Information, Misallocation and Aggregate Productivity

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This paper

“Misallocation,” i.e., dispersion in MP’s ⇒ large losses in TFP and output

- But sources of distortions still unclear...
- Role of imperfect information? Informational role of financial markets?

1. What we do

- Heterogeneous firms choose inputs under imperfect info
- Firms learn from internal sources and noisy asset prices
- Quantify frictions using stock market/production data in US, China, India

2. What we find

- Significant micro uncertainty, esp. in China and India
  → accounts for 20-50% (+...) of MRPK dispersion
- Sizable aggregate impact
  → TFP losses: 7-10% in China and India, 4% in US; lower bound...?
- Only limited learning from markets; firm internal sources are key
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Overview

- Simplified model
- Full model and numerical results
- Robustness
- Other evidence
Simplified model

Homogeneous good, only capital, no aggregate risk

- Continuum of producers: \( Y_{it} = A_{it} K_{it}^{\alpha} \), \( a_{it} \sim iid, \mathcal{N}(0, \sigma_{\mu}^2) \)

Input choice under incomplete info:

- Profit maximization: \( \max_{K_{it}} \mathbb{E}_{it} [A_{it}] K_{it}^{\alpha} - RK_{it} \)
- Conditional on info \( I_{it} \), \( a_{it} \sim \mathcal{N}(E_{it} a_{it}, \mathbb{V}) \)

\( \mathbb{V} \) is key object:

- Misallocation: \( \sigma_{mpk}^2 = \mathbb{V} \)
- Aggregate TFP: \( a = a^* - \frac{1}{2} \frac{\alpha}{1-\alpha} \sigma_{mpk}^2 = a^* - \frac{1}{2} \frac{\alpha}{1-\alpha} \mathbb{V} \)

\( \Rightarrow TFP \downarrow \) in \( \mathbb{V} \); size of effect \( \uparrow \) in \( \alpha \)
Simplified model

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\( \nabla \) is key object:

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\( \Rightarrow \) TFP ↓ in \( \nabla \); size of effect ↑ in \( \alpha \)
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Characterizing $\nabla$

The firm’s information set $\mathcal{I}_{it}$

1. Private signal: $s_{it} = a_{it} + e_{it}$, $e_{it} \sim \mathcal{N}(0, \sigma_e^2)$

2. Stock price: $p_{it} \approx a_{it} + \eta_{it}$, $\eta_{it} \sim \mathcal{N}(0, \sigma_\eta^2)$

If $(a_{it}, e_{it}, \eta_{it})$ independent (relaxed later):

$$\nabla = \frac{1}{\frac{1}{\sigma_\mu^2} + \frac{1}{\sigma_e^2} + \frac{1}{\sigma_\eta^2}}$$
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Identifying information frictions

The challenge: information $I_{it}$ not directly observable

$$k_{it} = \frac{\mathbb{E}_{it} [a_{it}]}{1 - \alpha}$$

→ In principle, could identify $\nabla$ from $\sigma_{mpk}, \sigma_k^2, \sigma_{ak}$, etc...

But, suppose:

$$k_{it} = \frac{\mathbb{E}_{it} [a_{it} + \tau_{it}]}{1 - \alpha}$$

→ Other ‘distortions’ complicate inference from these moments

Our strategy:

- Use correlation of stock returns with $\Delta k_{it}$ and $\Delta a_{it}$ (denoted $\rho_{pk}, \rho_{pa}$)
- Model implies tight connection between these correlations and $\nabla$
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- Model implies tight connection between these correlations and $\nabla$
Identification - our strategy

1. Directly measure $a_{it} = y_{it} - \alpha k_{it}$ (and so, $\sigma^2_\mu$)

   \[
   \rho_{pa} = \frac{1}{\sqrt{1 + \frac{\sigma^2_n}{\sigma^2_\mu}}} \quad \frac{\nu}{\sigma^2_\mu} = 1 - \left(\frac{\rho_{pa}}{\rho_{pk}}\right)^2
   \]

   $\rho_{pa}$ → noise in prices
   $\rho_{pk}$ relative to $\rho_{pa}$ → firm uncertainty

3. Straightforward to add persistence.
   
   - E.g., with permanent shocks, $\rho_{pk} - \rho_{pa}$ → $\frac{\nu}{\sigma^2_\mu}$

