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Labor Lunch Seminar

October 13, 2017
Introduction

- The question of whether markets are “imperfectly competitive” has a long tradition in Economics.

- **IO and trade**: markups can account for macroeconomic secular trends (Hall, 1988; DeLoecker and Eeckhout, 2017)
  - ↓ in labor share
  - slowdown in aggregate output

- **Labor**: monopsony could rationalize differences in wages of similar workers across firms (Card et al., 2016; Manning, 2003)

- Many recent papers estimating **markups**; fewer estimating **markdowns**
  - Moreover, the standard method to estimate markups in the trade and IO literature assumes that labor markets are perfectly competitive.

- More generally, measurement of market power of firms in output and input markets has typically been done separately for each market.
• We fill this gap by approaching this question from a joint perspective (product and labor markets)

• We combine classic ideas from the theory of monopoly and monopsony (Robinson, 1933) with recent methods from IO and labor economics

• We derive an equation of **combined market power** in both markets similar to DeLoecker and Warzynski (AER 2012)

• We propose different methods to separate this measure into output vs labor market power
  • We developed 4 different methods (today we focus on one)

• We use a rich panel of Colombian manufacturing plants for 2002-2012
Why do we care

- Markups are a key element in drawing a picture of the competitiveness of an industry

- Markdowns help identify foci of frictions that give employers monopsony power in labor markets

- Labor market and product market policies are very different
  - Target policies more effectively (antitrust, employment protection, etc.)

- Market power enables a better understanding of market outcomes
  - **Wage Inequality and Labor Share**
    Gains in productivity and declining labor share

  - **TFP and Resource Misallocation**
    Market power is a source of production misallocation
    \[ P_i/MR_i = wedge_i^P \text{ and/or } W_i/MRPL_i = wedge_i^L \]
    The ability of firms to set \( W_i \) and \( P_i \) is disciplined by market competition
**Wage Inequality**

**Output and Compensation per Hour**

![Graph showing the trend of log output and log compensation per hour from 1947 to 2007. The graph displays a steady increase in both indices, with a pre-1973 trend of 2.2% per year.]

Source: D. Card’s lecture 7 (250A) based on Fleck, Glaser and Sprague (2011)

"Ignoring the existence of employer market power could lead to incorrect conclusions on the driving force behind changes in wage inequality" (Manning, 2003)

Measuring the elasticity of LS to the firm “turns out to be substantively important for understanding the sources for wage inequality” (Card et al., 2016)
Labor Share

Evolution of the labor share and inverse of the markup in the U.S.

Source: De Loecker and Eeckhout (2017)
Pat Cason-Merenda had worked as a registered nurse at the Detroit Medical Center for four years, unaware that she was being underpaid. That changed when a class-action lawsuit alleged that her employer, along with seven other hospitals, had colluded to suppress the wages of more than 20,000 nurses. The suit claimed the hospitals conspired to keep pay low by inappropriately sharing information about nurses' salaries and pay increases. By this year, the hospitals agreed to pay $90 million dollars to settle the wage-fixing case.

Stories like this are too common, thanks to many employers' exercising monopsony power over workers. A monopsony is the flip side of a monopoly: It occurs when a buyer, rather than a seller, has sufficient market power to set its own price. While economics textbooks often describe the labor market as perfectly competitive, in reality employers often use their power to underpay workers.

In addition to holding down workers' paychecks, monopsony power can depress overall hiring and output, as employers are unable to find enough workers at the wage they offer. If monopsony power creates barriers to workers switching jobs, it can slow labor turnover, reducing dynamism and innovation. Counteracting monopsony power would lead to higher wages, lower unemployment and stronger economic output.

Some employers act as monopsonists by illegally colluding, as alleged in the case of Detroit hospitals. Others require employees to sign noncompete agreements that prevent them from working for a competitor in the future. And nearly all employment arrangements involve a degree of implicit monopsony power: Frictions, such as finding new child-care arrangements or spending time searching for work, can make it costly for workers to change jobs. Many companies exercise monopsony power even though they are not the only employer in town.

By JASON FURMAN and ALAN B. KRUEGER
Nov. 3, 2016 7:33 p.m. ET

Pat Cason-Merenda had worked as a registered nurse at the Detroit Medical Center for four years, unaware that she was being underpaid. That changed when a class-action...
In The Economics of Imperfect Competition, Joan Robinson states:

“It is commonly said that exploitation (the payment to labour of less than its proper wage) arises from the unequal bargaining strength of employers and employed, and that it can be remedied by the action of trade unions, or of the State, which places the workers upon an equality in bargaining with the employers. Bargaining strength, as we shall define, is important in many cases, but the fundamental cause of exploitation will be found to be the lack of the perfect elasticity in the supply of labour or in the demand for commodities.”

