\mathbf{E}[\boldsymbol{q}_i' \boldsymbol{c}_i]} = \frac{\mathbf{E}[\boldsymbol{q}_i]' \mathbf{E}[\boldsymbol{p}_i] + \mathbf{tr}\left[\mathbf{Cov}(\boldsymbol{p}_i, \boldsymbol{q}_i)\right]}{\mathbf{E}[\boldsymbol{q}_i' \boldsymbol{c}_i]}$$

- Data increases $\mathbf{Cov}(\boldsymbol{p}_i, \boldsymbol{q}_i)$
- Firms use data to create an aggregation effect: figure out which goods are more profitable and produce more of them.

Proposition

Data creates a wedge between product and firm markups

To Measure Data: Use the Markup Gap



- Symmetric firms. Parameter values: $c_1 = c_2 = 1$. $\underline{p} = 5$, $\rho_1 = \rho_2 = 1$, $\phi = 0.1$, $A = I$
- Product and firm markups can both fall, both rise, or split

Industry Markups, Data and Aggregation

- The unweighted average firm markup: $\bar{M}^f = (1/N)\sum_{i=1}^N M_i^f$
- The cost-weighted markup for an industry

$$M^c = \sum_{i=1}^{N} w_i^c M_i^f \quad \text{where cost weights are} \quad w_i^c = \frac{\mathbf{E}\left[\boldsymbol{q}_i'\boldsymbol{c}_i\right]}{\sum_{i=1}^N \mathbf{E}\left[\boldsymbol{q}_i'\boldsymbol{c}_i\right]}.$$

- The sales-weighted markup

$$M^s = \sum_{i=1}^{N} w_i^s M_i^f \quad \text{where sales weights are} \quad w_i^s = \frac{\mathbf{E}\left[\boldsymbol{q}_i'\boldsymbol{p}_i\right]}{\sum_{i=1}^N \mathbf{E}\left[\boldsymbol{q}_i'\boldsymbol{p}_i\right]}.$$

- The industry-aggregate markup is

$$M^{ind} = \frac{\mathbf{E}\left[\sum_{i=1}^N \boldsymbol{q}_i'\boldsymbol{p}_i\right]}{\mathbf{E}\left[\sum_{i=1}^N \boldsymbol{q}_i'\boldsymbol{c}_i\right]}$$

Industry Markup = Cost-weighted Markup

$$
\begin{aligned}
M^c &= \sum_{i=1}^{N} w_i^c M_i^f \\
&= \sum_{i=1}^{N} \frac{\mathbf{E}\left[\boldsymbol{q}_i' \boldsymbol{c}_i\right]}{\sum_{i=1}^{N} \mathbf{E}\left[\boldsymbol{q}_i' \boldsymbol{c}_i\right]} M_i^f \\
&= \sum_{i=1}^{N} \frac{\mathbf{E}\left[\boldsymbol{q}_i' \boldsymbol{c}_i\right]}{\sum_{i=1}^{N} \mathbf{E}\left[\boldsymbol{q}_i' \boldsymbol{c}_i\right]} \frac{\mathbf{E}[\boldsymbol{q}_i' \boldsymbol{p}_i]}{\mathbf{E}[\boldsymbol{q}_i' \boldsymbol{c}_i]} \\
&= \frac{\mathbf{E}\left[\sum_{i=1}^{N} \boldsymbol{q}_i' \boldsymbol{p}_i\right]}{\mathbf{E}\left[\sum_{i=1}^{N} \boldsymbol{q}_i' \boldsymbol{c}_i\right]} = M^{ind}
\end{aligned}
$$

