Concentration in U.S. Local Labor Markets: Evidence from Vacancy and Employment Data

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Disclaimer

Any opinions and conclusions expressed herein are those of the authors and do not necessarily represent the views of the U.S. Census Bureau. All results have been reviewed to ensure that no confidential information is disclosed.
Concentration in the labor market

- Concentration in output markets:
  - Sales Autor et al. (2017); Rossi-Hansberg et al. (2018)
  - Markups and mega-firms de Loecker and Eeckhout (2017); Hall (2018)

Parallel in labor markets?

- Recent evidence Matsudaira (2014); Webber (2015); Azar et al. (2017, 2018); Benmelech et al. (2018); Rinz (2018)
- Structural approach Berger et al. (2018); Jarosch et al. (2019)
- Renewed attention in news and policy circles
- Emphasis on negative “effects” of labor market concentration on wages
Why Aren’t Americans Getting Raises? Blame the Monopsony

Instead of bidding up wages, firms collude to keep pay low and enforce noncompete clauses.

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 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
More and more companies have monopoly power over workers’ wages. That’s killing the economy.

The trend can explain slow growth, “missing” workers, and stagnant salaries.

By Suresh Naidu, Eric Posner, and Glen Weyl | Apr 6, 2018, 9:50am EDT
This paper

1. Reconcile different approaches in literature
   - HHI v. markdown rates
   - National v. local concentration

2. Update facts on labor market concentration using data on universe of employers and vacancies
   - Concentration across time and space

3. Highlight effects of concentration on skill content of jobs
Data
Data


**Longitudinal Business Database (LBD):** universe of U.S. employers since 1976. Contains location, sector, employment (head count), and payroll.
What is a labor market?

We choose a sector-geography pair:

- BGT: 4d SOC occupation – MSA/CBSA
- LBD: 3d NAICS industry – county

→ Results largely unaffected by different choices.
What is a labor market?

Geographical boundaries:
- MSAs approximate accurately local labor markets for both application and job-to-job flows (Manning and Petrongolo, 2017; Marinescu and Rathelot, 2018)

Sectoral mobility:
- Most job applications are directed to same job title and concentration at 6d SOC is elevated. (Marinescu and Wolthoff, 2016; Azar et al. 2017)
- Substantial flows between 2d SOC, especially for displaced workers (in CPS 2017, over 70%). (Macaluso, 2017)
Measurement
A measure of labor market concentration

- Baseline measure of concentration for labor market $m$.
- Herfindahl-Hirschman index (HHI):

$$HHI_{mt} = \sum_{f \in F(m)} \left( \frac{x_{mft}}{X_{mt}} \right)^2$$

where $X_{mt} = \sum_{f' \in F(m)} x_{mf't}$ and

- $f$ is a firm (single or multi-establishment)
- $x_{.t}$ can be employment, job creation, vacancies or sales
- $m$ is sector $\times$ geography (including national)
A measure of monopsony power: markdowns

- Monopsony: a firm’s ability to compensate workers below its MRPL
- Measured through a firm’s “markdown”

\[
\max_{N \geq 0} Y(N) - w(N) \cdot N
\]

\[
Y'(N^*) = w'(N^*)N^* + w(N^*)
\]

\[
Y'(N^*) = \left[ \frac{\varepsilon_S + 1}{\varepsilon_S} \right] w(N^*)
\]

markdown

where \( \varepsilon_S = \frac{dN}{dw} \frac{w}{N} \bigg|_{N=N^*} \) is a firm’s labor supply elasticity.
→ Do large firms have larger markdowns?
◇ Markdown is increasing in \( \frac{N_i}{N} \) ⇔ \( \varepsilon_S \) is decreasing in \( \frac{N_i}{N} \).

- Verify using markup and production function estimation on administrative data for U.S. manufactures
- Plant’s cost minimization problem:
  \[
  \min_{N \geq 0} w(N) \cdot N \quad \text{s.t.} \quad Y(N) \geq Y
  \]
- Optimality condition can be written as:
  \[
  \frac{w'(N) \cdot N}{w(N)} + 1 = \lambda \frac{Y'(N)}{w(N)}
  \]
  \[
  \frac{\varepsilon_S + 1}{\varepsilon_S} = \mu^{-1} \cdot \theta_N \cdot \alpha_N^{-1}
  \]
  markup \quad output elasticity \quad labor share
## Markdown rates in manufacturing

### Mean, Median, IQR

<table>
<thead>
<tr>
<th>Industry Group</th>
<th>Mean</th>
<th>Median</th>
<th>IQR_{75-25}</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Computer and Electronic Products</strong></td>
<td>3.032</td>
<td>2.355</td>
<td>1.399</td>
</tr>
<tr>
<td>Petroleum Refining</td>
<td>2.708</td>
<td>2.434</td>
<td>1.906</td>
</tr>
<tr>
<td>Chemicals</td>
<td>2.077</td>
<td>1.640</td>
<td>0.989</td>
</tr>
<tr>
<td>Food and Kindred Products</td>
<td>2.012</td>
<td>1.747</td>
<td>0.902</td>
</tr>
<tr>
<td>Plastics and Rubber</td>
<td>1.972</td>
<td>1.808</td>
<td>0.591</td>
</tr>
<tr>
<td>Lumber</td>
<td>1.930</td>
<td>1.547</td>
<td>0.501</td>
</tr>
<tr>
<td>Paper and Allied Products</td>
<td>1.862</td>
<td>1.697</td>
<td>0.577</td>
</tr>
<tr>
<td>Printing and Publishing</td>
<td>1.826</td>
<td>1.345</td>
<td>0.470</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td>1.788</td>
<td>1.499</td>
<td>0.644</td>
</tr>
<tr>
<td>Apparel and Leather</td>
<td>1.666</td>
<td>1.028</td>
<td>0.426</td>
</tr>
<tr>
<td>Primary Metals</td>
<td>1.579</td>
<td>1.452</td>
<td>0.511</td>
</tr>
<tr>
<td>Textile Mill Products</td>
<td>1.537</td>
<td>1.210</td>
<td>0.416</td>
</tr>
<tr>
<td>Fabricated Metal Products</td>
<td>1.517</td>
<td>1.268</td>
<td>0.368</td>
</tr>
<tr>
<td>Electrical Machinery</td>
<td>1.457</td>
<td>1.371</td>
<td>0.381</td>
</tr>
<tr>
<td>Furniture and Fixtures</td>
<td>1.358</td>
<td>1.157</td>
<td>0.333</td>
</tr>
<tr>
<td><strong>Non-electrical Machinery</strong></td>
<td>1.308</td>
<td>1.236</td>
<td>0.538</td>
</tr>
</tbody>
</table>