J. Robinson, 1933, p. 281
Outline of the talk

- Model (Cost minimizing firm and upward-sloping labor supply)

- Empirical strategy
  - Combined measure of market power
  - Source of market power (labor and products)

- Data

- Results
  - Production function estimation
  - Market power estimation
  - Labor supply elasticity
  - Markups, Markdowns, and plant characteristics

- Conclusion and next steps
Firm’s problem

Suppose there is a cost-minimizing firm free of any adjustment cost using the following production technology:

\[ Q_{it} = Q_{it}(X_{it}^1, \ldots, X_{it}^{V-1}, L_{it}, K_{it}, \omega_{it}) \]

- \( X_{it}^v \): variable input \( v \) (\( V \) variable inputs)
- \( L_{it} \): labor
- \( K_{it} \): capital stock
- \( \omega_{it} \): productivity measure

The associated lagrangian \( \mathcal{L}(X_{it}^1, \ldots, X_{it}^{V-1}, L_{it}, K_{it}, \omega_{it}) \) is:

\[
\sum_{v=1}^{V-1} P_{it}^v X_{it}^v + w_{it}(L_{it})L_{it} + r_{it}K_{it} + \lambda_{it}(Q_{it} - Q_{it}(\cdot))
\]
Firm’s problem

FOC w.r.t. labor (or any other variable input):

\[
\begin{aligned}
\frac{w_{it} \left(1 + \frac{1}{\epsilon_{it}^{Lw}}\right)}{1/M D_{it}} &= \lambda_{it} \frac{\partial Q_{it}(\cdot)}{\partial L_{it}} \\
\end{aligned}
\]

Rearranging terms and using \(\lambda_{it} = \frac{P_{it}}{M U_{it}}\)

\[
\begin{aligned}
\frac{w_{it} L_{it}}{M D_{it}} &= \frac{P_{it} Q_{it}}{M U_{it}} \left(\frac{\partial Q_{it}(\cdot)}{\partial L_{it}} \frac{L_{it}}{Q_{it}}\right) \\
\frac{M U_{it}}{M D_{it}} &= \theta_{it} \frac{P_{it} Q_{it}}{w_{it} L_{it}} \\
\end{aligned}
\]

Combined measure of market power is

\[
M P_{it} \equiv \frac{M U_{it}}{M D_{it}} = \frac{\theta_{it}}{\alpha_{it}^L} \quad \text{MAIN EQUATION}
\]

Where

\[
M U_{it} \equiv \frac{P_{it}}{m c_{it}} = \frac{|\epsilon_{it}^P|}{|\epsilon_{it}^P| - 1} \quad M D_{it} \equiv \frac{w_{it}}{MR PL_{it}} = \frac{\epsilon_{it}^{Lw}}{\epsilon_{it}^{Lw} + 1}
\]
Empirical strategy

[1] Combined market power: can be deduced as soon as $\alpha_{it}^v$ and $\theta_{it}^v$ are pinned down

- Estimate $\theta_{it}^v$ using standard production function estimation techniques from IO literature
- Use the main equation to compute combined market power $MP_{it}$

[2] Source of market power: either $\epsilon_{it}^p$ or $\epsilon_{it}^{Lw}$ need to be estimated as well

- Estimate the elasticity of the labor supply to the individual firm $\epsilon_{it}^{Lw}$
- Pin down markdowns $MD_{it}$
- Then back out markups $MU_{it}$ using our main equation and [1]

Alternatives (in progress): note our model is over-identified

- $\theta_{it}^v$ could be estimated with a reduced-form labor approach (scale effect)
- $\epsilon_{it}^p$ could be estimated with a classic BLP framework
- Different instruments to identify $\epsilon_{it}^{Lw}$
[1] Combined market power

• $\alpha_{it}^L$: wage bill as a share of value added is directly observed in the data

• $\theta_{it}^L$: output elasticity of labor estimated using “proxy methods” of Ackerberg, Caves, and Frazer (2015)

• We consider Cobb-Douglas and Translog value-added specifications:

  \[
  y_{it} = \beta_{ll_{it}} + \beta_{lk_{it}}k_{it} + \omega_{it} + \eta_{it} \\
  \Rightarrow \quad \theta_{it}^L = \beta_l
  \]

  \[
  y_{it} = \beta_{ll_{it}} + \beta_{l1l_{it}}^2 + \beta_{lk_{it}}k_{it} + \beta_{kk_{it}}^2 + \beta_{lk_l_{it}k_{it}} + \omega_{it} + \eta_{it} \\
  \Rightarrow \quad \theta_{it}^L = \beta_l + 2\beta_{l1l_{it}} + \beta_{lk_{it}}k_{it}
  \]

• We estimate these functions by 2-digit industries

• Compute market power as: $MP_{it} = \theta_{it}^L / \alpha_{it}^L$

• (1) Invert materials’ demand function to control for unobserved productivity: \( m_{it} = f_t(k_{it}, l_{it}, \omega_{it}) \). Then, \( \omega_{it} = f_t^{-1}(k_{it}, l_{it}, m_{it}) \)

\[
\begin{align*}
    y_{it} &= \beta_l l_{it} + \beta_k k_{it} + f_t^{-1}(k_{it}, l_{it}, m_{it}) + \eta_{it} \\
    y_{it} &= \Phi_t(k_{it}, l_{it}, m_{it}) + \eta_{it}
\end{align*}
\]

