Data and markups: A macro-finance perspective

by Jan Eeckhout (UPF) and Laura Veldkamp (Columbia and NBER)

Discussion by Nicolas Crouzet (Kellogg)

EFG meeting, Summer 2024

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Broad question

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Upbeat view — helps firms improve planning and mitigate risks

The upbeat view of data

Lineage is a logistics firm

- Specializes in refrigerated warehouses

75 patents as of 2024; many for ML tools

Example: Sybil algorithm

- Input:
  - historical data on stocking patterns
- Outputs:
  - predictions for pallet arrival times
  - instructions for optimal placement

Chaos Meets Sybil: How Lineage is Using Data Science to Beat Uncertainty

AUGUST 24, 2023

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- Extensive history of individual spending
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The strategy, as described in redacted parts of FTC lawsuit, is part of agency's case that Amazon has outsize influence on consumer prices

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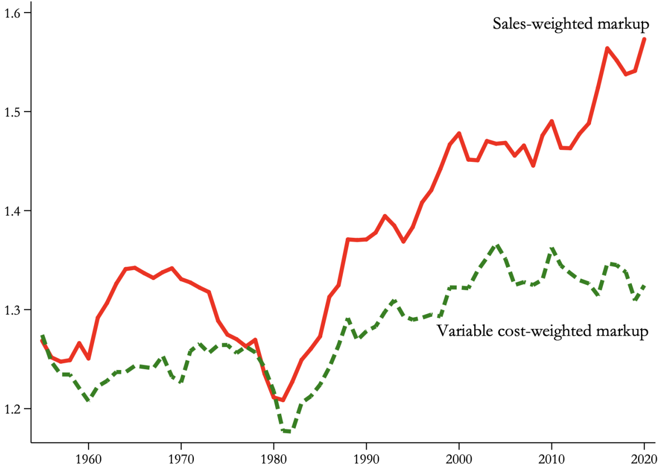
"Measured markups" $\propto$ revenue/variable costs [Hall, 1988; De Loecker, Eeckhout, Unger, 2020]

The graph seen ’round the world

[De Loecker, Eeckhout, Unger, 2020]



Average measured markup, US public firms

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Data creates a wedge btw. "measured" and "true" markups

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Firms are uncertain about <u>demand</u> for their products.

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Firms are uncertain about demand for their products.

Data is a collection of signals that help firms forecast demand.

Three questions

1. In reality, how important is demand forecasting to firms, and does it relate to markups?

2. In the model, how does data affect markups and their measurement?

3. What are some other ways of thinking about the impact of data on firms?

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    36 (or 17%) teach marketing —– how to forecast demand

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How much firms actually spend on data analytics/demand forecasting

How this changes over time, across firms, etc

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  - Identify 20 commodity or service groups potentially related to data analytics
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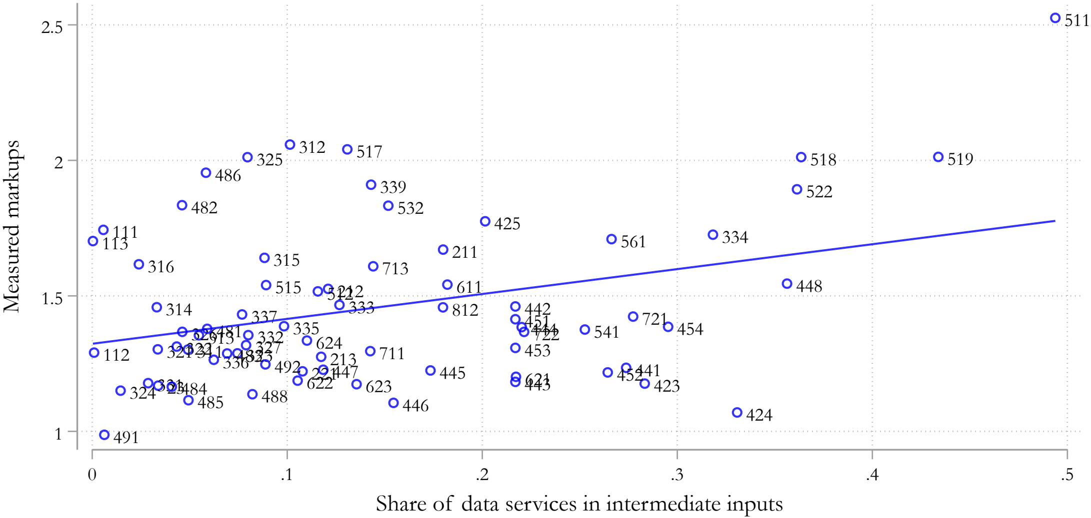
Measured this way, data spending share is remarkably stable [Graph]