Next: Robustness to other distortions $\tau_{it}$, measurement error etc.
1. Directly measure $a_{it} = y_{it} - \alpha k_{it}$ (and so, $\sigma^2_\mu$)

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Next: Robustness to other distortions \( \tau_{it} \), measurement error etc.
Identification - other frictions

Distortions from correlated and uncorrelated factors (with \( a_{it} \)):

\[
\tau_{it} = \gamma\mu_{it} + \varepsilon_{it}, \quad \varepsilon_{it} \sim \mathcal{N}(0, \sigma_{\varepsilon}^2)
\]

\[
\Rightarrow k_{it} = \frac{(1 + \gamma) E[a_{it}] + \varepsilon_{it}}{1 - \alpha}
\]

1. Only correlated distortions (\( \gamma \neq 0, \sigma_{\varepsilon}^2 = 0 \)):

\[
\Rightarrow \sigma_{mpk}^2 > \nabla; \quad \text{but, } 1 - \left( \frac{\rho_{pa}}{\rho_{pk}} \right)^2 = \frac{\nabla}{\sigma_{\mu}^2} \text{ still holds}
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2. Only uncorrelated distortions (\( \gamma = 0, \sigma_{\varepsilon}^2 \neq 0 \)):

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Note: Results extend to permanent shocks as well
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Identification - Robustness

1. Unaffected by correlation in firm/market information

3. Robust to heterogeneity in $\alpha$: $k_{it} = \frac{E_{it}(a_{it})}{1-\alpha_i} = \frac{1-\alpha}{1-\alpha} E_{it}(a_{it})$

   - Correlated: $\frac{1-\alpha}{1-\alpha_i} \propto E_{it}(a_{it}) \Rightarrow k_{it} = \frac{(1+\gamma)E_{it}(a_{it})}{1-\alpha}$

   - Uncorrelated: does not affect $(\rho_{pk}, \rho_{pa})$
Identification - Robustness

1. Unaffected by correlation in firm/market information

2. Ambiguous effects from measurement error

- \( \ln y_{it} : 1 - \frac{\rho_{pa}^2 \left( \frac{\sigma^2_\mu}{\sigma^2_\mu + \sigma^2_{\epsilon_y}} \right)}{\rho_{pk}^2} > 1 - \frac{\rho_{pa}^2}{\rho_{pk}^2} = \frac{\gamma}{\sigma^2_\mu} \)

- \( \ln k_{it} : 1 - \frac{\rho_{pa}^2 \left( \frac{\sigma^2_\mu}{\sigma^2_\mu + \alpha^2 \sigma^2_{\epsilon_k} \epsilon_k} \right)}{\rho_{pk}^2 \left( \frac{\sigma^2_\mu - \gamma}{\sigma^2_\mu - \gamma + \sigma^2_{\epsilon_k} + \sigma^2_\mu - \gamma} \right)} > 1 - \frac{\rho_{pa}^2}{\rho_{pk}^2} = \frac{\gamma}{\sigma^2_\mu} \) iff \( \frac{\gamma}{\sigma^2_\mu} < \frac{2\alpha - 1}{\alpha^2} \)

3. Robust to heterogeneity in \( \alpha \): \( k_{it} = \frac{E_{it}(a_{it})}{1-\alpha_i} = \frac{1-\alpha}{1-\alpha_i} \frac{E_{it}(a_{it})}{1-\alpha} \)

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Quantitative analysis: Model

1. Monopolistic competition: \( Y_t = \left( \int A_{it} Y_{it}^{\theta-1} \, di \right)^{\frac{\theta}{\theta-1}} \)

2. Production: \( Y_{it} = K_{it}^{\alpha_1} L_{it}^{\alpha_2} \)
   - Case 1: both factors chosen under imperfect info
   - Case 2: only \( K \) chosen under imperfect info, \( L \) adjusts ex-post

\[ \Rightarrow \text{Preserves } \max_{K_{it}} \prod \mathbb{E}_{it} [A_{it}] K_{it}^{\alpha} - RK_{it}; \text{ with } \alpha_{\text{Case 1}} > \alpha_{\text{Case 2}} \]

3. AR(1) process for log \( A_{it} \): \( a_{it} = \rho a_{it-1} + \mu_{it}, \quad \mu_{it} \sim \mathcal{N}(0, \sigma^2_{\mu}) \)

4. Explicit model of stock market trading

\[ \Rightarrow \text{Preserves } p_{it} \approx^I a_{it} + \eta_{it} \]
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The stock market