• (2) Productivity follows a Markov process \( p(\omega_{it+1}|\omega_{it}) \):

\[
\begin{align*}
    \omega_{it} &= E(\omega_{it}|\omega_{it-1}) + \xi_{it} = g(\omega_{it-1}) + \xi_{it} \\
    \omega_{it} &= \gamma_1 \omega_{it-1} + \gamma_2 \omega^2_{it-1} + \gamma_3 \omega^3_{it-1} + \xi_{it}
\end{align*}
\]

\[
\begin{align*}
    \xi_{it}(\beta) &= (\phi_{it} - \beta_l l_{it} - \beta_k k_{it}) - \gamma_1 (\phi_{it-1} - \beta_l l_{it-1} - \beta_k k_{it-1}) \\
    &\quad - \gamma_2 (\phi_{it-1} - \beta_l l_{it-1} - \beta_k k_{it-1})^2 \\
    &\quad - \gamma_3 (\phi_{it-1} - \beta_l l_{it-1} - \beta_k k_{it-1})^3
\end{align*}
\]

• Solve with NLGMM the following moment conditions:

\[
E \left[ \xi_{it}(\beta) \left( \begin{array}{c} l_{it-1} \\ k_{it} \end{array} \right) \right] = 0
\]
[2] Labor supply elasticity and markdown

- We pin down markdowns by estimating the elasticity of the labor supply to the individual firm:
  \[ MD_{it} = \epsilon_{it}^L / (\epsilon_{it}^L + 1) \]

- Wage-posting model (based on Card et al. 2016): assumes that for any worker \( n \), the indirect utility of working at firm \( i \) is given by:
  \[ U_{nit} = x_{it}\gamma + \beta w_{it} + \psi_i + e_{it} + \epsilon_{nit} \]

- Assuming that \( \epsilon_{nit} \) are independent draws from a type I EV distribution, the labor share working at firm \( i \) is:
  \[ s_{it} = \frac{\exp(x_{it}\gamma + \beta w_{it} + \psi_i + e_{it})}{\sum_k \exp(x_{kt}\gamma + \beta w_{kt} + \psi_k + e_{kt})} \]

- Taking logs, we arrive to the estimating equation:
  \[ \ln s_{it} = x_{it}\gamma + \beta w_{it} + \psi_i + \gamma_{m(i,t)} + e_{it} \]

- Markets are defined as region-industry-year dummies: \( \gamma_{m(i,t)} \)
[2] Labor supply elasticity and markdown

- The **labor supply elasticity** is:

\[
\frac{\partial s_{it}}{\partial w_{it}} \frac{w_{it}}{s_{it}} \equiv c_{it}^L = \beta w_{it}(1 - s_{it})
\]

- **OLS** leads to a biased $\beta$ because the wage that firm $i$ posts is correlated with the error term (e.g. firms with better amenities)

- We rely on **IV regressions** and instrument $w_{it}$ with materials, electricity, and number of inputs used in the production process

- Same proxy for productivity shocks as the production function literature

- **Exclusion restriction**: after controlling for firm fixed effects
  - workers don’t supply labor to firms based on the use inputs
  - labor supply shocks do not affect use of intermediate inputs

- Can be estimated for different types of workers (e.g. by skill group)
Identification of labor supply

TFP shocks $\rightarrow$ ↑ intermediate inputs $\rightarrow$ ↑ labor demand
Data: Colombia’s EAM panel

• We use plant-level data from Colombia’s Encuesta Anual Manufacturera (EAM) from 2002 to 2012

• The EAM is a uniquely rich census of manufacturing plants with +10 workers that provides information on:
  • Sales and Value added
  • Input use: Quantity vs Costs
  • Output produced: Quantity vs Prices
  • Employment and earnings: Blue collar and white collar
  • Exports and Imports

• We observe approximately 5000-7000 plants each year producing 4,000 distinct eight-digit product codes.

• Manufacturing represents 20% of total employment in Colombia.