Source: ASM data on U.S. manufacturing plants 1976-2014. Markdowns are obtained under the assumption of a translog specification for gross output.
Markdowns increase with a firm’s employment share

<table>
<thead>
<tr>
<th>Dependent variable: plant-level (log) markdowns</th>
</tr>
</thead>
<tbody>
<tr>
<td>log firm share</td>
</tr>
<tr>
<td><strong>Cobb-Douglas</strong></td>
</tr>
<tr>
<td>log firm share</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Observations (in millions)</td>
</tr>
</tbody>
</table>

Source: ASM data on U.S. manufacturing plants 1976-2014. All regression specifications include \textit{industry, state, year, and firm age} fixed effects and controls. Standard errors are clustered at the industry (3-digit NAICS) level.

\[ \rightarrow 1 \text{ SD} \uparrow \text{ in a firm’s share is associated with a } 3.7\% \uparrow \text{ in the firm’s markdown rate} \]

\[ \rightarrow \text{ indexes based on firm-level employment shares (e.g., HHI) capture concentration as well as monopsony power} \]
Two **aggregate** statistics of labor market concentration:

\[
\text{NATIONAL}_t \equiv \sum_{j \in J} \omega_{jt} HHI_{jt}
\]

\[
\text{LOCAL}_t \equiv \sum_{j \in J} \sum_{\ell \in L} \omega_{j\ell t} HHI_{j\ell t}
\]

where \( \omega_{mt} \) denotes the employment/vacancies/sales share of market \( m \) for \( m = \{j, (j, \ell)\} \).

In the data:

- Industry-based **national** concentration is *increasing*.
- **Local** labor market concentration is *decreasing*. 
Local v. national (LBD 1976-2014)
National versus local

Statistical decomposition of local concentration:

\[
\sum_{j \in J} \sum_{\ell \in L} \omega_{j\ell t} HHI_{j\ell t} = \sum_{j \in J} \omega_{jt} \left[ \sum_{\ell \in L} s_{\ell t}^j HHI_{j\ell t} \right] \\
= \sum_{j \in J} \omega_{jt} \left[ HHI_{jt} + \text{cov}(s_{\ell t}^j, HHI_{j\ell t}) \right] \\
= \sum_{j \in J} \omega_{jt} HHI_{jt} + \sum_{j \in J} \omega_{jt} \text{cov}(s_{\ell t}^j, HHI_{j\ell t}) - \sum_{j \in J} \omega_{jt} (HHI_{jt} - \overline{HHI}_{jt})
\]

\[
\text{LOCAL}_{t} = \text{NATIONAL}_{t} + \text{OP}_{t} - \text{SPATIAL}_{t}
\]

where:

- \[ s_{\ell t}^j = \frac{\omega_{j\ell t}}{\omega_{jt}} \]
- \[ \overline{HHI}_{jt} = \frac{1}{|L|} \sum_{\ell \in L} HHI_{j\ell t} \]
Trend in $OP_t = \sum_{j \in J} \omega_{jt} \text{cov}(s^j_{lt}, HHI_{jlt})$

**Figure 1:** The OP covariance term has been increasing over time, so it cannot account for the divergence.
Interpreting the components

- $\text{OP}_t$: Olley-Pakes covariance
- Covariance between the size of a local labor market (relative to industry) and its concentration
- Negative and increasing
- Locations with larger industry shares are on average less concentrated
- This negative association is weaker in the 2000s than in the 1970s
Trend in $SPATIAL_t = \sum_{j \in J} \omega_{jt} (HHI_{jt} - \overline{HHI}_{jt})$

Figure 2: A pronounced increase in spatial dispersion can account for the divergence between NATIONAL and LOCAL.
Interpreting the components

- **SPATIAL}_t$: spatial dispersion
  - SPATIAL}_t ∈ [−1, 1] (but always < 0 empirically)
  
  - SPATIAL}_t = −1: many “small” local monopsonists
  - SPATIAL}_t = 0: equally spaced economy
  - SPATIAL}_t = 1: industry leader is only local monopsonist

→ as SPATIAL}_t ↑, locations become more and more “alike” in terms of industry and firm distribution
**SPATIAL\(_t\) for an industry \(j\)**

More formally, \(SPATIAL_t = 1\)

Table 1: “small” local monopsonies

<table>
<thead>
<tr>
<th>region</th>
<th>(x)</th>
<th>(y)</th>
<th>(z)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>9</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>B</td>
<td>0</td>
<td>9</td>
<td>0</td>
</tr>
<tr>
<td>C</td>
<td>0</td>
<td>0</td>
<td>9</td>
</tr>
</tbody>
</table>