Unit measure of firm equity traded by 2 type of agents

1. Investors: can purchase up to single unit at price $p_{it}$
2. Noise traders: purchase random quantity $\Phi(z_{it})$, $z_{it} \sim \mathcal{N}(0, \sigma_z^2)$

Information of investors:

- Private signal: $s_{ijt} = a_{it} + v_{ijt}$, $v_{ijt} \sim \mathcal{N}(0, \sigma_v^2)$
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Trading: buy asset if $E_{ijt} \Pi_{it} \geq p_{it}$ or $s_{ijt} > \hat{s}_{it}$

Market clearing: $1 - \Phi\left(\frac{\hat{s}_{it} - a_{it}}{\sigma_v}\right) + \Phi(z_{it}) = 1$

⇒ Info in price: $\hat{s}_{it} = a_{it} + \sigma_v z_{it}$ \[\sigma_\eta^2 = \sigma_v^2 \sigma_z^2\]
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$[\frac{\sigma^2_v}{\sigma^2_z} = \sigma^2_v \sigma^2_z]$
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## Parameterization: general parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Target/Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time period</td>
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<td></td>
</tr>
<tr>
<td>$\beta$</td>
<td>Discount rate</td>
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</tr>
<tr>
<td>$\alpha_1$</td>
<td>Capital share</td>
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</tr>
<tr>
<td>$\alpha_2$</td>
<td>Labor share</td>
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</tr>
<tr>
<td>$\theta$</td>
<td>Elasticity of substitution</td>
<td>6</td>
</tr>
</tbody>
</table>

- If $K$ and $L$ both chosen under imperfect information (case 1)
  \[ \alpha = \frac{\theta - 1}{\theta} = 0.83 \]
- If only $K$ chosen under imperfect information (case 2)
  \[ \alpha = 0.62 \]
## Parameterization: country-specific parameters

<table>
<thead>
<tr>
<th>Parameter</th>
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<tbody>
<tr>
<td>$\rho$</td>
<td>Persistence of fundamentals</td>
<td>From observed</td>
</tr>
<tr>
<td>$\sigma_{\mu}^2$</td>
<td>Shocks to fundamentals</td>
<td>$a_{it} = rev_{it} - \alpha k_{it}$</td>
</tr>
<tr>
<td>$\sigma_e^2$</td>
<td>Firm private info</td>
<td>$\rho_{pi}$</td>
</tr>
<tr>
<td>$\sigma_v^2$</td>
<td>Investor private info</td>
<td>$\rho_{pa}$</td>
</tr>
<tr>
<td>$\sigma_z^2$</td>
<td>Noise trading</td>
<td>$\sigma_p^2$</td>
</tr>
</tbody>
</table>
⇒ Same intuition as in simplified version:

- $\rho_{pa} \rightarrow \text{noise in prices}$
- $(\rho_{pi} - \rho_{pa}) \rightarrow V$
The impact of informational frictions

<table>
<thead>
<tr>
<th>Case 2 ($\alpha = 0.62$)</th>
<th>( \frac{\gamma}{\sigma_{\mu}^2} )</th>
<th>( \frac{\gamma}{\sigma_{mrk}^2} )</th>
<th>( a^* - a )</th>
</tr>
</thead>
<tbody>
<tr>
<td>US</td>
<td>0.41</td>
<td>0.22</td>
<td>0.04</td>
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<tr>
<td>China</td>
<td>0.63</td>
<td>0.34</td>
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<tr>
<td>India</td>
<td>0.77</td>
<td>0.48</td>
<td>0.10</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Case 1 ($\alpha = 0.83$)</th>
<th>( \frac{\gamma}{\sigma_{\mu}^2} )</th>
<th>( \frac{\gamma}{\sigma_{mrk}^2} )</th>
<th>( a^* - a )</th>
</tr>
</thead>
<tbody>
<tr>
<td>US</td>
<td>0.63</td>
<td>0.35</td>
<td>0.40</td>
</tr>
<tr>
<td>China</td>
<td>0.65</td>
<td>0.39</td>
<td>0.55</td>
</tr>
<tr>
<td>India</td>
<td>0.86</td>
<td>0.56</td>
<td>0.77</td>
</tr>
</tbody>
</table>

- Substantial posterior uncertainty (US firms best informed)  
  ⇒ significant misallocation, losses in TFP and output

