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
What is this paper about?

Broad question: How does greater data availability affect the production and investment decisions of firms?

Upbeat view — helps firms improve planning and mitigate risks
Morose view — allows firms to create or further exploit market power

Answer: Model where data reduces firms' forecast variance + interacts with market power

Narrow question: What do measured markups really capture?
"Measured markups" \(\propto\) revenue/variable costs [Hall, 1988; De Loecker, Eeckhout, Unger, 2020]

Answer: Divergence in markup trends could be informative about firms' use of data
Data creates a wedge btw. "measured" and "true" markups
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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
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[Hall, 1988; De Loecker, Eeckhout, Unger, 2020]
The morose view of data

Online retailers now have access to
  Extensive history of individual spending
  Predictive power of LLM

Concerns
  Price discrimination
  Algorithmic collusion

Recent FTC/DOJ action on price fixing

... in Atlantic City casinos
  Casinos coordinated on same algorithm
  ... algorithm was called "Rainmaker"
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Amazon Used Secret ‘Project Nessie’ Algorithm to Raise Prices
The strategy, as described in redacted parts of FTC lawsuit, is part of agency’s case that Amazon has outsized influence on consumer prices

By Dana Mattioli[Follow]
Updated Oct. 3, 2023 4:54 pm ET
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Updated Oct. 3, 2023 4:54 pm ET

FTC and DOJ File Statement of Interest in Hotel Room Algorithmic Price-Fixing Case
Statement of interest explains that hotel companies cannot use algorithms to evade antitrust laws

March 28, 2014
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[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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“Measured markups” $\propto \text{revenue/variable costs}$

**Answer:** Divergence in markup trends *could* be informative about firms’ use of data

Data creates a wedge btw. “measured” and “true” markups
But wait. What is “data”? (In this paper.)
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Firms are uncertain about demand 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?
1. In reality, how important is demand forecasting to firms, and does it relate to markups?
How important is demand forecasting to firms?

At Kellogg, there are 208 faculty members. Among them, 36 (or 17%) teach marketing—how to forecast demand. 15 (or 7%) teach operations—how to use demand forecasts in operational decisions.

Firms talk (a lot) about demand forecasting. Examples include 10Ks, CEO/CFO surveys.

Firms that provide data analytics services have experienced rapid revenue growth. For example, Amazon’s AWS arm generated $90.8bn in revenue in 2023, up from $3.1bn in 2013.

But all this is anecdotal. We would like systematic data on how much firms actually spend on data analytics/demand forecasting. How this changes over time, across firms, etc.
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   [Examples]
   10Ks
   CEO/CFO surveys

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   e.g. Amazon's AWS arm generated $90.8bn in revenue in 23, up from $3.1bn in 13

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A heroic upper bound

2007, 2012 and 2017 detailed IO tables

Identify 20 commodity or service groups potentially related to data analytics e.g. "Data processing, hosting, and related services", "Computer systems design services"

mostly in groups 51 (information) and 54 (professional and business services)

For each 3D industry, compute spending on these groups relative to total intermediate spending

This is an upper bound because not all of this intermediate spending is for demand forecasting!

Measured this way, data spending share is remarkably stable

15% in 2007, 2012 and 2017

IQR = 5 − 20%
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Measured markups and data share of intermediate spending, 2017

\[ \beta = 0.92, \text{t-stat} = 3.06 \]
What to make of this?

Little change in overall spending on data services

Some evidence that industries that spend more on data services charge higher markups; broadly consistent with message of the paper

Many, many caveats

Data-related services are not limited to demand forecasting

Only includes externally purchased, data-related services

What we really want is a marginal q of data

By how much does an extra dollar spent on data analytics really reduce forecast variance of demand?

How does this translate into enterprise value? How does it vary across firms?

Need (much) more measurement!
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2. In the model, how does data affect markups and their measurement?
First, narrow question: how data affects the measurement of markups

Second, broad question: what the model says about the upbeat vs. morose view of data
\[ \hat{\mu}_i = \text{Revenue}_i - \text{Variable cost}_i, \]

\[ \hat{\mu} = \sum_i w_i \hat{\mu}_i, \]

\[ w_i = \text{sales share}_i; \]

\[ w_i = \text{cost share}_i. \]
\[ \hat{\mu}_i = \frac{\text{Revenue}_i}{\text{Variable cost}_i} \]
Measured markups

\[ \hat{\mu}_i = \frac{\text{Revenue}_i}{\text{Variable cost}_i} \implies \hat{\mu} = \sum_i w_i \hat{\mu}_i \]
Measured markups

\[
\hat{\mu}_i = \frac{\text{Revenue}_i}{\text{Variable cost}_i} \quad \rightarrow \quad \hat{\mu} = \sum_i w_i \hat{\mu}_i
\]

\(w_i = \text{sales share}_i; \quad w_i = \text{cost share}_i\)
The paper’s point on measured markups

\[ \hat{\mu}_i = \text{Revenue}_i - \text{Variable cost}_i \]

\[ \hat{\mu} = \sum w_i \hat{\mu}_i \]

Step 1: when we measure firm-level markups this way, we are actually getting:

\[ \hat{\mu}_i = \text{markup}_i + \text{data effect}_i. \]

Step 2: when we aggregate markups, the data effect can be amplified comparing aggregate markups built with different weights, and these might be informative about data effects.