- 15% in 2007, 2012 and 2017
- IQR = 5% – 20%

Measured markups and data share of intermediate spending, 2017



[$\beta = 0.92$, t-stat $= 3.06$]

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Need (much) more measurement!

2. In the model, how does data affect markups and their measurement?

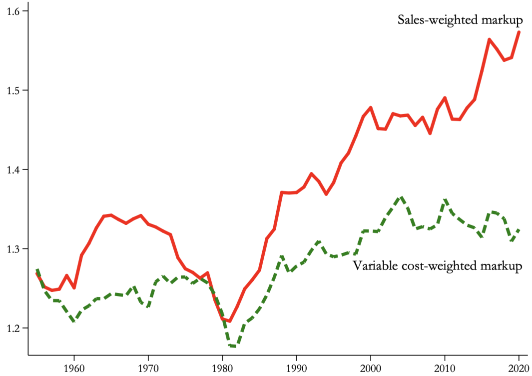
Where I'm going

First, **narrow question:** how data affects the <u>measurement</u> of markups

Second, **broad question:** what the model says about the upbeat vs. morose view of data

Measured markups

[De Loecker, Eeckhout, Unger, 2020]



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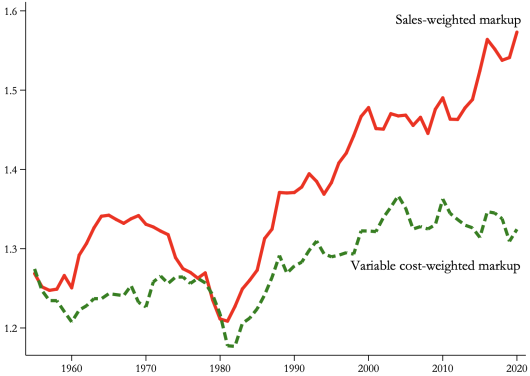

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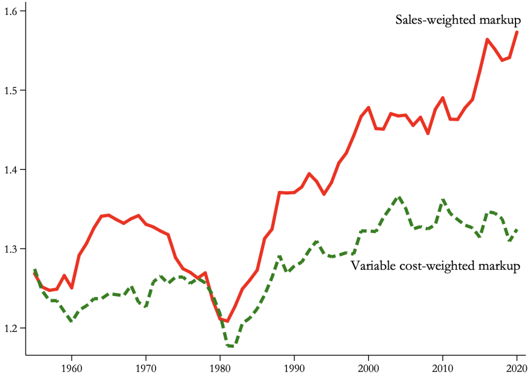

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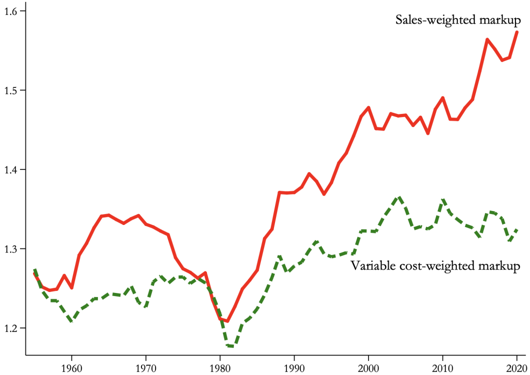

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$$w_i = \text{sales share}_i; \quad w_i = \text{cost share}_i$$

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Interpreting measured markups when firms produce one good

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$\left\{ \mathbb{E}[.] \text{ represents the firm's own forecasts before observing any signals.} \right\}$

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$$\begin{bmatrix}\text{Expected}\\ \text{markup}\end{bmatrix} + \begin{bmatrix}\text{Data}\\ \text{effect}\end{bmatrix}$$

Interpreting measured markups when firms produce one good

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$\hat{\delta}_i \neq \hat{\mu}_i$; data effect is there b/c $\hat{\delta}_i$ uses (ratio of) expectations.