- Effects increase with $\alpha$
Discussion

1. Case 1 vs. Case 2

- Interpret our results as bounds; but can we say something more...?
- Suggestive statistics from the US data
  - \( \frac{\sigma^2_{mrpl}}{\sigma^2_{mrpk}} = 0.57 \)
  - \( \frac{\nabla}{\sigma_{\mu}} \) computed with \( N_{it} \approx 0.5 \frac{\nabla}{\sigma_{\mu}} \) computed with \( K_{it} \)

2. Transitory vs. permanent MRPK deviations

- Informational frictions \( \rightarrow \) transitory deviations
- US data: transitory \( \approx 1/3 \) of total
  - \( \nabla \) accounts for 60% in case 2; entirety in case 1
Discussion

1. Case 1 vs. Case 2
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2. Transitory vs. permanent MRPK deviations
   - Informational frictions \( \rightarrow \) transitory deviations
   - US data: transitory \( \approx 1/3 \) of total
     - \( \nabla \) accounts for 60% in case 2; entirety in case 1
Sources of learning

<table>
<thead>
<tr>
<th>Case</th>
<th>Share from source</th>
<th>Δa</th>
<th>Private</th>
<th>Market</th>
</tr>
</thead>
<tbody>
<tr>
<td>US</td>
<td>5%</td>
<td></td>
<td>92%</td>
<td>8%</td>
</tr>
<tr>
<td>China</td>
<td>4%</td>
<td></td>
<td>96%</td>
<td>4%</td>
</tr>
<tr>
<td>India</td>
<td>3%</td>
<td></td>
<td>89%</td>
<td>11%</td>
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<td>Case 1</td>
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<td></td>
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</tr>
<tr>
<td>US</td>
<td>23%</td>
<td></td>
<td>91%</td>
<td>9%</td>
</tr>
<tr>
<td>China</td>
<td>30%</td>
<td></td>
<td>96%</td>
<td>4%</td>
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<tr>
<td>India</td>
<td>12%</td>
<td></td>
<td>96%</td>
<td>4%</td>
</tr>
</tbody>
</table>

1. Significant learning ⇒ significant aggregate gains

2. Learning primarily from private sources
   Interpretation? Manager skill/incentives, info collection/processing, etc...

3. Only small role for market-generated info ⇐ just too much noise in prices
## Effect of US information structure

<table>
<thead>
<tr>
<th></th>
<th>Case 2</th>
<th>Case 1</th>
<th>Δa</th>
<th>Δa</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Market Information</strong></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>China</td>
<td>1%</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>India</td>
<td>1%</td>
<td>4%</td>
<td></td>
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</tr>
<tr>
<td><strong>Private Information</strong></td>
<td></td>
<td></td>
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<tr>
<td>China</td>
<td>3%</td>
<td>6%</td>
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<td></td>
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<tr>
<td>India</td>
<td>5%</td>
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<tr>
<td><strong>Shocks</strong></td>
<td></td>
<td></td>
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<tr>
<td>China</td>
<td>1%</td>
<td>10%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>India</td>
<td>2%</td>
<td>20%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

1. Gains from US private info > US market info

2. Differences in fundamentals → differential impact of friction
Robustness: correlated information

Are we picking up correlation between firm and investors’ signals?

- Correlated errors \( \rightarrow \uparrow \rho_{pk} \rightarrow \uparrow \nabla \)?

- Strategy: Re-estimate \( \nabla \) assuming \( s_{ijt} = s_{it} + v_{ijt} = a_{it} + e_{it} + v_{ijt} \)

<table>
<thead>
<tr>
<th>Case 2 (( \alpha = 0.62 ))</th>
<th>( \frac{\nabla}{\sigma^2_{\mu}} )</th>
<th>( \frac{\nabla}{\sigma^2_{\mu}} ) baseline</th>
<th>( a^* - a )</th>
<th>( a^* - a ) baseline</th>
</tr>
</thead>
<tbody>
<tr>
<td>US</td>
<td>0.41</td>
<td>0.41</td>
<td>0.040</td>
<td>0.040</td>
</tr>
<tr>
<td>China</td>
<td>0.58</td>
<td>0.63</td>
<td>0.070</td>
<td>0.075</td>
</tr>
<tr>
<td>India</td>
<td>0.68</td>
<td>0.77</td>
<td>0.100</td>
<td>0.114</td>
</tr>
</tbody>
</table>

\( \Rightarrow \) Results almost identical to baseline!
Robustness: correlated information

Are we picking up correlation between firm and investors’ signals?