• This data has been used by other papers as well: Fieler et al. (2016); Kuegler & Verhoogen (2012); Eslava et al. (2004).
## Summary statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>10th Perc.</th>
<th>50th Perc.</th>
<th>90th Perc</th>
<th>N</th>
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<tbody>
<tr>
<td>Labor force</td>
<td>74.74</td>
<td>135.58</td>
<td>8</td>
<td>27</td>
<td>178</td>
<td>80329</td>
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<tr>
<td>Skilled</td>
<td>26.39</td>
<td>51.29</td>
<td>2</td>
<td>8</td>
<td>66</td>
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<tr>
<td>Unskilled</td>
<td>46.59</td>
<td>87.73</td>
<td>4</td>
<td>16</td>
<td>43</td>
<td>80329</td>
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<tr>
<td>Share Skilled</td>
<td>37.09%</td>
<td>0.22</td>
<td>11.76%</td>
<td>33.33%</td>
<td>68.00%</td>
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<tr>
<td>Wage per worker</td>
<td>16.73</td>
<td>9.89</td>
<td>8.53</td>
<td>14.01</td>
<td>27.45</td>
<td>80329</td>
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<tr>
<td>Wage per skilled worker</td>
<td>23.24</td>
<td>19.36</td>
<td>7.48</td>
<td>18.39</td>
<td>44.52</td>
<td>80329</td>
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<tr>
<td>Wage per unskilled worker</td>
<td>13.44</td>
<td>11.06</td>
<td>8.14</td>
<td>11.77</td>
<td>19.35</td>
<td>80329</td>
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<tr>
<td>Materials (% Revenue)</td>
<td>55.07%</td>
<td>0.19</td>
<td>29.78%</td>
<td>54.96%</td>
<td>81.33%</td>
<td>80329</td>
</tr>
<tr>
<td>Electricity (% Revenue)</td>
<td>2.18%</td>
<td>0.032</td>
<td>0.60%</td>
<td>1.22%</td>
<td>4.91%</td>
<td>80329</td>
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<tr>
<td>Capital (% Revenue)</td>
<td>42.41%</td>
<td>3.53</td>
<td>4.60%</td>
<td>21.61%</td>
<td>78.53%</td>
<td>80329</td>
</tr>
<tr>
<td>Revenue (million pesos)</td>
<td>13106</td>
<td>37437</td>
<td>299</td>
<td>1728</td>
<td>28888</td>
<td>80329</td>
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<tr>
<td>VA per worker (million pesos)</td>
<td>52.14</td>
<td>136.64</td>
<td>9.56</td>
<td>27.99</td>
<td>97.27</td>
<td>80329</td>
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<td>Single product</td>
<td>32.87%</td>
<td>0.47</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>80329</td>
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<tr>
<td>Number of products</td>
<td>3.56</td>
<td>3.53</td>
<td>1.00</td>
<td>2.00</td>
<td>8.00</td>
<td>80329</td>
</tr>
<tr>
<td>Importer</td>
<td>0.18</td>
<td>0.39</td>
<td>0.00</td>
<td>0.00</td>
<td>1.00</td>
<td>80329</td>
</tr>
<tr>
<td>Exporter</td>
<td>0.24</td>
<td>0.43</td>
<td>0.00</td>
<td>0.00</td>
<td>1.00</td>
<td>80329</td>
</tr>
</tbody>
</table>
## Industry composition

<table>
<thead>
<tr>
<th>ISIC</th>
<th>N</th>
<th>(%)</th>
<th>Labor share</th>
<th>Wagebill /VA</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
</tr>
<tr>
<td>Food products and Beverages</td>
<td>15</td>
<td>15743</td>
<td>19.60%</td>
<td>22.55%</td>
</tr>
<tr>
<td>Textiles</td>
<td>17</td>
<td>3701</td>
<td>4.61%</td>
<td>7.00%</td>
</tr>
<tr>
<td>Wearing apparel, dressing and dyeing of fur</td>
<td>18</td>
<td>8285</td>
<td>10.31%</td>
<td>10.84%</td>
</tr>
<tr>
<td>Leather and leather products</td>
<td>19</td>
<td>3459</td>
<td>4.31%</td>
<td>3.21%</td>
</tr>
<tr>
<td>Wood, cork, and straw products</td>
<td>20</td>
<td>1537</td>
<td>1.91%</td>
<td>0.92%</td>
</tr>
<tr>
<td>Paper and paper products</td>
<td>21</td>
<td>2119</td>
<td>2.64%</td>
<td>3.28%</td>
</tr>
<tr>
<td>Publishing, printing and media</td>
<td>22</td>
<td>5310</td>
<td>6.61%</td>
<td>4.81%</td>
</tr>
<tr>
<td>Coke and refined petroleum products</td>
<td>23</td>
<td>452</td>
<td>0.56%</td>
<td>0.42%</td>
</tr>
<tr>
<td>Chemicals</td>
<td>24</td>
<td>6849</td>
<td>8.53%</td>
<td>10.31%</td>
</tr>
<tr>
<td>Rubber and plastic</td>
<td>25</td>
<td>6565</td>
<td>8.17%</td>
<td>7.88%</td>
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<tr>
<td>Non-metallic mineral products</td>
<td>26</td>
<td>4007</td>
<td>4.99%</td>
<td>5.68%</td>
</tr>
<tr>
<td>Basic metals</td>
<td>27</td>
<td>1567</td>
<td>1.95%</td>
<td>2.40%</td>
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<tr>
<td>Fabricated metal products</td>
<td>28</td>
<td>5442</td>
<td>6.77%</td>
<td>4.81%</td>
</tr>
<tr>
<td>Machinery and equipment</td>
<td>29</td>
<td>4799</td>
<td>5.97%</td>
<td>4.45%</td>
</tr>
<tr>
<td>Office, accounting and computing machinery</td>
<td>30</td>
<td>34</td>
<td>0.04%</td>
<td>0.02%</td>
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<tr>
<td>Electrical machinery and apparatus</td>
<td>31</td>
<td>1663</td>
<td>2.07%</td>
<td>2.23%</td>
</tr>
<tr>
<td>Radio, TV and communication equipment</td>
<td>32</td>
<td>185</td>
<td>0.23%</td>
<td>0.20%</td>
</tr>
<tr>
<td>Medical, precision and optical instruments</td>
<td>33</td>
<td>664</td>
<td>0.83%</td>
<td>0.56%</td>
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<tr>
<td>Motor vehicles, trailers and semi-trailers</td>
<td>34</td>
<td>1865</td>
<td>2.32%</td>
<td>2.37%</td>
</tr>
<tr>
<td>Other transport equipment</td>
<td>35</td>
<td>501</td>
<td>0.62%</td>
<td>0.87%</td>
</tr>
<tr>
<td>Furniture</td>
<td>36</td>
<td>5526</td>
<td>6.88%</td>
<td>4.93%</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>80329</strong></td>
<td><strong>100%</strong></td>
<td></td>
<td><strong>0.471</strong></td>
</tr>
</tbody>
</table>
• **Model** (Cost minimizing firm and upward-sloping labor supply)