Does aggregation help?

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Look at version of the model with no risk aversion + large # of firms. (And one good, as before.)

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$\bar{c}$ = average unit cost, κ_i = data of firm i, > 0

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$$\hat{\mu} \;=\; \underbrace{\sum_i w_i \frac{\bar{c}}{c_i}}_{\left[\substack{\text{Average}\\ \text{exp. markup}}\right]} \;+\; 0$$

Even aggregating, $\hat{\delta} \neq \hat{\mu}$; covariance term is not XS mean-zero.

What is this simple version of the model missing?

The simple version of the model I used here does not have

- multiple goods per firm
- multiple attributes per good

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Conference calls?

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- Data also enables price discrimination and tacit collusion — not in the model

3. What are some other ways of thinking about the impact of data on firms?

3 other ways of thinking about data in the context of firms

Data helps firms create new products [Argente, Lee, Moreira, 2024]

(+) Consumer surplus from expanded varieties

(−) Incumbency advantage (can learn from a large customer base)

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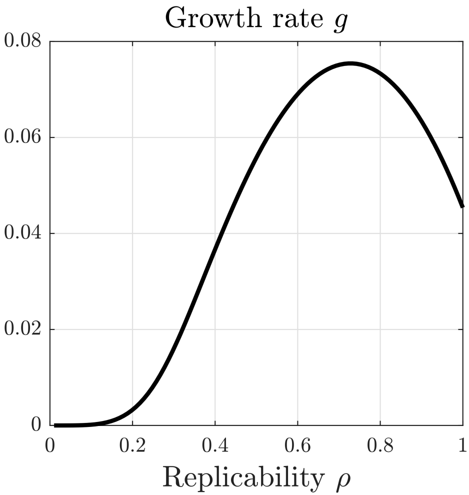

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[But also: recruiting and workforce management; regulatory compliance; ...]

Conclusion

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Ambitious, thought-provoking paper on an important topic

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Research going forward

- Urgently need more systematic data on (firms' use of) data
- Theory will probably not be one-size-fits-all

More

Some examples on demand forecasting

[Back]

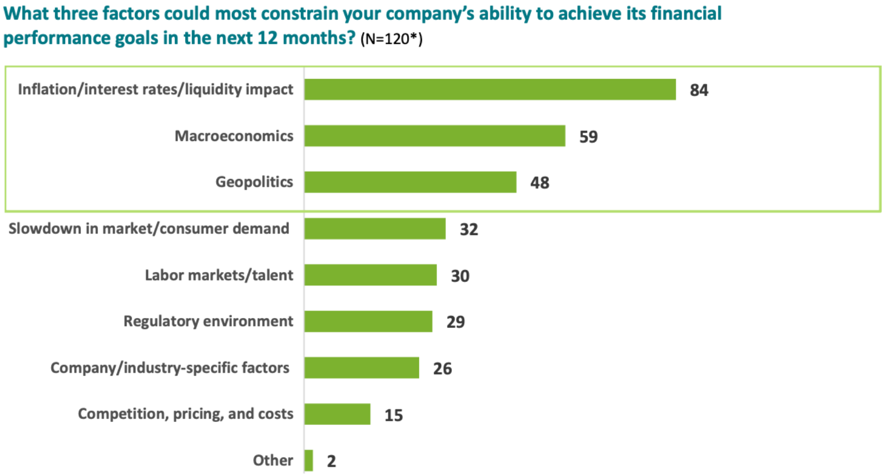
Amazon's 2023 10-K, Item 1A (Risk factors)

> *"Failures to adequately predict customer demand and consumer spending patterns [...] result in excess or insufficient fulfillment or data center capacity, service interruptions, and increased costs."*

> *"Our failure to adequately predict seller demand for storage [...] may result in us being unable to secure sufficient storage space [...] or cause other unexpected costs and other harm to our business and reputation."*