- Correlated errors → ↑ $\rho_{pk}$ →↑ $\nabla$?
- Strategy: Re-estimate $\nabla$ assuming $s_{ijt} = s_{it} + v_{ijt} = a_{it} + e_{it} + v_{ijt}$

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<th>$\frac{\nabla}{\sigma^2_{\mu}}$</th>
<th>$\frac{\nabla}{\sigma^2_{\mu}}$ baseline</th>
<th>$a^* - a$</th>
<th>$a^* - a$ baseline</th>
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</table>

$\Rightarrow$ Results almost identical to baseline!
**Robustness: measurement error in revenues**

What if observed \(\hat{y}_{it} = y_{it} + \epsilon_{it}^y\) \(\epsilon_{it}^y \sim \mathcal{N}(0, \sigma_{\epsilon y}^2)\)?

- \(\sigma_{\epsilon y}^2 \rightarrow \downarrow \) \(\rho_{pa} \rightarrow \uparrow \) \(\nabla\)
- **Strategy:** Re-estimate \(\nabla\) with corrected moments

<table>
<thead>
<tr>
<th></th>
<th>Baseline</th>
<th>(\sigma_{\epsilon y}^2 = 10% \sigma^2(\Delta y))</th>
<th>(\sigma_{\epsilon y}^2 = 25% \sigma^2(\Delta y))</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>(\nabla)</td>
<td>(\nabla)</td>
<td>(\nabla)</td>
</tr>
<tr>
<td></td>
<td>(\frac{\sigma^2}{\mu})</td>
<td>(\frac{\sigma^2}{\mu})</td>
<td>(\frac{\sigma^2}{\mu})</td>
</tr>
<tr>
<td>Case 2</td>
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<tr>
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<td>0.08</td>
<td>0.05</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>0.41</td>
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<td>China</td>
<td>0.16</td>
<td>0.14</td>
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<td></td>
<td>0.63</td>
<td>0.58</td>
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<tr>
<td>India</td>
<td>0.22</td>
<td>0.17</td>
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<td></td>
<td>0.77</td>
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<td>0.61</td>
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<tr>
<td>US</td>
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<td>0.18</td>
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<td>India</td>
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</tr>
<tr>
<td></td>
<td>0.86</td>
<td>0.91</td>
<td>0.89</td>
</tr>
</tbody>
</table>

\(\Rightarrow\) Upward bias in \(\nabla\), but cross-country results biased downward.
Robustness: measurement error in revenues

What if observed $\hat{y}_{it} = y_{it} + \epsilon_{it}$, $\epsilon_{it} \sim N(0, \sigma_{\epsilon y}^2)$?

- $\sigma_{\epsilon y}^2 \rightarrow \downarrow \rho_{pa} \rightarrow \uparrow \nabla$
- Strategy: Re-estimate $\nabla$ with corrected moments

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$\Rightarrow$ Upward bias in $\nabla$, but cross-country results biased downward.
Robustness: measurement error in capital

What if observed \( \hat{k}_{it} = k_{it} + \epsilon_{it} \), \( \epsilon_{it} \sim N(0, \sigma_{\epsilon k}^2) \)?

• \( \sigma_{\epsilon k}^2 \rightarrow \downarrow \rho_{pa}, \rho_{pk} \rightarrow \) ?

• Strategy: Re-estimate \( \nabla \) with corrected moments

<table>
<thead>
<tr>
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<tr>
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<td>\nabla</td>
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⇒ Our approach underestimates uncertainty!
Robustness: measurement error in capital

What if observed $\hat{k}_{it} = k_{it} + \epsilon_{it}^k$? 

$\epsilon_{it}^k \sim N(0, \sigma_{\epsilon_k}^2)$?

- $\sigma_{\epsilon_k}^2 \rightarrow \downarrow \rho_{pa}, \rho_{pk} \rightarrow \uparrow$?

- Strategy: Re-estimate $\nabla$ with corrected moments

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⇒ Our approach underestimates uncertainty!
Robustness: adjustment costs

Are we re-labeling adjustment costs as info frictions?