- Cost-weighted markups do not capture changes in distribution

Industry Markup Measures Diverge

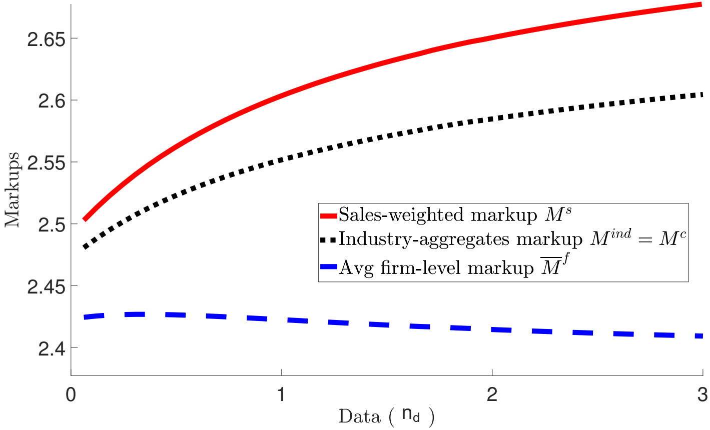
Proposition

Growing data increases *(for* $\chi \in (\underline{\chi}, \bar{\chi})$*)*

1. *the difference between cost-weighted and unweighted firm markups* $E[M^c - \overline{M}^f]$,
   (b/c high-data/ high-markup firms produce more)
2. *the difference between sales weighted and cost-weighted markups* $E[M^s - M^c]$;
   (b/c high-data/ high-markup firms have higher sales, relative to costs)
3. *the difference between the sales weighted and industry-aggregates markup* $E[M^s - M^{ind}]$.
   (b/c cost-weighted and industry-aggregated are the same)

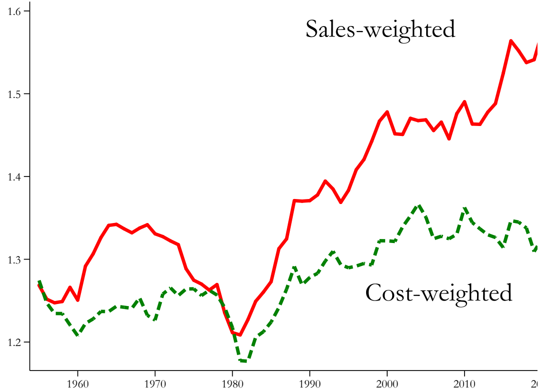
Restriction on χ makes sure the firms produce something and that firms size is not extreme.

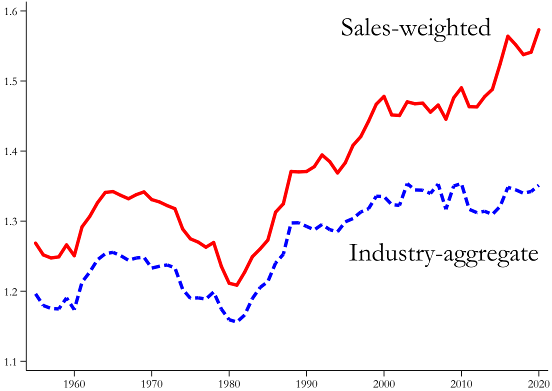
Diverging Industry Markup Measures



Investment cost function is $g(\chi_c, c_i) = \chi_c / c_i^2$, with $\chi_c = 1$. Parameters are $\bar{p} = 5$, $\rho_1 = 1$, $\rho_2 = 5$, $\phi = 0.8$ and $A = I$. Firm 1's data is measured on the x-axis. Firm 2's data is fixed at $\Sigma_{\epsilon_2}^{-1} = 1$.

Empirical Evidence: Firm/Industry Markup Divergence





- 2/3 of the rise comes from sales-weighting (De Loecker-Eeckhout-Unger (2020))
- There is a composition effect in the data. Growing stocks of data explains why that composition effect is present and why it is *growing*

Cyclical Markup Divergence

- A markup dispute:
  - Bils (1985, 1987): markups are counter-cyclical. Measured at aggregate level
  - Ramey and Nekarda (2020): no evidence of counter-cyclicality in disaggregated markups
  - → A problem for New Keynesian models
- Suppose recessions are times when demand falls, but demand variance (uncertainty) rises

⇒ Both can be right: Product markups procyclical and firm/industry markups counter-cyclical

Proposition. **Product and Firm markups diverge when volatility rises.** Suppose $(c_i = c_j \ \forall\, i, j)$ and $\Sigma_{b,j} \to \infty$. Then:

A. The product-level markup converges to a constant

B. Firm/industry markups asymptote to a function increasing in variance $\lim_{\Sigma_{b,k}\to\infty} \partial \mathbf{E}[M_{ij}^{f}]/\partial\Sigma_{b,j}, \partial \mathbf{E}[M_{ij}^{m}]/\partial\Sigma_{b,j} > 0$

Dynamic Competition and Endogenous Data

- Same model as before with
  - Persistent demand shocks b makes data a long-lived asset:

$$b_t = \rho b_{t-1} + \eta_{bt} \qquad \eta_{bt} \sim iid\ N(0, \sigma_\eta I)$$

  - Transitory noise keeps all uncertainty from being resolved:

$$\tilde{b}_t = b_t + \epsilon_{bt} \qquad \epsilon_{bt} \sim iid\ N(0, \sigma_\epsilon I)$$

- Data is a by-product of economic activity: $n_{it} = q_{i,t-1} a_{i,t-1}$
  - Firms get more data about attributes (a) they produce
  - → Production is active experimentation
- Firms maximize present value of profit, V (Bellman eqn in data)

Bellman eq.