• **Empirical strategy**
  - Combined measure of market power
  - Source of market power

• **Data**

• **Results**
  - [1] Production function estimation
  - [3] Labor supply elasticity
  - [4] Markups, Markdowns, and plant characteristics

• Conclusion and next steps
### Production function estimation

**Table: Output elasticities-Varying coefficients**

<table>
<thead>
<tr>
<th></th>
<th>OLS</th>
<th>FE</th>
<th>ACF</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td></td>
</tr>
<tr>
<td><strong>Panel A: Cobb-Douglas</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Labor</td>
<td>0.859</td>
<td>0.622</td>
<td>0.900</td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td>(0.033)</td>
<td>(0.105)</td>
</tr>
<tr>
<td>Capital</td>
<td>0.203</td>
<td>0.073</td>
<td>0.200</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.023)</td>
<td>(0.120)</td>
</tr>
<tr>
<td>Observations</td>
<td>71,928</td>
<td>71,928</td>
<td>56,146</td>
</tr>
<tr>
<td>RTS</td>
<td>1.062</td>
<td>0.695</td>
<td>1.100</td>
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<tr>
<td><strong>Panel B: Translog</strong></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Labor</td>
<td>0.848</td>
<td>0.629</td>
<td>0.904</td>
</tr>
<tr>
<td></td>
<td>(0.117)</td>
<td>(0.068)</td>
<td>(0.138)</td>
</tr>
<tr>
<td>Capital</td>
<td>0.209</td>
<td>0.075</td>
<td>0.212</td>
</tr>
<tr>
<td></td>
<td>(0.105)</td>
<td>(0.032)</td>
<td>(0.089)</td>
</tr>
<tr>
<td>Observations</td>
<td>71,928</td>
<td>71,928</td>
<td>56,146</td>
</tr>
<tr>
<td>Average RTS</td>
<td>1.057</td>
<td>0.704</td>
<td>1.117</td>
</tr>
</tbody>
</table>

Note: Elasticities are computed by industries and then averaged.
[2] Market power estimation \((MP = \frac{MU}{MD})\)

Table: Market Power - Summary Statistics

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>St. Dev.</th>
<th>p25</th>
<th>p50</th>
<th>p75</th>
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</thead>
<tbody>
<tr>
<td>Market Power (Cobb-Douglas)</td>
<td>2.24</td>
<td>0.78</td>
<td>1.73</td>
<td>2.02</td>
<td>2.50</td>
</tr>
<tr>
<td>Market Power (Translog)</td>
<td>2.20</td>
<td>0.70</td>
<td>1.74</td>
<td>2.03</td>
<td>2.46</td>
</tr>
<tr>
<td>Correlation</td>
<td></td>
<td></td>
<td>0.938</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: Outliers above and below the 2nd and 98th percentiles are trimmed.

Compared to other papers using the same approach...