- **Strategy:** Simulate moments under full-info and quadratic adj. costs
- **Estimate $V$ using these moments**

<table>
<thead>
<tr>
<th></th>
<th>Adj. Cost</th>
<th>$V$</th>
<th>Baseline $V$</th>
</tr>
</thead>
<tbody>
<tr>
<td>US</td>
<td>0.03</td>
<td>0.08</td>
<td></td>
</tr>
<tr>
<td>China</td>
<td>0.06</td>
<td>0.16</td>
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</tr>
<tr>
<td>India</td>
<td>0.08</td>
<td>0.22</td>
<td></td>
</tr>
</tbody>
</table>

- $V$ (and agg effects) about 1/3 of baseline estimates

⇒ Unlikely that adj. costs are driving our estimates
Robustness: adjustment costs

Are we re-labeling adjustment costs as info frictions?

- **Strategy:** Simulate moments under full-info and quadratic adj. costs
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- \( V \) (and agg effects) about 1/3 of baseline estimates

⇒ Unlikely that adj. costs are driving our estimates
Robustness: financial frictions

Are we picking up financing-related effects of stock prices?

- Stock prices $\uparrow \rightarrow$ Funding constraints $\downarrow \rightarrow \rho_{pk} \uparrow \rightarrow \nabla \uparrow$?

- Strategy: Estimate $\nabla$ for ‘unconstrained’ firms

<table>
<thead>
<tr>
<th></th>
<th>Baseline</th>
<th>Small Issuers</th>
<th>Top Quartile</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\rho_{pi}$</td>
<td>$\rho_{pa}$</td>
<td>$\frac{\nabla^2}{\mu}$</td>
<td>$\frac{\nabla^2}{\mu}$</td>
</tr>
<tr>
<td>US</td>
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$\Rightarrow$ Unlikely that the financing channel is driving our results
Robustness: financial frictions

Are we picking up financing-related effects of stock prices?

- Stock prices $\uparrow \rightarrow$ Funding constraints $\downarrow \rightarrow \rho_{pk} \uparrow \rightarrow \nabla \uparrow$?
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$\Rightarrow$ Unlikely that the financing channel is driving our results
Other evidence: Cross-section

- Compute $\nabla$ by sector in the US
- Compare to mean squared error in firm revenue forecasts
Other evidence: Cross-section

- Compute $\nabla$ by sector in the US
- Compare to mean squared error in firm revenue forecasts
Other evidence: Time series

- Compute $V$ over time in the US
- Compare to other indicators of micro uncertainty
Other evidence: Time series

- Compute $\nabla$ over time in the US
- Compare to other indicators of micro uncertainty

Source: Jurado, Ludvigson and Ng, "Measuring Uncertainty", AER
Related literature

Misallocation

- Hsieh and Klenow (09), Restuccia and Rogerson (08), Bartelsman et al. (13)...
- Financial frictions: Buera, Kaboski and Shin (11), Midrigan and Xu (13),...
- Adjustment costs: Asker, Collard-Wexler and De Loecker (13)
- Information frictions: Jovanovic (13)

Stock price informativeness

- Morck, Yeung and Yu (00), Durnev, Yeung and Zarowin (03),...

The “feedback” effect (Bond, Edmans and Goldstein (12))

- Investment: Chen, Goldstein and Jiang (07), Bakke and Whited (10), Morck, Schleifer and Vishny (90)
- R&D spending: Bai, Philippon and Savov (13)
- Mergers and acquisitions: Luo (05)
Conclusion

Theory linking micro uncertainty to misallocation and aggregates

- Substantial uncertainty and associated aggregate losses
- Limited informational role for stock markets
- Significant role for private learning \(\Rightarrow\) drives cross-country differences

Where next?

- Entry/exit
- Other frictions...
Full-info TFP

Simplified model:

\[ a^* = \frac{1}{2} \frac{\sigma^2}{1 - \alpha} \]

General model:

\[ a^* = \frac{1}{2} \left( \frac{\theta}{\theta - 1} \right) \frac{\sigma_a^2}{1 - \alpha} \]
Identification with iid shocks

\[ \rho_{pa} = \frac{1}{\sqrt{1 + \frac{\sigma_v^2 \sigma_z^2}{\sigma_\mu^2}}} \]

\[ \rho_{pk} = \frac{1}{\sqrt{\left(1 + \frac{\sigma_v^2 \sigma_z^2}{\sigma_\mu^2}\right) \left(1 - \frac{\psi}{\sigma_\mu^2}\right)}} \]

\[ \sigma_p^2 = \left(\frac{1 - \beta}{1 - \alpha}\right)^2 \left(\frac{\sigma_z^2 + 1}{\sigma_z^2 + \frac{1}{\rho_{pa}^2}}\right)^2 \frac{1}{\rho_{pa}^2} \sigma_\mu^2 \]