Where I differ: in some versions of the model,

\[ \hat{\mu}_i = \text{markup} \]

with no data effect. (This is about how “measured markups” are interpreted in the model.)
The paper’s point on measured markups

\[
\hat{\mu}_i = \frac{\text{Revenue}_i}{\text{Variable cost}_i} \quad \hat{\mu} = \sum_i w_i \hat{\mu}_i
\]

Step 1: when we measure firm-level markups this way, we are actually getting: \(\hat{\mu}_i\) = markup\(i\) + data effect\(i\).

Step 2: when we aggregate markups, the data effect can be amplified comparing aggregate markups built with different weights\(w_i\) could be informative about data effect.

Where I differ: in some versions of the model, \(\hat{\mu}_i\) = markup with no data effect. (This is about how “measured markups” are interpreted in the model.)
The paper’s point on measured markups

\[ \hat{\mu}_i = \frac{\text{Revenue}_i}{\text{Variable cost}_i} \quad \hat{\mu} = \sum_i w_i \hat{\mu}_i \]
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- comparing aggregate markups built with different weights \(w_i\) could be informative about data effect

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with no data effect. (This is about how “measured markups” are interpreted in the model.)
Interpreting measured markups when firms produce one good

In the data, firm-level markups are measured using:

\[ \hat{\mu}_i = \frac{\text{Revenue}_i}{\text{Variable cost}_i} \]
Interpreting measured markups when firms produce one good

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\[
\hat{\mu}_i = \frac{\text{Revenue}_i}{\text{Variable cost}_i}
\]

In the model, firm-level measured markups are defined as:

\[
\hat{\delta}_i = \frac{\mathbb{E}[\text{Revenue}_i]}{\mathbb{E}[\text{Variable cost}_i]}
\]

\{ \mathbb{E}[.] \text{ represents the firm’s own forecasts before observing any signals.} \}
Interpreting measured markups when firms produce one good

In the data, firm-level markups are measured using:

$$\hat{\mu}_i = \frac{\text{Revenue}_i}{\text{Variable cost}_i}$$

In the model, firm-level measured markups are defined as:

$$\hat{\delta}_i = \frac{\mathbb{E}[p_i q_i]}{c_i \mathbb{E}[q_i]}$$

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Interpreting measured markups when firms produce one good

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$$\hat{\mu}_i = \frac{\text{Revenue}_i}{\text{Variable cost}_i}$$

In the model, firm-level measured markups are defined as:

$$\hat{\delta}_i = \frac{\mathbb{E}[p_i] \mathbb{E}[q_i]}{c_{i} \mathbb{E}[q_i]} + \frac{\text{Cov}(p_i, q_i)}{c_{i} \mathbb{E}[q_i]}$$

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In the model, firm-level measured markups are defined as:

$$\hat{\delta}_i = \frac{\mathbb{E} [p_i]}{c_i} + \frac{\text{Cov}(p_i, q_i)}{c_i \mathbb{E} [q_i]}$$

{$$\mathbb{E} [.]$$} represents the firm’s own forecasts before observing any signals.
Interpreting measured markups when firms produce one good

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\[ \hat{\delta}_i = \frac{\mathbb{E}\left[p_i\right]}{c_i} + \frac{\text{Cov}(p_i, q_i)}{c_i \mathbb{E}\left[q_i\right]} \]

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

\{ \mathbb{E}[.] \text{ represents the firm’s own forecasts before observing any signals.} \}
Interpreting measured markups when firms produce one good

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\[ \hat{\mu}_i = \frac{p_i q_i}{c_i q_i} \]

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\[ \hat{\delta}_i = \frac{\mathbb{E}[p_i]}{c_i} + \frac{\text{Cov}(p_i, q_i)}{c_i \mathbb{E}[q_i]} \]

\[ \begin{bmatrix} \text{Expected markup} \\ \text{data effect} \end{bmatrix} \]

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Interpreting measured markups when firms produce one good

In the data, firm-level markups are measured using:

\[ \hat{\mu}_i = \frac{p_i q_i}{c_i q_i} \]

In the model, firm-level measured markups are defined as:

\[ \hat{\delta}_i = \frac{\mathbb{E}[p_i]}{c_i} + \frac{\text{Cov}(p_i, q_i)}{c_i \mathbb{E}[q_i]} \]

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[Expected markup] + [Data effect]

\[ \hat{\delta}_i \neq \hat{\mu}_i; \text{ data effect is there b/c } \hat{\delta}_i \text{ uses (ratio of) expectations.} \]
Does aggregation help?