Some examples on demand forecasting

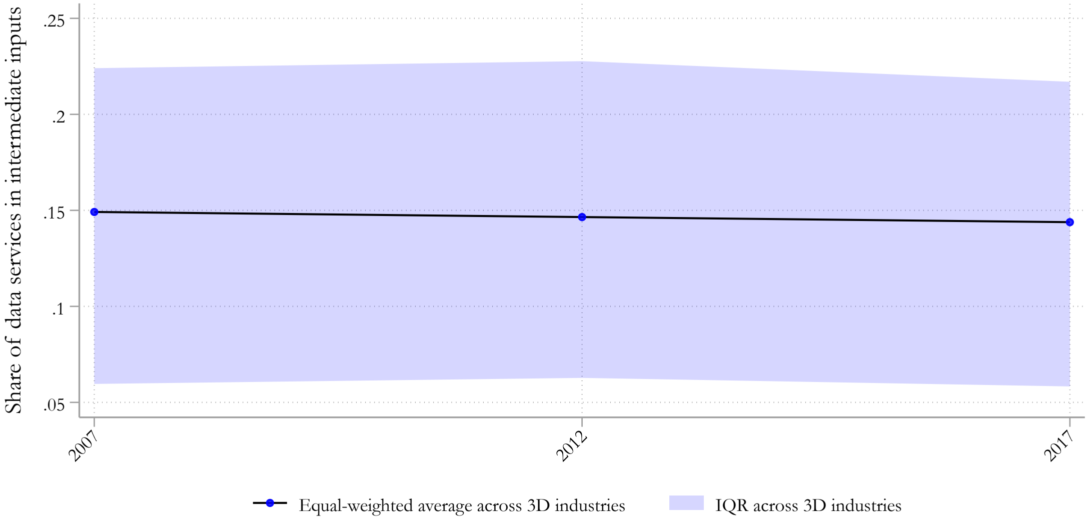
[Back]



[From Deloitte's CFO signals survey, 23Q4]

The data share of intermediate inputs

[Back]



Measured markups with multiple goods

Multiple goods (1/3)

[Back]

Consider a firm producing $j = 1, ..., N$ goods. Let:

$$\mathbf{q}_i \,:\, N \times 1, \quad \mathbf{p}_i \,:\, N \times 1, \quad \mathbf{c}_i \,:\, N \times 1.$$

Measured markup in the data is the cost-weighted average product markup:

$$\begin{aligned} \hat{\mu}_i &= \frac{\mathbf{p}_i' \, \mathbf{q}_i}{\mathbf{c}_i' \, \mathbf{q}_i} \\ &= \sum_j w_{i,j}^{\mu} \frac{p_{i,j}}{c_{i,j}} \\ w_{i,j}^{\mu} &\equiv \frac{c_{i,j} \, q_{i,j}}{\mathbf{c}_i' \, \mathbf{q}_i} \end{aligned}$$

Multiple goods (2/3)

[Back]

Consider a firm producing $j = 1, ..., N$ goods. Let:

$$\mathbf{q}_i \,:\, N \times 1, \quad \mathbf{p}_i \,:\, N \times 1, \quad \mathbf{c}_i \,:\, N \times 1.$$

Measured markup in the model is:

$$\begin{aligned}
\hat{\delta}_i &= \frac{\mathbb{E}\left[\mathbf{p}_i' \, \mathbf{q}_i\right]}{\mathbb{E}\left[\mathbf{c}_i' \, \mathbf{q}_i\right]} \\
&= \frac{\mathbb{E}\left[\mathbf{p}_i\right]' \; \mathbb{E}\left[\mathbf{q}_i\right]}{\mathbf{c}_i' \, \mathbb{E}\left[\mathbf{q}_i\right]} + \frac{tr\left(\mathbb{C}\mathrm{ov}\left(p_i, q_i\right)\right)}{\mathbf{c}_i' \, \mathbb{E}\left[\mathbf{q}_i\right]} \\
\hat{\delta}_i &= \sum_j w_{i,j}^{\delta} \frac{\mathbb{E}\left[p_{i,j}\right]}{c_{i,j}} + \frac{tr\left(\mathbb{C}\mathrm{ov}\left(p_i, q_i\right)\right)}{\mathbf{c}_i' \, \mathbb{E}\left[\mathbf{q}_i\right]} \\
w_{i,j}^{\delta} &\equiv \frac{c_{i,j} \, \mathbb{E}\left[q_{i,j}\right]}{\mathbf{c}_i' \, \mathbb{E}\left[\mathbf{q}_i\right]}
\end{aligned}$$

First term in definition of δ_i is analog to $\hat{\mu}_i$. Second term shows up b/c taking expectations.