Table 2: equally spaced economy

<table>
<thead>
<tr>
<th>region</th>
<th>(x)</th>
<th>(y)</th>
<th>(z)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>3</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>B</td>
<td>3</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>C</td>
<td>3</td>
<td>3</td>
<td>3</td>
</tr>
</tbody>
</table>

\[
- HHI_j = 3 \cdot \left( \frac{1}{3} \right)^2 = \frac{1}{3}
\]

\[
- \overline{HHI}_j = \frac{1 + 1 + 1}{3} = 1
\]

\[
- SPATIAL_t = \frac{1}{3} - 1
\]

\[
- \text{as } N_f \to \infty, \ SPATIAL_t \to -1
\]

\[
- HHI_j = 3 \cdot \left( \frac{1}{3} \right)^2 = \frac{1}{3}
\]

\[
- \overline{HHI}_j = \frac{3 \cdot \frac{1}{3}}{3} = \frac{1}{3}
\]

\[
- SPATIAL_t = 0
\]
Labor market concentration in the U.S.
Statistics on concentration

- Compare unweighted and weighted HHI distributions.
- Weights are determined by a market’s “size” (vacancies or employment).
- HHI measures are multiplied by a factor 10,000.
- 2,500 is DOJ threshold for “highly concentrated” product markets.

→ conclusion: the average market is moderately concentrated, but the average job is in a fairly competitive market.
Unweighted HHI distribution

Source: BGT 2010-17
Weighted HHI distribution

Source: BGT/OES 2010-17
## Local labor markets

<table>
<thead>
<tr>
<th></th>
<th>1st quartile</th>
<th>2nd quartile</th>
<th>3rd quartile</th>
<th>4th quartile</th>
</tr>
</thead>
<tbody>
<tr>
<td>workers per firm</td>
<td>&lt;15</td>
<td>&lt;15</td>
<td>20</td>
<td>30</td>
</tr>
<tr>
<td>vacancies per firm</td>
<td>84</td>
<td>125</td>
<td>155</td>
<td>173</td>
</tr>
<tr>
<td>workers per firm-county</td>
<td>&lt;15</td>
<td>&lt;15</td>
<td>&lt;15</td>
<td>&lt;15</td>
</tr>
<tr>
<td>vacancies per firm-MSA</td>
<td>5</td>
<td>5</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>vacancies per market</td>
<td>596</td>
<td>171</td>
<td>77</td>
<td>23</td>
</tr>
<tr>
<td>workers per market</td>
<td>3,200</td>
<td>1,500</td>
<td>450</td>
<td>200</td>
</tr>
<tr>
<td>city size</td>
<td>822,007</td>
<td>447,774</td>
<td>368,849</td>
<td>362,460</td>
</tr>
<tr>
<td>yearly income</td>
<td>48,000</td>
<td>32,000</td>
<td>28,600</td>
<td>30,000</td>
</tr>
<tr>
<td>% part-time</td>
<td>0.12</td>
<td>0.20</td>
<td>0.25</td>
<td>0.22</td>
</tr>
<tr>
<td>educ. years</td>
<td>15.00</td>
<td>13.00</td>
<td>13.00</td>
<td>13.00</td>
</tr>
<tr>
<td>unempl. rate</td>
<td>0.08</td>
<td>0.08</td>
<td>0.08</td>
<td>0.08</td>
</tr>
</tbody>
</table>

**Table 3:** Source: LBD 1976-2014; BGT/ACS/CPS 2010-17.

→ firms active in concentrated markets are larger *nationwide*
→ concentrated markets are smaller
Local labor market concentration across time (BGT)

Concentration based on vacancies in BGT ($\text{LOCAL}_{2007} = 1$)
Local labor market concentration across time (LBD)

Concentration based on employment in LBD ($\text{LOCAL}_{1976} = 1$)

Levels

Hershbein, Macaluso and Yeh (2019)
Manufacturing

Concentration based on employment in LBD (LOCAL_{1976} = 1)

Hershbein, Macaluso and Yeh (2019)
Monopsony and upskilling
Concentration and wages

\[ \log w_{imt} = \mu + \alpha o(i) + \alpha c(i) + \alpha j(i) + \alpha t + X_i \beta + \gamma \log(\text{HHI}_{mt}) + \varepsilon_{it} \]

Specification:
- 18-65, full-time, full-year
- FE: occupation, industry, year, state, city
- age, age square, sex, race, education, marital status
- city size, local labor market tightness
- outside options (skill remoteness_{mt}, a skill distance-weighted average of local vacancy shares)
Table 4: Increases in the local HHI are associated with decreases in wages concentrated among college-educated workers.

<table>
<thead>
<tr>
<th></th>
<th>Coefficient</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>log(HHI)</td>
<td>-0.010</td>
<td>0.014</td>
</tr>
<tr>
<td>(0.002)</td>
<td></td>
<td>(0.006)</td>
</tr>
<tr>
<td>log(HHI)*HS</td>
<td>-0.007</td>
<td>0.007</td>
</tr>
<tr>
<td>log(HHI)*SC</td>
<td>-0.013</td>
<td>0.007</td>
</tr>
<tr>
<td>log(HHI)*C</td>
<td>-0.033</td>
<td>0.010</td>
</tr>
<tr>
<td>log(city size)</td>
<td>0.758</td>
<td>0.253</td>
</tr>
<tr>
<td>(0.083)</td>
<td></td>
<td>(0.091)</td>
</tr>
<tr>
<td>log(tightness)</td>
<td>0.335</td>
<td>0.312</td>
</tr>
<tr>
<td>(0.086)</td>
<td></td>
<td>(0.073)</td>
</tr>
<tr>
<td>log(remoteness)</td>
<td>-0.073</td>
<td>-0.075</td>
</tr>
<tr>
<td>(0.031)</td>
<td></td>
<td>(0.026)</td>
</tr>
</tbody>
</table>

N=3,932,553

Concentration and skill demand

Do firms in concentrated markets demand higher-skilled workers?