- DLW (2012) find median MP 1.17-1.28 for Slovenian manufacturing firms
- DL et al (2016) find mean and median markups of 2.70 and 1.34 for Indian manufacturing firms
- Lamorgese et al (2014) find mean markups by sector between 1.32 and 1.88 for Chilean firms
- Substantial variation across sectors and across firms within sectors

The results are very similar for the CD and TL specifications. We stick to CD from now onwards.
[3] Labor supply elasticity

**Table: Pool of workers**

<table>
<thead>
<tr>
<th>Dep variable</th>
<th>First Stage</th>
<th>OLS</th>
<th>IV</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) (2)</td>
<td>(3) (4)</td>
<td>(5) (6)</td>
</tr>
<tr>
<td>Wage</td>
<td>OLS</td>
<td>IV</td>
<td></td>
</tr>
<tr>
<td>Materials (log)</td>
<td>2.1563*** 0.3374***</td>
<td>0.0645 0.038</td>
<td></td>
</tr>
<tr>
<td>Wage</td>
<td></td>
<td>0.0555*** -0.0128***</td>
<td>0.2007*** 0.5563***</td>
</tr>
<tr>
<td>F statistic-FS</td>
<td>20592</td>
<td>1820.44</td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>77989</td>
<td>77989</td>
<td></td>
</tr>
</tbody>
</table>

**Panel A: Instrument Materials (log)**

| Electricity (log) | 2.4255*** 0.3813*** |
| Electricity (log) | 0.0599 0.0512 |
| Wage         |             | 0.2248*** 0.5746*** |
| F statistic-FS | 1626.64      | 57.76    |
| N            | 79503       | 79503   |

**Panel B: Instrument Electricity (log)**

| Number of inputs | 1.7970*** 0.0978 |
| Number of inputs | 0.1197 0.0952 |
| Wage         |             | 0.2569*** 12.312 |
| F statistic-FS | 225.368      | 1.05504  |
| N            | 78000       | 78000   |

**Panel C: Number of Inputs (log)**

| Market fixed effects | Yes | Yes |
| Firm fixed effects | No | Yes |

Note: *** p < 0.01, ** p < 0.05, * p < 0.1
Labor supply elasticity

- **First stage**: strong, positive, and similar in magnitude
- **Second stage**: the three IV estimates give a positive and significant effect
- **Heterogeneity of labor supply**: separate into skilled and unskilled workers
  Surprisingly, much larger labor supply coefficients for unskilled workers
- We focus the attention to the LS estimates instrumented with materials
- We use $\hat{\beta}$ to compute labor supply elasticities to the individual firm

$$\frac{\partial s_{it}}{\partial w_{it}} \frac{w_{it}}{s_{it}} = \hat{\epsilon}_{it}^{Lw} = \hat{\beta}w_{it}(1 - s_{it})$$
[3] Labor supply elasticity

Figure: Distribution of labor supply elasticity to the individual firm

Note: median elasticity (market FE) of 2.74 (pool), 1.86 (skilled), 4.00 (unskilled)
Labor supply elasticity

- Pool of workers: median elast of 2.74 (market FE) and 7.62 (firm FE)
- Relatively little variation across industries
- Labor supply relatively more elastic for unskilled workers in manufacturing
  - One would expect frictions to affect strongly unskilled workers
  - Minimum wage generates perfectly elastic labor supply curves in some range of workers’ wages and it is typically more binding for unskilled workers
  - Operating mechanisms are subject of future research
- Our estimates are an order of magnitude higher than other papers but still reject the assumption of perfect competition in labor markets
- We next compute markdowns as \( MD_{it} = \epsilon_{Lw}^{it} / (1 + \epsilon_{Lw}^{it}) \) and using our main equation we back out markups as \( MU_{it} = MP_{it} \times MD_{it} \)
# [4] Markups and Markdowns

## Table: Imperfect Competition in Product and Labor Markets - Summary Statistics

<table>
<thead>
<tr>
<th></th>
<th>(1) MP</th>
<th>(2) MU</th>
<th>(3) MD</th>
<th>(4) MD-Unskilled</th>
<th>(5) MD-Skilled</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>All industries</strong></td>
<td>2.02</td>
<td>1.78</td>
<td>0.89</td>
<td>0.90</td>
<td>0.77</td>
</tr>
<tr>
<td>Food products and Beverages</td>
<td>2.09</td>
<td>1.83</td>
<td>0.89</td>
<td>0.91</td>
<td>0.76</td>
</tr>
<tr>
<td>Textiles</td>
<td>1.82</td>
<td>1.62</td>
<td>0.89</td>
<td>0.91</td>
<td>0.80</td>
</tr>
<tr>
<td>Apparel</td>
<td>1.96</td>
<td>1.68</td>
<td>0.86</td>
<td>0.89</td>
<td>0.73</td>
</tr>
<tr>
<td>Leather and leather products</td>
<td>2.04</td>
<td>1.75</td>
<td>0.86</td>
<td>0.89</td>
<td>0.71</td>
</tr>
<tr>
<td>Wood, cork, and straw products</td>
<td>1.94</td>
<td>1.68</td>
<td>0.87</td>
<td>0.90</td>
<td>0.72</td>
</tr>
<tr>
<td>Paper and paper products</td>
<td>2.27</td>
<td>2.01</td>
<td>0.90</td>
<td>0.91</td>
<td>0.82</td>
</tr>
<tr>
<td>Publishing, printing and media</td>
<td>2.21</td>
<td>1.98</td>
<td>0.90</td>
<td>0.91</td>
<td>0.77</td>
</tr>
<tr>
<td>Rubber and plastic</td>
<td>1.93</td>
<td>1.72</td>
<td>0.90</td>
<td>0.91</td>
<td>0.80</td>
</tr>
<tr>
<td>Basic metals</td>
<td>2.07</td>
<td>1.82</td>
<td>0.89</td>
<td>0.91</td>
<td>0.80</td>
</tr>
<tr>
<td>Fabricated metal products</td>
<td>1.98</td>
<td>1.76</td>
<td>0.89</td>
<td>0.91</td>
<td>0.79</td>
</tr>
<tr>
<td>Machinery and equipment</td>
<td>2.03</td>
<td>1.79</td>
<td>0.89</td>
<td>0.90</td>
<td>0.78</td>
</tr>
<tr>
<td>Electrical machinery and apparatus</td>
<td>2.04</td>
<td>1.82</td>
<td>0.90</td>
<td>0.91</td>
<td>0.80</td>
</tr>
<tr>
<td>Medical instruments</td>
<td>1.91</td>
<td>1.66</td>
<td>0.89</td>
<td>0.90</td>
<td>0.77</td>
</tr>
<tr>
<td>Motor vehicles and trailers</td>
<td>2.03</td>
<td>1.78</td>
<td>0.89</td>
<td>0.90</td>
<td>0.77</td>
</tr>
<tr>
<td>Other transport equipment</td>
<td>2.03</td>
<td>1.75</td>
<td>0.88</td>
<td>0.90</td>
<td>0.75</td>
</tr>
<tr>
<td>Furniture</td>
<td>2.03</td>
<td>1.77</td>
<td>0.87</td>
<td>0.90</td>
<td>0.74</td>
</tr>
</tbody>
</table>