Multiple goods (3/3)

[Back]

Consider a firm producing $j = 1, ..., N$ goods. Let:

$$\mathbf{q}_i : N \times 1, \quad \mathbf{p}_i : N \times 1, \quad \mathbf{c}_i : N \times 1.$$

Imagine we defined the measured markup in the model as:

$$\hat{\gamma}_i = \mathbb{E}\left[\frac{\mathbf{p}_i' \mathbf{q}_i}{\mathbf{c}_i' \mathbf{q}_i}\right].$$

Then:

$$\hat{\gamma}_i = \sum_j \mathbb{E}\left[w_{i,j}^{\mu}\right] \frac{\mathbb{E}\left[p_{i,j}\right]}{c_{i,j}} + tr\left(\mathbb{C}\text{ov}\left(p_i, w_{i,j}^{\mu}\right)\right)$$

$$\mathbb{E}\left[w_{i,j}^{\mu}\right] = c_{i,j}\mathbb{E}\left[\frac{q_{i,j}}{\mathbf{c}_i' \mathbf{q}_i}\right]$$

Discussion of the risk channel

The risk channel

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$$\max_{q_i} \quad \left(\mathbb{E}_i \left[\, p_i \mid s_i \, \right] - c_i \right) \, q_i$$

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$$\max_{q_i} \quad \left(\mathbb{E}_i \left[\, p_i \mid s_i \, \right] - c_i \right) \, q_i \quad - \quad \frac{\rho}{2} \, \mathbb{V}_i \left[\, (\, p_i \; - \; c_i \,) \, q_i \mid s_i \, \right]$$

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The paper interprets ρ as "risk pricing by firms"

In the traditional finance sense, e.g. "riskier" firms must have higher expected profits

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If closely held firm managed by un-diversified owner: yes.

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Normative perspective

Managers should care about beta, not variance [Brealey, Myers, Allen, 2003; David, Schmid, Zeke, 2023]

If s_i is idiosyncratic, should it even be relevant to investors' welfare?

The risk channel

$$\max_{q_i} \quad \left(\mathbb{E}_i\left[\, p_i \mid s_i \, \right] - c_i \right) \, q_i \quad - \quad \frac{\rho}{2} \, \mathbb{V}_i\left[\left(p_i - c_i \right) q_i \mid s_i \right]$$

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Positive perspective

Managers of public firms do, in fact, use betas [Graham, Harvey, 2001; Gormsen and Huber, 2024]

To the extent idio. risk is priced, it <u>may</u> be with the wrong sign [Ang, Hodrick, Xing, Zhang, 2006]

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real, not financial costs; driven by idiosyncratic risk

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What else could the "risk channel" capture?

<u>convex</u> costs associated with over- or under-capacity

e.g. for goods producers, costs of stocking out and/or inventory carrying costs

real, not financial costs; driven by idiosyncratic risk

<u>caveat</u>: these costs may be asymmetric, unlike in the model

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- Normative perspective
  - Adds force that makes more data always good for welfare
  - (no subtle equilibrium effects on risk prices) [Di Tella, Tonetti, 2024]

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Positive perspective

$$\underset{\text{Measured markup" }\hat{\delta}}{\text{"Measured}} \quad = \quad \underbrace{\left[\begin{array}{c}\text{"Risk-neutral"}\\\text{markup}\end{array}\right]}_{\left(\overset{=}{\textbf{with data}}\right)} + \underbrace{\left[\begin{array}{c}\text{Compensation}\\\text{for risk}\end{array}\right]}_{\left(\overset{\downarrow}{\textbf{with data}}\right)} + \underbrace{\left[\begin{array}{c}\text{Demand}\\\text{forecasting effect}\end{array}\right]}_{\left(\overset{\uparrow}{\textbf{with data}}\right)}$$