- We refer to this phenomenon as upskilling.

\[
\text{skill demand}_{fmt} = \mu + \alpha_f + \alpha_o(m) + \alpha_c(m) + \alpha_t + \gamma \log(HHI_{mt}) + \varepsilon_{fmt}
\]

- $\gamma \approx$ semi-elasticity of firm-level skill demand to market concentration.
- We find $\gamma > 0$.

→ conclusion: monopsony manifests itself through changes in the quality of labor.
Measuring skill demand from job postings

Follow Hershbein and Kahn (2018) and Deming and Kahn (2018):

- Parse skill content of jobs from BGT job postings
- Categorize words/phrases into skill categories (”team player” → social; “problem solving” → cognitive)
- Count words that refer to a skill category in each ad
- Aggregate at the firm-market-level, obtain count of ads mentioning each skill category as measure of skill demand

**Assumption.** The more of a firm’s job ads mention words related to skill $x$, the higher the firm-level demand for skill $x$. 
**Table 5:** The stated demand for various skills (number of ads mentioning skills) is positively related to local concentration.

<table>
<thead>
<tr>
<th>Skill type</th>
<th>% of 0s</th>
<th>Mean</th>
<th>SD</th>
<th>$\gamma$</th>
<th>% of mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Social</td>
<td>49</td>
<td>0.89</td>
<td>3.36</td>
<td>0.12</td>
<td>13.5</td>
</tr>
<tr>
<td>Cognitive</td>
<td>59</td>
<td>0.66</td>
<td>3.09</td>
<td>0.07</td>
<td>10.6</td>
</tr>
<tr>
<td>Organizational</td>
<td>61</td>
<td>0.57</td>
<td>2.11</td>
<td>0.08</td>
<td>14.0</td>
</tr>
<tr>
<td>Computer, gen.</td>
<td>76</td>
<td>0.30</td>
<td>1.42</td>
<td>0.05</td>
<td>16.6</td>
</tr>
<tr>
<td>Computer, spec.</td>
<td>95</td>
<td>0.07</td>
<td>1.20</td>
<td>0.02</td>
<td>28.6</td>
</tr>
<tr>
<td>Any computer</td>
<td>75</td>
<td>0.33</td>
<td>1.84</td>
<td>0.06</td>
<td>18.2</td>
</tr>
</tbody>
</table>

$N = 15,032,577$
Heterogeneity in upskilling

Table 6: Increases in the local HHI are associated with increases in the demand for skills concentrated among low-skill workers.

<table>
<thead>
<tr>
<th></th>
<th>High-skill</th>
<th>Low-skill</th>
</tr>
</thead>
<tbody>
<tr>
<td>Social</td>
<td>0.080</td>
<td>0.130</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>Cognitive</td>
<td>0.041</td>
<td>0.092</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>Organizational</td>
<td>0.06</td>
<td>0.06</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.002)</td>
</tr>
</tbody>
</table>

$N = 15,032,577$
Conclusions: what we do

1. Estimate plant-level markdown rates
   - Positive relationship between a firm’s employment share and its markdown rate

2. Local v. national labor market concentration
   - statistical decomposition to interpret divergence over time
   - U.S. markets are becoming more and more “alike” in terms of industry-firm structure

3. Limited cross-sectional incidence and negative time trend for local concentration in both employment and vacancies

4. Wage compression + upskilling
   - heterogeneity across skill groups
Conclusions: what’s next

- Investigate relationship between concentration, markdowns, and markups.

- Heterogeneity and composition effects in SPATIAL.

- A framework to interpret wage compression and upskilling effects.
Thank you!

Comments: cla.macaluso@gmail.com
Appendix
Interpretation of covariance term

- Fix some industry $j$.
- Covariance term can be rewritten as:

$$\text{cov}(s^j_{lt}, \text{HHI}_{jl t}) \equiv \sum_{\ell \in L} (s^j_{lt} - \bar{s}^j_{t})(\text{HHI}_{jl t} - \overline{\text{HHI}}_{jt})$$

$$= \sum_{\ell \in L} \left( s^j_{lt} - \frac{1}{L} \right) \text{HHI}_{jl t}$$

where $s^j_{lt} - \frac{1}{L}$ is a deviation relative to a scenario in which employment is equally distributed across space.
Interpretation of covariance term (2)

- Alternative decomposition:

\[
\sum_{j \in J} \sum_{\ell \in L} \omega_{j\ell t} HHI_{j\ell t} = \overline{HHI}_t + \text{cov}(\omega_{j\ell t}, HHI_{j\ell t})
\]

\[
= \sum_{j \in J} \omega_{jt} HHI_{jt} - \sum_{j \in J} \omega_{jt} (HHI_{jt} - \overline{HHI}_jt)
\]

\[
+ \text{cov}(\omega_{j\ell t}, HHI_{j\ell t}) - \sum_{j \in J} \left(\omega_{jt} - \frac{1}{|J|}\right) \overline{HHI}_jt
\]

- Then, the OP term from original decomposition satisfies:

\[
\text{OP}_t \equiv \sum_{j \in J} \omega_{jt} \text{cov}(s^j_{\ell t}, HHI_{j\ell t})
\]

\[
= \text{cov}(\omega_{j\ell t}, HHI_{j\ell t}) - \sum_{j \in J} \left(\omega_{jt} - \frac{1}{|J|}\right) \overline{HHI}_jt
\]
Interpretation of spatial term

- Equal employment across regions: \(\text{EMP}_{j\ell t} = \frac{1}{|L|} \text{EMP}_{jt}\).