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

\[ \hat{\delta}_i = \frac{\bar{c}}{c_i} + \frac{\kappa_i}{c_i(\bar{c} - c_i)} \]

\[ \begin{align*} 
& \text{[Expected]} & \text{[Data]} \\
& \text{markup} & \text{effect} \\
\end{align*} \]

\( \bar{c} = \) average unit cost, \( \kappa_i = \) data of firm \( i, > 0 \)
Does aggregation help?

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

\[
\hat{\delta} = \sum_i w_i \frac{\bar{c}}{c_i} + \sum_i w_i \frac{\kappa_i}{c_i (\bar{c} - c_i)}
\]

\[
\begin{bmatrix}
\text{Average} \\
\text{exp. markup}
\end{bmatrix} + \begin{bmatrix}
\text{Average} \\
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\quad \text{[Average exp. markup]} + \text{[Average data effect]}
\]

\[
\hat{\mu}_i = \frac{p_i}{c_i} \\
\quad \text{[Markup]}
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\]

\[
\hat{\mu}_i = \frac{\bar{c}}{c_i} + \text{[demand shock] [XS mean-zero]}
\]

\[
\text{[Expected markup]}
\]

\[
\text{[Average exp. markup] [Average data effect]}
\]
Does aggregation help?

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

\[
\hat{\delta} = \sum_i w_i \frac{c}{c_i} + \sum_i w_i \frac{\kappa_i}{c_i(\bar{c} - c_i)}
\]

\[
\left[ \text{Average exp. markup} \right] + \left[ \frac{\text{Average data effect}}{} \right]
\]

\[
\hat{\mu} = \sum_i w_i \frac{c}{c_i} + 0
\]

\[
\left[ \text{Average exp. markup} \right]
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$$\hat{\delta} = \sum_i w_i \frac{\bar{c}}{c_i} + \sum_i w_i \frac{\kappa_i}{c_i (\bar{c} - c_i)}$$

\[
\begin{bmatrix}
\text{Average exp. markup} \\
\text{data effect}
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\]

$$\hat{\mu} = \sum_i w_i \frac{\bar{c}}{c_i} + 0$$

\[
\begin{bmatrix}
\text{Average exp. markup}
\end{bmatrix}
\]

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

\[ \hat{\mu} \] = cost-weighted average product-level markup; reflects reallocation
\[ \hat{\delta} \] still contains an extra \( \text{Cov}(p, q) \) term, but again b/c \( \hat{\delta} \) involves expectations

But \( \hat{\mu} \) may be a better proxy for \( \hat{\delta} \) in this case.

Could check in simulations.
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Data will make firms reallocate production toward higher-markup goods.
What is this simple version of the model missing? [Multiple goods case]

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How then could we measure the data effect?

Recall: 

\[ \hat{\delta}_i = \frac{E[Revenue_i]}{E[Variable costs_i]} \]

Need measures of firm-level expected revenue and expected variable costs

- Analyst forecasts?
- Conference calls?
How then could we measure the data effect?

Want to combine measured markups $\hat{\mu}_i$ with an empirical proxy for $\hat{\delta}_i$. 

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Data reduces forecast variance of demand

- Unambiguously good for profits, investment, welfare
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**Morose view** — anti-competitive effects

- Data makes firms reallocate production toward higher-markup goods.
  - Effect is subtle:
    - More data is always good for welfare, so effect never dominates
  - "Data amplifies market power" only when firms are sufficiently risk averse

- Is this the "empirically plausible" scenario?
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- Data also enables price discrimination and tacit collusion — not in the model
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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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Data is a form of capital that can be replicated

(+ ) Economies of scope/scale

(−) Imperfect exclusivity (so weak incentive to invest)
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[Crouzet, Eisfeldt, Eberly, Papanikolaou, 2024]
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[De Ridder, 2024; Crouzet, Eberly, Eisfeldt, Papanikolaou, 2024]

[But also: recruiting and workforce management; regulatory compliance; ...]
Conclusion
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Ambitious, thought-provoking paper on an important topic

Do measured markups really capture firm's use of data? Or, need to combine them with forecasts to extract the data component?