Note: This table reports the median of our different measures of market power

- Manufacturing workers are paid a wage that is 11% lower than MRPL (10% for unskilled workers and 23% for skilled workers)

- Little variation of elasticities across industries. Could suggest that policies set at the national level, like the minimum wage, could be optimal

- Colombian manufacturing plants set prices 78% higher than marginal cost

- There is more variation in markups across industries than markdowns

- Both markets exhibit imperfect competition, but variation across industries is driven by the ease of firms to set prices above marginal costs
• Markups and Markdowns positively correlated \( \Rightarrow \) firms that have more market power in product markets share more rents with their workers.
"All labor markets are monopsonistic but less so in agglomerations" (Manning, 2010)

- low productive firms sort into small markets with more labor frictions and it is more difficult for workers to move across firms
- larger firms locate in more productive locations and they enjoy more market power
### [4] Market power and plant characteristics

<table>
<thead>
<tr>
<th></th>
<th>MP (1)</th>
<th>MU (2)</th>
<th>MD (3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Size (log sales)</td>
<td>0.0668</td>
<td>0.1026</td>
<td>0.0150</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.009)</td>
<td>(0.0008)</td>
</tr>
<tr>
<td>TFP (logs)</td>
<td>0.0660</td>
<td>0.7878</td>
<td>-0.0032</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.00006)</td>
</tr>
<tr>
<td>VA per worker (logs)</td>
<td>0.1889</td>
<td>0.3026</td>
<td>0.0225</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.002)</td>
<td>(0.0001)</td>
</tr>
<tr>
<td>Exporter</td>
<td>0.0466</td>
<td>0.1169</td>
<td>0.0310</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.004)</td>
<td>(0.0004)</td>
</tr>
<tr>
<td>Importer</td>
<td>0.1097</td>
<td>0.1519</td>
<td>0.0338</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.005)</td>
<td>(0.0004)</td>
</tr>
<tr>
<td>Skilled/Unskilled</td>
<td>-0.0055</td>
<td>-0.0083</td>
<td>0.0051</td>
</tr>
<tr>
<td></td>
<td>(0.0016)</td>
<td>(0.0019)</td>
<td>(0.0001)</td>
</tr>
<tr>
<td>Observations</td>
<td>43,666</td>
<td>43,666</td>
<td>77,120</td>
</tr>
</tbody>
</table>

Note: dependent variable is log marketpower. MP: combined market power, MU: markups, MD: markdowns. Each entry corresponds to a separate regression. All the specifications include industry and year effects. Standard errors are clustered at the plant level.
• Analysis confirms product and labor markets (in manufacturing) are not perfectly competitive

• Manufacturing firms enjoy more market power in product than in labor markets

• Little variation of labor MP across industries $\implies$ Homogeneous policies could be optimal (e.g. minimum wages)

• A negative correlation between product and labor market power. This pattern may be explained by the agglomeration story of Manning (2010)

• A positive (negative) correlation between product MP (labor MP) and:
  • Firm size, Productivity, Exporter status, Importer status
Next steps

(1) Other instruments: Bartik shocks using input-product prices and quantities

(2) Estimate output elasticity of labor $\theta_{it}^L$ through the “scale effect”

(3) Counterfactuals:
   - Borrow from the classic framework of Hsieh and Klenow (2009)
   - Simple idea: in a world with variable MU and MD, MRPL and MRPK may differ across firms diminishing TFP due to resource misallocation
   - Eliminate variable market power and measure TFP gains at the sector level

(4) Estimate price demand elasticity, get $MU_{it}$, then back out $MD_{it}$

(5) Exploit the information of prices and quantities:
   - Construct a Price Index at the firm level (physical quantities)
   - Estimate markups by product
Many thanks!