- Equal distribution of employment across regions for each multi-unit firm: 
  \(\text{emp}_{f\ell t} = \frac{1}{|L|} \text{emp}_{ft}\).

\[
\begin{align*}
HHI_{jt} &= \left( \frac{1}{\text{EMP}_{jt}} \right)^2 \sum_{f \in F(j)} \text{emp}_{ft}^2 \\
&= \left( \frac{1}{|L| \cdot \text{EMP}_{j\ell t}} \right)^2 \sum_{f \in F(j)} (|L| \cdot \text{emp}_{f\ell t})^2 \\
&= \frac{1}{|L|} \sum_{\ell \in L} \sum_{f \in F(j)} \left( \frac{\text{emp}_{f\ell t}}{\text{EMP}_{j\ell t}} \right)^2 \\
&= \frac{1}{|L|} \sum_{\ell \in L} HHI_{j\ell t} = \overline{HHI}_{jt}
\end{align*}
\]
Sales HHI v. employment HHI

- Generalized, monopolistically competitive environment à la Arkolakis et al. (2018)
  - Demand curve $q_{\nu}(p, I) = Q(p, I)D\left(\frac{p(\nu)}{P(p, I)}\right)$
  - Encompass a wide variety of demand systems including CES, additively separable (but non-CES), symmetric translog, QMOR and Kimball
- No wage dispersion within labor market / perfect mobility within labor market
- Constant marginal cost of production $c$ in labor only
Let $v = P(p, I)/c(\nu)$ denote relative efficiency, then we have:

\[
HHI^{\text{rev}} = \sum_{\nu \in \Omega} \left( \frac{\mu(\nu)}{\nu} \frac{D \left( \frac{\mu(\nu)}{\nu} \right)}{\sum_{\nu' \in \Omega} \frac{\mu(\nu')}{\nu'} \frac{D \left( \frac{\mu(\nu')}{\nu'} \right)}{\nu'}} \right)^2 \tag{1}
\]

\[
HHI^{\text{emp}} = \sum_{\nu \in \Omega} \left( \frac{\frac{1}{\nu} D \left( \frac{\mu(\nu)}{\nu} \right)}{\sum_{\nu' \in \Omega} \frac{1}{\nu'} D \left( \frac{\mu(\nu')}{\nu'} \right)} \right)^2 \tag{2}
\]

Hence, $HHI^{\text{rev}} = HHI^{\text{emp}}$ holds whenever markups are equalized across firms in a given market, i.e. $\mu(\nu) = \overline{\mu}$ for all $\nu \in \Omega$.

This requires size-invariant markups: CES preferences.
## Markup rates in US Manufacturing

<table>
<thead>
<tr>
<th>Industry Group</th>
<th>$\mu^{CRS}$</th>
<th>$\mu^{GMM}$</th>
<th>SD($\mu^{GMM}$)</th>
<th>$\beta_{ols}$</th>
<th>$\beta_{gmm}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Computer and Electronics</td>
<td>1.406</td>
<td>1.249</td>
<td>0.635</td>
<td>0.410</td>
<td>0.407</td>
</tr>
<tr>
<td>Chemicals</td>
<td>1.403</td>
<td>1.420</td>
<td>0.770</td>
<td>0.560</td>
<td>0.597</td>
</tr>
<tr>
<td>Printing and Publishing</td>
<td>1.386</td>
<td>1.296</td>
<td>0.652</td>
<td>0.363</td>
<td>0.376</td>
</tr>
<tr>
<td>Electrical Machinery</td>
<td>1.358</td>
<td>1.404</td>
<td>0.555</td>
<td>0.539</td>
<td>0.573</td>
</tr>
<tr>
<td>Apparel and Leather</td>
<td>1.331</td>
<td>1.570</td>
<td>1.035</td>
<td>0.440</td>
<td>0.569</td>
</tr>
<tr>
<td>Non-electrical Machinery</td>
<td>1.322</td>
<td>1.437</td>
<td>0.695</td>
<td>0.482</td>
<td>0.518</td>
</tr>
<tr>
<td>Food and Kindred Products</td>
<td>1.319</td>
<td>1.161</td>
<td>0.605</td>
<td>0.585</td>
<td>0.595</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td><strong>1.308</strong></td>
<td><strong>1.329</strong></td>
<td><strong>0.630</strong></td>
<td><strong>0.521</strong></td>
<td><strong>0.554</strong></td>
</tr>
<tr>
<td>Plastics and Rubber</td>
<td>1.303</td>
<td>1.366</td>
<td>0.512</td>
<td>0.545</td>
<td>0.593</td>
</tr>
<tr>
<td>Furniture and Fixtures</td>
<td>1.303</td>
<td>1.428</td>
<td>0.488</td>
<td>0.544</td>
<td>0.588</td>
</tr>
<tr>
<td>Fabricated Metal Products</td>
<td>1.280</td>
<td>0.999</td>
<td>0.548</td>
<td>0.433</td>
<td>0.353</td>
</tr>
<tr>
<td>Primary Metals</td>
<td>1.275</td>
<td>1.420</td>
<td>0.713</td>
<td>0.565</td>
<td>0.619</td>
</tr>
<tr>
<td>Paper and Allied Products</td>
<td>1.241</td>
<td>1.136</td>
<td>0.382</td>
<td>0.564</td>
<td>0.582</td>
</tr>
<tr>
<td>Textile Mill Products</td>
<td>1.229</td>
<td>1.236</td>
<td>0.620</td>
<td>0.527</td>
<td>0.565</td>
</tr>
<tr>
<td>Petroleum Refining</td>
<td>1.190</td>
<td>1.220</td>
<td>0.412</td>
<td>0.722</td>
<td>0.735</td>
</tr>
<tr>
<td><strong>Lumber</strong></td>
<td><strong>1.186</strong></td>
<td><strong>1.169</strong></td>
<td><strong>0.519</strong></td>
<td><strong>0.558</strong></td>
<td><strong>0.612</strong></td>
</tr>
</tbody>
</table>