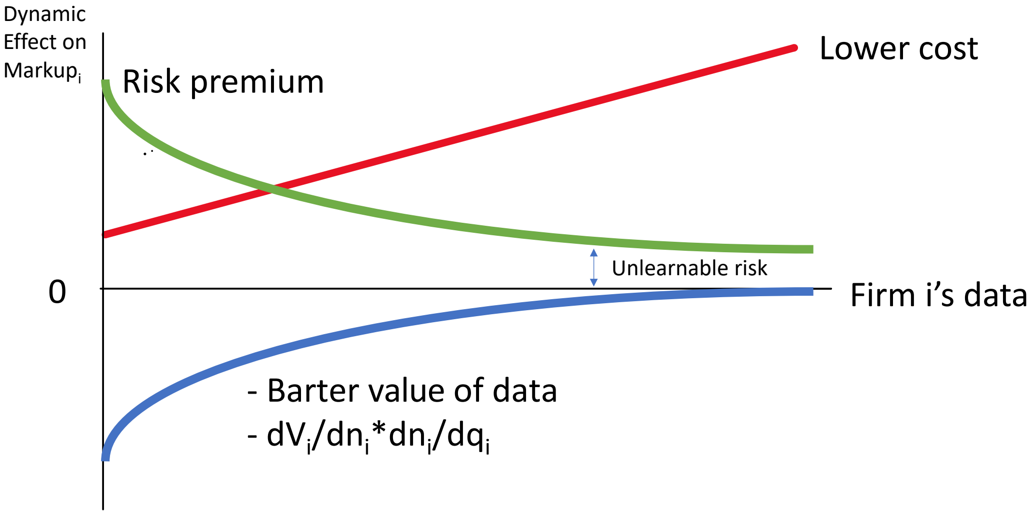
Dynamic Model: Data Barter

- FOC as before, with new term $\partial V/\partial q_i$: marginal value of data from extra transaction

$$\boldsymbol{q}_i a_i = \left(\rho_i \mathbf{Var}\left[\tilde{\boldsymbol{p}}|\mathcal{I}_i\right] + \frac{\partial \mathbf{E}\left[\tilde{\boldsymbol{p}}|\mathcal{I}_i\right]}{\partial \boldsymbol{q}_i}\right)^{-1} \left(\mathbf{E}\left[\tilde{\boldsymbol{p}}|\mathcal{I}_i\right] - \boldsymbol{c}_i + \frac{\partial V}{\partial q_i}\right)$$

- Payment p is less because firms are compensated with data $(\partial V/\partial q_i)$ – **Data barter**
- Three main forces at work, besides market power, in dynamic product markups:
  1. Barter trade: zero or discount-price transactions $(\partial V/\partial q_i)$. Lowers prices
  2. Risk premium raises prices, but declines with data
  3. Lower cost c_i raises markups. Data strengthens this force

Lifecycle of Firm Markups



Conclusions

- A model to interpret existing facts, and enable new measurement
- Start from a simple premise: Firms use data to predict uncertain outcomes
- Markups capture 3 forces:
  1. market power
  2. risk
  3. data barter

  → How to tease out data from market power?
- Measure data with covariances
  - Covariances are the aggregation wedges in markups at higher levels of aggregation

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Appendix Slides

Bertrand Price Competition

- Our inverse demand was: $p = \bar{p} - \Phi^{-1} q + b$. Rewrite as $q = \Phi(\bar{p} - p + b)$ and allow for different degrees of substitution between firms ϕ_{ij}:

$$q_i = \sum_{j=1}^{nF} \phi_{ij}(\bar{p}_j - p_j + b_j).$$

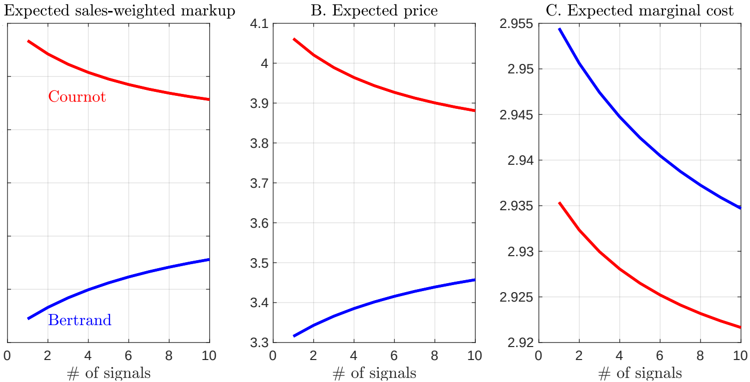
- Substitute this into the objective and take FOC wrt p_i:

$$p_i = c_i + \left(\rho_i \mathbf{Var}\left[q_i \mid \mathcal{I}_i\right] - \frac{\partial \mathbf{E}\left[q_i \mid \mathcal{I}_i\right]}{\partial p_i} \right)^{-1} \mathbf{E}\left[q_i \mid \mathcal{I}_i\right]$$

- More data, lower var, makes firms price higher. Less risk = more profit. Markup still mixes up data and market power.
- More data still raises the covariance between price and quantity (Key to the main results)
- Numerical simulations reveal: lower level of markups

More Data with Cournot v. Bertrand

When data increases, markups and prices may change in opposite directions.



Parameters are: $g(\chi_c, c_i) = \chi_c (\overline{c} - c_i)^2 / 2$ with $\chi_c = 10$ and $\overline{c} = 3$, $\overline{p} = 5$, $\sigma_b = 1$, $\mu_b = 0$, $\sigma_e = 2$, $\rho_1 = \rho_2 = 1$ and $\Psi = [1, 0.5; 0.5, 1]$.

Product Markups

Product-level markup for k produced by firm i:

$$M^p_{ik} := \mathbf{E}[\boldsymbol{p}_i(k)]/\boldsymbol{c}_i(k)$$

Simple case with 1 attribute: (either common or firm-specific shocks)

$$= \frac{1}{\widetilde{\boldsymbol{c}}_i}\left(\underline{\boldsymbol{p}} - (\phi + \bar{\boldsymbol{H}})^{-1}\left(\sum_{i'} \boldsymbol{H}_{i'}\left(\overline{\boldsymbol{p}} - \widetilde{\boldsymbol{c}}_{i'}\right)\right)\right)$$

$$M^p_{ik} = \frac{1}{a'_k c_i} a'_k(\underline{p} + E[b|\mathcal{I}]) - \frac{1}{\phi} a'_k (I + \bar{H})^{-1}\left(\frac{1}{c_i}\bar{H}\underline{p} + \sum_i j\frac{E[b|\mathcal{I}] - c_j}{c_i}\right)$$

What makes product markups large?

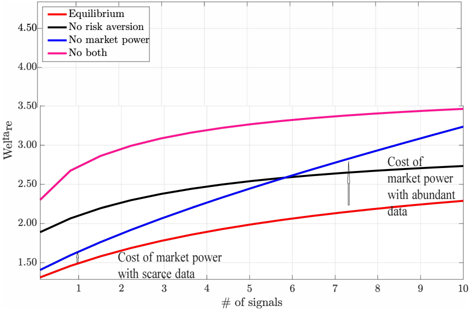
- Low costs ($\widetilde{\boldsymbol{c}}_i$)
- Low price elasticity of demand ϕ and supply $\bar{H}$: High price sensitivity to supply $1/\phi$:

  Second term is roughly $-H/(1+H)$. Markup decreasing in H.

Welfare Effects of Data (Symmetric)

Symmetric Data Improves Welfare. *When the number of data points are symmetric, more data points will increase social welfare*

But, abundant data makes market power more costly (additive in H):



A single-good duopoly example. $\chi_c = 1$, $g(\chi_c, c_i) = \chi_c\left(\overline{c} - c_i\right)^2/2$ with $\chi_c = 1$ and $\overline{c} = 3$, $\overline{p} = 5$, $\phi = 1$, $\sigma_b = 1$, $\mu_b = 0$, $\sigma_e = 2$, and $\rho_1 = \rho_2 = 1$

Welfare Effects of Data (Asymmetric)