Research going forward urgently need more systematic data on (firms' use of) data. Theory will probably not be one-size-fits-all.
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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
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

What three factors could most constrain your company’s ability to achieve its financial performance goals in the next 12 months? (N=120*)

- Inflation/interest rates/liquidity impact: 84%
- Macroeconomics: 59%
- Geopolitics: 48%
- Slowdown in market/consumer demand: 32%
- Labor markets/talent: 30%
- Regulatory environment: 29%
- Company/industry-specific factors: 26%
- Competition, pricing, and costs: 15%
- Other: 2%

[From Deloitte’s CFO signals survey, 23Q4]
The data share of intermediate inputs

Share of data services in intermediate inputs

Equal-weighted average across 3D industries
IQR across 3D industries

2007 2012 2017
Measured markups with multiple goods
Consider a firm producing \( j = 1, \ldots, N \) goods. Let:

\[
\begin{align*}
q_i & : N \times 1, \quad p_i : N \times 1, \quad c_i : N \times 1.
\end{align*}
\]

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

\[
\hat{\mu}_i = \frac{p_i'^t q_i}{c_i'^t q_i} = \sum_j w_{i,j}^{\mu} \frac{p_{i,j}}{c_{i,j}}
\]

\[
w_{i,j}^{\mu} \equiv \frac{c_{i,j} q_{i,j}}{c_i'^t q_i}
\]
Consider a firm producing \( j = 1, \ldots, N \) goods. Let:

\[
q_i : N \times 1, \quad p_i : N \times 1, \quad c_i : N \times 1.
\]

Measured markup in the model is:

\[
\hat{\delta}_i = \frac{E[p_i'q_i]}{E[c_i'q_i]} = \frac{E[p_i]'E[q_i]}{c_i'E[q_i]} + \frac{tr(Cov(p_i, q_i))}{c_i'E[q_i]}
\]

\[
\hat{\delta}_i = \sum_j w_{i,j}^{\delta} \frac{E[p_{i,j}]}{c_{i,j}} + \frac{tr(Cov(p_i, q_i))}{c_i'E[q_i]}
\]

\[
w_{i,j}^{\delta} = \frac{c_{i,j}E[q_{i,j}]}{c_i'E[q_i]}
\]

First term in definition of \( \delta_i \) is analog to \( \hat{\mu}_i \). Second term shows up b/c taking expectations.
Consider a firm producing \( j = 1, \ldots, N \) goods. Let:

\[
q_i : N \times 1, \quad p_i : N \times 1, \quad c_i : N \times 1.
\]

Imagine we defined the measured markup in the model as:

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

Then:

\[
\hat{\gamma}_i = \sum_j \mathbb{E} \left[ \omega_{i,j}^\mu \right] \mathbb{E} \left[ p_{i,j} \right] c_{i,j} + \text{tr} \left( \text{Cov} (p_i, \omega_{i,j}^\mu) \right)
\]

\[
\mathbb{E} \left[ \omega_{i,j}^\mu \right] = c_{i,j} \mathbb{E} \left[ \frac{q_{i,j}}{c'_i q_i} \right]
\]
Discussion of the risk channel
The risk channel

The paper interprets $\rho$ as "risk pricing by firms" in the traditional finance sense, e.g. "riskier" firms must have higher expected profits. Is that the right interpretation?

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

Otherwise: not sure.
The risk channel

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

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The risk channel

$$\max_{q_i} \left( \mathbb{E}_i \left[ p_i \mid s_i \right] - c_i \right) q_i - \frac{\rho}{2} \nabla_i \left[ \left( p_i - c_i \right) q_i \mid s_i \right]$$
The risk channel

\[
\max_{q_i} \left( \mathbb{E}_i \left[ p_i \mid s_i \right] - c_i \right) q_i - \frac{\rho}{2} \nabla_i \left[ (p_i - c_i) q_i \mid s_i \right]
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$$
\max_{q_i} \left( E_i [ p_i | s_i ] - c_i \right) q_i - \frac{\rho}{2} \nabla_i \left[ (p_i - c_i) q_i | s_i \right]
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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

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

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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 may be with the wrong sign [Ang, Hodrick, Xing, Zhang, 2006]
Assessing the “risk channel”

What else could the “risk channel” capture?

Con vex 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

Caveat: these costs may be asymmetric, unlike in the model

Do we need a risk channel? What extra economic implications does it create?
Assessing the “risk channel”

What else could the “risk channel” capture?
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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

\[
\text{“Measured markup” } \hat{\delta} = \left[ \text{“Risk-neutral markup”} \right] + \left[ \text{Compensation for risk} \right] + \left[ \text{Demand forecasting effect} \right]
\]