ASM data on U.S. manufacturing plants 1976-2014. Mean estimates of a plant’s markup within an industry group. $\mu^{CRS}$: constant returns to scale and a Cobb-Douglas production function. $\mu^{GMM}$: Cobb-Douglas specification for gross output only. $\beta_{ols}$ and $\beta_{gmm}$: coefficients of the production function on intermediate inputs. All estimation procedures use deflated wage bill as labor input.
Markdown v. markup rates

**Markdown**

- Computer and Electronic Products
- Petroleum Refining
- Fabricated Metal Products
- Lumber
- Chemicals
- Apparel and Leather

**Markup**

Note: CRS estimates from ASM 1976-2014.

Hershbein, Macaluso and Yeh (2019)
Figure 1: Employment-weighted averages of plant-level markdowns from 1976 to 2014.
Estimating markdowns (2)

We obtain:

\[
\frac{\varepsilon_S + 1}{\varepsilon_S} = \mu^{-1} \cdot \theta_N \cdot \alpha_N^{-1}
\]

- \( \mu = \frac{P}{\lambda} \) is the price-cost markup.
- \( \theta_N = \frac{Y'(N) \cdot N}{Y(N)} \) is the output elasticity with respect to labor.
- \( \alpha_N = \frac{w(N) \cdot N}{P \cdot Y(N)} \) is the revenue share of labor.

Procedure from de Loecker and Warzynski (2012) on material inputs: markups

Production function estimation: output elasticities

Revenue shares are directly observable.
Markdowns with adjustment cost (1)

- Static convex adjustment costs $A(N)$.
- Cost minimization problem:

$$\min_{N \geq 0} w(N) \cdot N + A(N) \quad \text{s.t.} \quad Y(N) \geq Y$$

- First order condition can be written as:

$$\frac{\varepsilon S + 1}{\varepsilon S} + \frac{A'(N) \cdot N}{A(N)} \cdot \alpha_{A(N)} \cdot \alpha_N^{-1} = \mu^{-1} \cdot \theta_N \cdot \alpha_N^{-1}$$

where $\alpha_{A(N)}$ is the share of revenue that goes to labor adjustment costs.
Markdowns with adjustment cost (2)

- Back-of-the-envelope calculations for labor adjustment cost terms.
- Numbers from Cooper, Haltiwanger and Willis (2007):
  - $\frac{A'(N) \cdot N}{A(N)} \in \{1, 2\}$: linear or quadratic adjustment costs.
  - Hiring and firing costs are $0.775 + 0.235 = 1.01\%$ of gross profits.
  - Adjustment costs relative to revenues are thus smaller.
- Best fit to LRD is based on linear adjustment costs.
- Average payroll-to-sales ratio in manufacturing: $\approx 20\%$.
- Markdowns need to be adjusted by (at most):

$$\frac{A'(N) \cdot N}{A(N)} \cdot \alpha_A(N) \cdot \alpha_N^{-1} \approx 1 \times 1.01\% \times \frac{1}{20\%} = 5.05\%$$
Estimation procedure (1)

- To obtain markups, we need to estimate output elasticities.
- Follow insights of Levinsohn and Petrin (2003), and Ackerberg, Caves and Frazer (2015).

Output satisfies:

\[ y_{it} = f(x_{it}; \beta) + p_{it} + \varepsilon_{it} \]
\[ = f(k_{it}, l_{it}, m_{it}, e_{it}; \beta) + p_{it} + \varepsilon_{it}. \]

- Proxy method for unobserved productivity \( p_{it} \).
  - Material inputs satisfy \( m_{it} = m_t(k_{it}, p_{it}) \).
  - **Invertibility.** \( m_t^{-1}(k_{it}, \cdot) \) exists.

- Rewrite output as \( y_{it} = \phi(k_{it}, l_{it}, m_{it}, e_{it}) + \varepsilon_{it} \).
  - Estimate output non-parametrically and obtain \( \hat{\phi}_{it} = \hat{\phi}(k_{it}, l_{it}, m_{it}, e_{it}) \) and \( \hat{\varepsilon}_{it} \).
Estimation procedure (2)