(\(\downarrow\) in \(\sigma_v \sigma_z\))

(\(\uparrow\) in \(\psi\))

(\(\uparrow\) in \(\sigma_z\))
Identification with permanent shocks

\[ \frac{\nabla}{\sigma^2_\mu} = \frac{\rho_{pk} - \rho_{pa}}{\eta} \]

where

\[ \eta = \frac{1}{1 - \alpha \sigma_p} \]

\[ \frac{\sigma^2_v \sigma^2_z}{\sigma^2_\mu} = \frac{(1 - \eta^2)}{2 \rho^2_{pa}} + \frac{\eta}{\rho_{pa}} - 1 \]

\[ \frac{\sigma^2_z + 1}{\sigma^2_z + 1 + \frac{\sigma^2_v \sigma^2_z}{\sigma^2_\mu}} = \frac{1}{\eta} \]
Step 1. \( \text{cov} (p, k) = \text{cov}(p, a) \).

- follows from \( k = E (a|p, s_i) \)
- and since we can write \( a = E (a|p, s_i) + \varepsilon \)
- \( \text{cov} (a, p) = \text{cov} (E (a|p, s_i), p) + \text{cov} (\varepsilon, p) = \text{cov} (k, p) \).

Step 2. divide both sides by \( \sigma_a \sigma_p \) so we get

\[
\frac{[\text{cov} (p, k)]^2}{(\sigma_a \sigma_p)^2} = \rho (p, a)^2 \tag{1}
\]

Step 3. By the law of total covariance, \( \sigma_a^2 = \sigma_k^2 + V \) so

\[
\frac{\sigma_k^2}{\sigma_a^2} = 1 - \frac{V}{\sigma_a^2} \tag{2}
\]

Substituting (2) in (1) we get

\[
\left( 1 - \frac{V}{\sigma_a^2} \right) = \left( \frac{\rho (p, a)}{\rho (p, k)} \right)^2
\]

identical to our identification equation.
**Investment-Q regressions**

Reduced-form representation (with iid shocks):

\[
\Delta k_{it} = \lambda_1 (\Delta \mu_{it} + \Delta e_{it}) + \lambda_2 \Delta p_{it}
\]

Use model to derive:

\[
\lambda_2 \propto \frac{(1 + \gamma)V}{\sigma_{\eta}^2}
\]

Intuition: \( \lambda_2 \) could be large because of

- high uncertainty (high \( V \)) OR
- more information prices (low \( \sigma_{\eta}^2 \)) OR
- correlated distortions (high \( \gamma \))

Also, consistency of \( \lambda_2 \) requires \( \Delta e_{it} \perp \Delta \mu_{it}, \Delta p_{it} \)

- Correlated signals \( \rightarrow \) \( \Delta e_{it} \) correlated with \( \Delta p_{it} \) \( \rightarrow \) endogeneity
## Data and parameter values

<table>
<thead>
<tr>
<th>Target moments</th>
<th>Parameters</th>
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<td>$\rho_{pa}$</td>
<td>$\sigma_p^2$</td>
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<td>0.55</td>
</tr>
</tbody>
</table>

Data source: Compustat NA and Compustat Global.

- Cross-country variation in moments $\Rightarrow$ variation in parameters
- US: less fundamental uncertainty, better private info, less noise in markets
Full-information adjustment cost model

- Value function

\[
V \left( \tilde{A}_{it}, K_{it-1} \right) = \max_{K_{it}, N_{it}} G \tilde{A}_{it} K_{it}^{\tilde{\alpha}} - l_{it} - H (l_{it}, K_{it-1}) + \beta \mathbb{E} V \left( \tilde{A}_{it+1}, K_{it} \right)
\]

where \( l_{it} = K_{it} - (1 - \delta) K_{it-1} \) and \( H (l_{it}, K_{it-1}) = \zeta K_{it-1} \left( \frac{l_{it}}{K_{it-1}} \right)^2 \)

- Solve numerically for joint distribution of \( \tilde{A}_{it}, K_{it} \) in GE

- Target \( (\rho_{pa}, \sigma_p^2, \sigma_k^2) \) to estimate \( (\sigma_v^2, \sigma_z^2, \zeta) \)

- Simulate data to compute \( \rho_{pi} \)