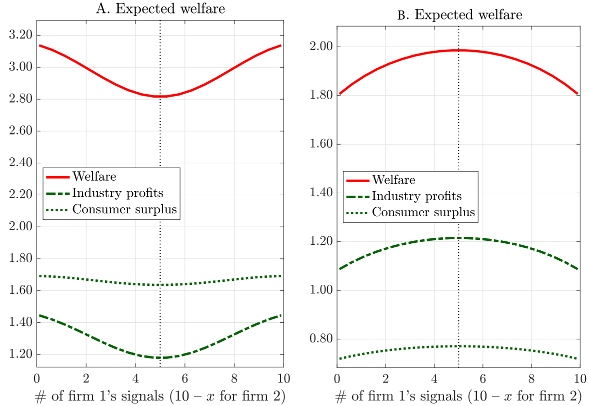
Data Asymmetry more nuanced – depends on price of risk vs. investment cost.

Data Asymmetry: When the number of data points are asymmetric, the change in asymmetry (more data to data-abundant firm) data has an ambiguous effect.

- If investment channel dominates (low χ_c, ρ), data asymmetry will reduce welfare;
- If risk dominates (high χ_c, ρ), welfare increases in data asymmetry.

More on welfare in the paper.

Welfare Effects of Data (Asymmetric)



Notes: Data asymmetry and welfare with dominant risk channel (left) or investment channel (right). This comparative static exercise is constructed over a single-good duopoly example. The investment cost function is assumed as $g(\chi_c, c_i) = \chi_c (\bar{c} - c_i)^2 / 2$. On the left, $\chi_c = 10$. On the right, $\chi_c = 1$. Other parameters are common to both plots: $\bar{c} = 3$, $\bar{p} = 5$, $\phi = 1$, $\sigma_b = 1$, $\mu_b = 0$, $\sigma_e = 2$, and $\rho_1 = \rho_2 = 1$.

Platforms

- This is not a model of competing platforms.

- What if normal firms sell on platforms?

  The platform becomes the source of data.

  Platforms give "insights" which are based on the sales of a firm and other similar firms.

  Given this data ($\{n_{di}\}$), firms allocate resources and price as in the static model.

- This does change the dynamic model.

  Data becomes a by-product of economic activity or a firm and its competitors.

  The nature of platform insights could help or hurt competition.

Dynamic Programming with Data

Optimal production $\{q_{i,t},\, a_{i,t}\}$ and data purchases / sales $\{m_{i,t},\, l_{i,t}\}$ solve

$$V(\Omega_t) = \max_{q_{i,t},a_{i,t},m_{i,t},l_{i,t}} (P_t - c)q_{i,t}a_{i,t} + \mathcal{P}_t(l_{i,t} - m_{i,t}) + \left(\frac{1}{1+r}\right) V(\Omega_{t+1}),$$

where the law of motion for $\Omega_{i,t}$ is

$$\Omega_{i,t+1} = \left[\rho^2 \Omega_{i,t}^{-1} + \sigma_\epsilon\right]^{-1} + (n_{i,t} + m_{i,t})\sigma_\epsilon^{-2}$$

and the number of data points produced by the firm is $n_{i,t} = q_{i,t}a_{i,t}$.

- What's the state variable? Every firm's stock of data, about every good: $\Omega_t := \{\Omega_{it}\}_{i=1}^{nF}$
- Can we shrink the state space? Yes, if two types of firms; or, if some aggregate statistic for other firm's data could accurately forecast the price. (an approximation)

Product Innovation and Firm Scope

- Let firm $i \in \{1, 2, \ldots, n_F\}$ choose $n \times 1$ vector a_i that describes their location in the product space, such that $\sum_j a_{ij} = 1$
- Firm's production problem:

$$max_{a_i, q_i} \mathbf{E}\left[\pi_i | \mathcal{I}_i\right] - \frac{\rho_i}{2} \mathbf{Var}\left[\pi_i | \mathcal{I}_i\right] - g(\chi_c, \tilde{\boldsymbol{c}}_i)$$

$$\text{s.t.} \quad \pi_i = q_i \boldsymbol{a}_i' \left(\tilde{\mathbf{p}} - \boldsymbol{c}_i\right) \quad \text{and} \quad \sum_j a_{ij} = 1$$

- Result:
  - This is just a linear rotation of the original problem
  - Data can inform what products to bring to market
- Next step:
  - Explore: how firms use data to adapt to changing conditions by changing product mix
  - Firm size distribution, trends in scope, competition in a product space with active experimentation, a new interpretation of skill in entrepreneurship