- Unobserved productivity \( p_{it}(\beta) \) satisfies \( p_{it}(\beta) = \varphi_{it} - \mathbf{x}'_{it}\beta \).
- First-order Markov productivity dynamics: \( p_{it} = g_t(p_{it-1}) + \xi_{it} \).
  - Approximate \( g_t(\cdot) \) with a third-order polynomial and obtain productivity shocks as a function of parameters \( \beta \) only.
- Identifying moments:
  \[
  \mathbb{E}(\xi_{it}(\beta)\mathbf{z}_{it}) = \mathbf{0}_{B \times 1}
  \]
  where \( \mathbf{z}_{it} \) are instruments and \( B = \text{dim}(\beta) \).
- Capital \( k_{it} \) is predetermined as of time \( t \).
- Identifying assumption. Tomorrow’s innovation to productivity is orthogonal to today’s input decisions.
  \[ \Rightarrow \text{Cobb-Douglas production: } \mathbf{z}_{it} = (k_{it}, \ell_{it-1}, m_{it-1}, e_{it-1})'. \]
Our sample (BGT)

- Civilian jobs only, location, occupation, and employer non-missing, in continental US
- Active firms (5 ads+ per year)
- 9 years (2007; 2010–2017), 382 CBSAs, 108 occupations (SOC4)
- Mean postings per market-year: 277 (median = 34)
- Average number of active employers per market: 30 (median = 7)
Representativeness of BGT

- Comparison between BGT and JOLTS (based on industry)

![Bar chart comparing BGT and JOLTS Vacancies across different industries.](chart.png)
Representativeness of BGT (2)

- Comparison between BGT and CPS/OES (based on occupation)
Our sample (LBD)

- Employment (and job creation) at all private non-farm establishments in continental US
- 38 years (1976–2014), 3000+ counties, 200+ sectors (NAICS3)
- Mean employees per market-year: 14,300 (median = 13500)
- Average number of employers per market: 28 (median = 29)
What is a labor market?

- **Occupations**: 4-digit SOC
  - Life Scientists (1910), Physical Scientists (1920), Social Scientists (1930), Life, Physical and Social Science Technicians (1940), ...

- **Industry**: 3-digit NAICS
  - Food Manufacturing (311), Beverage and Tobacco Product Manufacturing (312), Textile Mills (313), Apparel Manufacturing (315), ...

- Connection between 4-digit SOC and 3-digit NAICS:
  - (BGT) Kalamazoo, MI - Physical Scientists
  - (LBD) Kalamazoo county, MI - Professional, Scientific, and Technical Services
Local concentration: BGT
Local concentration: LBD
Boundaries of a local labor market

- Skill remoteness by Macaluso (2017): outside options are governed by skill distances and specialization patterns.
  \[ \text{remoteness}_{oct} = \sum_k \omega_{kct} d_{ok} \]

- Schubert, Stansbury and Taska (2018): outside options are determined by occupational and migration flows.

- BGT resume/IRS CBSA migration data are used to compute these flows at 6-digit SOC/MSA level.

- Azar et al. (2017/18): restrict variation to national-level changes in occupational hiring over time.

- Inverse number of firms outside CBSA: \(1 / \sum_{\ell' \neq \ell} N_{j\ell't}\)

- Rinz (2018): restrict variation to broader, non-local forces.

- Leave-one-out instrument: \(\sum_{\ell' \neq \ell} \omega^{-\ell}_{j\ell't} HHI_{j\ell't} \)
Table 7: SPATIAL=1: the industry leader is the only local monopsony.

<table>
<thead>
<tr>
<th>region</th>
<th>x</th>
<th>y</th>
<th>z</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>23</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>B</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>C</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 8: industry leader is only local monopsony

- $HHI_j \approx 1$
- $HHI_j = \frac{1 + 2 \cdot \frac{1}{2}}{3} = \frac{2}{3}$
- $\text{SPATIAL}_t = 1 - \frac{2}{3}$
- as $N_x \to \infty$, $\text{SPATIAL}_t \to 1$
Small local monopsonies: each firm operates as a local monopsonist. However, none of the monopsonists is large relative to the aggregate.

<table>
<thead>
<tr>
<th>Region/Firm</th>
<th>1</th>
<th>2</th>
<th>...</th>
<th>n – 1</th>
<th>n</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>a</td>
<td>0</td>
<td>...</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>0</td>
<td>a</td>
<td>...</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>...</td>
<td>0</td>
<td>0</td>
<td>_</td>
<td>_</td>
<td>_</td>
</tr>
<tr>
<td>m – 1</td>
<td>0</td>
<td>0</td>
<td>...</td>
<td>a</td>
<td>0</td>
</tr>
<tr>
<td>m</td>
<td>0</td>
<td>0</td>
<td>...</td>
<td>0</td>
<td>a</td>
</tr>
</tbody>
</table>

\[
HHI_j = \sum_{i=1}^{n} \left( \frac{a}{n \cdot a} \right)^2 = \frac{1}{n}
\]

\[
\overline{HHI}_j = \frac{1}{m} \sum_{i=1}^{m} a = 1
\]

\[
\lim_{n \to +\infty} \text{SPATIAL}_j = \lim_{n \to +\infty} \left( \frac{1}{n} - 1 \right) = -1
\]
Perfect spatial dispersion: employment is perfectly dispersed across firms in each local market. This example is independent of the number of markets $m$ and firms $n$.

<table>
<thead>
<tr>
<th>REGION/FIRM</th>
<th>1 2 ... n-1 n</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>a a ... a a</td>
</tr>
<tr>
<td>2</td>
<td>a a ... a a</td>
</tr>
<tr>
<td>:</td>
<td>a a ... a :</td>
</tr>
<tr>
<td>m-1</td>
<td>a a ... a a</td>
</tr>
<tr>
<td>m</td>
<td>a a ... a a</td>
</tr>
</tbody>
</table>

$$H_{j} = \frac{1}{n} \sum_{i=1}^{n} \left( \frac{ma}{n \cdot ma} \right)^2 = \frac{1}{n}$$

$$\overline{H_{j}} = \frac{1}{m} \sum_{i=1}^{m} \frac{a}{n \cdot a} = \frac{1}{n}$$

$SPATIAL_{j} = 0$, for all $n > 1$
Dominating local monopsony: there is exactly one local monopsonist and this monopsony is large relative to the aggregate.