Any feedback is very welcome:

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romand@berkeley.edu
Other Instruments

- Labor supply shocks correlated with materials violate our exclusion restriction.
- Therefore, we have thought in other instruments:
  - 1. Bartik shocks using leave-out mean of input and product prices:

\[
\Delta \ln s_{it} = \Delta x_{it} \gamma + \beta \Delta w_{it} + e_{it}
\]

\[
\Delta w_{it} = \alpha + \theta \text{Instr.}_{it} + \nu_{it}
\]

\[
\text{Instr.}_{it} = \sum_{k}^{K} \omega_{ik,t-1} \Delta p_{k,-i,t}
\]

where \(k\) denotes product or input.

- 2. Bartik shocks using customs data and changes in the exchange rate:

\[
\text{Instr.}_{it} = \sum_{k}^{K} \psi_{it}^{k} \sum_{n}^{N} \omega_{ikn,t-1} \Delta rer_{n,t}
\]

where \(n\) is country and \(rer\) is the real exchange rate between country \(n\) and Colombia.
Another way to estimate the output-labor elasticity is to estimate a labor-demand type specification

$$\ln L_{it} = \alpha_0 + \alpha_1 \ln VA_{it} + \epsilon_{it}$$

where $\alpha_1 = \frac{1}{\theta_L}$

We can use the exchange rate instrument for value added to identify $\alpha_1$
Using the framework developed by Hsieh and Klenow (2009) we can run different counterfactuals of reducing market power:

For example, constant markups or markdowns across firms

We will be able to estimate the relative gains on TFP of reducing market power in product vs labor markets:

\[
\text{TFP}_s \equiv \left[ \sum_{i=1}^{M_s} \left( A_{si} \cdot \frac{\text{TFPR}_{si}}{\text{TFPR}_{s}} \right)^{\sigma - 1} \right]^{\frac{1}{\sigma - 1}} \tag{1}
\]

At the social optimum \( \text{TFPR}_{si} \) should be equalized across firms. With variable markups it takes the following functional form:

\[
\text{TFPR}_{si} \propto \frac{MU_{si}}{MD_{si}^{1-\theta_{L,s}}}
\]
Alternative approach: Price demand elasticity

- We could estimate price demand elasticities. For single-product firms (33% of the sample):

\[ MU_{it} = \frac{|\epsilon_{it}^D|}{|\epsilon_{it}^D| - 1} \]

- For multi-product firms (67% of the sample):

Substitutes: \( MU_{irt} > \frac{|\epsilon_{irt}^D|}{|\epsilon_{irt}^D| - 1} \)

Complements: \( MU_{irt} < \frac{|\epsilon_{irt}^D|}{|\epsilon_{irt}^D| - 1} \)

\( r \) is a product subindex.

- To avoid this problem we can follow Balat et al. (2016) to express output of a firm in same units (transformation rates)

- This strategy is similar to De Loecker et al. (2016) that consider only single-product firms for the production function estimation
The production function is a two-tier structure.

In the upper-tier there is a composite input that is transformed into different products.

We assume that the composite input can be transformed into product $r$ at a constant rate $\mu^r_t$:

$$\exp(q_{itr}) = \mu^r_t \exp(y_{itr})$$

We can write the production function as:

$$\log \left( \sum_{r \in R_{it}} \frac{\exp(q_{itr})}{\mu^r_t} \right) = f(l, k, m, \omega; \beta)$$

To estimate transformation rates we will use single product firms.
Using single-product firms we estimate

\[ q_{irt} = \sum_{r \in R_t} \log \mu_t^r D_{irt} + \beta_l l_{it} + \beta_k k_{it} + \omega_{it} + \epsilon_{it} \]

where \( D_{irt} \) is a dummy variable that takes the value of one if single-product firm \( i \) produces product \( r \)

- After we estimate \( \mu_t^r \) we can construct the output level produce by all firms in the connected set of products of single product firms in the same units.

- We can estimate the price demand elasticity at the firm level using a similar argument that with the labor supply elasticity.

- We can use materials as an instrument for price.
• If the restriction of a minimum wage $\hat{w}_{it}$ is binding, then firm $i$ takes the wage as given. The FOC is

$$\hat{w}_{it} = \lambda \frac{\partial Q_{it}}{\partial L_{it}}$$

$$MU_{it} = \frac{\theta_{it}^L}{\alpha_{it}^L}$$

where $\hat{w}_{it}$ is the minimum wage

• In other words, our measure of market power corresponds to markup if the minimum wage is binding

• Something we could do: group firms based on exposure to the MW (e.g. average wage per worker relative to the MW) and estimate our LS model