In particular, suppose firm $K$ dominates the industry by being a monopsonist in some market $r$: it has $a = \alpha \cdot mn$ employees for some large $\alpha > 1$. The latter coefficient means that firm $K$ is $\alpha$ times larger than the remaining stock of employment in the country.

For simplicity, we assume that each other firm has exactly one employee in each market.
Details on SPATIAL limiting values

<table>
<thead>
<tr>
<th>Region/Firm</th>
<th>$K$</th>
<th>$1$</th>
<th>$2$</th>
<th>...</th>
<th>$n-1$</th>
<th>$n$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$r$</td>
<td>$a$</td>
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<td>$0$</td>
<td>...</td>
<td>$0$</td>
<td>$0$</td>
</tr>
<tr>
<td>$1$</td>
<td></td>
<td>$0$</td>
<td>$1$</td>
<td>$1$</td>
<td>...</td>
<td>$1$</td>
</tr>
<tr>
<td>$2$</td>
<td></td>
<td>$0$</td>
<td>$1$</td>
<td>$1$</td>
<td>...</td>
<td>$1$</td>
</tr>
</tbody>
</table>
| ...         |     |     | $1$ | $1$ | ...   | ...
| $m-1$       | $0$ | $1$ | $1$ | ... | $1$   | $1$ |
| $m$         | $0$ | $1$ | $1$ | ... | $1$   | $1$ |

$$HHI_j = \left( \frac{a}{a + m \cdot n} \right)^2 + \sum_{i=1}^{n} \left( \frac{m}{a + m \cdot n} \right)^2 = \left( \frac{a}{a + m \cdot n} \right)^2 + n \left( \frac{m}{a + m \cdot n} \right)^2$$

$$\overline{HHI}_j = \frac{1 + m \cdot \left[ \sum_{i=1}^{n} \left( \frac{1}{n} \right)^2 \right]}{m+1} = \frac{1}{m+1} + \frac{m}{m+1} \cdot \frac{1}{n}$$

$$\text{SPATIAL}_j = \left( \frac{\alpha}{1+\alpha} \right)^2 + \frac{1}{n} \left( \frac{m \cdot n}{a + m \cdot n} \right)^2 - \frac{1}{m+1} - \frac{m}{m+1} \cdot \frac{1}{n}$$

$$\text{SPATIAL}_j = \left( \frac{\alpha}{1+\alpha} \right)^2 + \frac{1}{n} \left( \frac{1}{\alpha + 1} \right)^2 - \frac{1}{m+1} - \frac{m}{m+1} \cdot \frac{1}{n}$$

$$\lim_{m,n \to +\infty} \text{SPATIAL}_j = \left( \frac{\alpha}{1+\alpha} \right)^2 \quad \implies \quad \lim_{m,n,a \to +\infty} \text{SPATIAL}_j = +1$$
Previous wages results

- **Azar et al. (2017):** posted wages on careerbuilder.com
  - Jump from 25th to 75th percentile leads to 17% decline.
  - Our preferred estimate implies a decline of 6.5% instead.

- **Benmelech et al. (2018):** average wages in ASM/CM
  - HHI elasticities $\in [-0.049, -0.023]$

- **Rinz (2018):** average wages in LBD
  - HHI elasticities $\in [-0.0512, -0.0411]$

- Our baseline specification implies smaller but comparable estimates relative to Benmelech et al. (2018) and Rinz (2018).
Results are not driven by high-level concentration markets.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>log(HHI)</td>
<td>0.12</td>
<td>0.12</td>
<td>0.07</td>
</tr>
<tr>
<td></td>
<td>(40.8)</td>
<td>(38.7)</td>
<td>(26.5)</td>
</tr>
<tr>
<td>Comp. (g)</td>
<td>0.07</td>
<td>0.07</td>
<td>0.08</td>
</tr>
<tr>
<td></td>
<td>(24.6)</td>
<td>(26.8)</td>
<td>(35.2)</td>
</tr>
<tr>
<td>Comp. (s)</td>
<td>0.05</td>
<td>0.05</td>
<td>0.06</td>
</tr>
<tr>
<td></td>
<td>(30.3)</td>
<td>(32.0)</td>
<td>(14.4)</td>
</tr>
<tr>
<td>Any comp.</td>
<td>0.02</td>
<td>0.02</td>
<td>0.06</td>
</tr>
<tr>
<td></td>
<td>(4.1)</td>
<td>(4.3)</td>
<td>(15.3)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>High HHI?</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
<td>N</td>
</tr>
<tr>
<td>Employers</td>
<td>15,026,645</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>#clusters</td>
<td>204,458</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>290,445</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Note:** t-statistics in parentheses. Each coefficient is from a separate regression.
An example of upskilling

Skill group: **social**.

Hershbein, Macaluso and Yeh (2019)
List of low-skill occupations

Protective Service, Food, Cleaning & Maintenance, Personal Care, Sales, Office and Administration, Construction, Installation & Repair, Production and Transportation.
An example of upskilling

Demand for **social** skills

<table>
<thead>
<tr>
<th></th>
<th>0.101</th>
<th>0.104</th>
<th>0.117</th>
</tr>
</thead>
<tbody>
<tr>
<td>log(HHI)</td>
<td>(28.74)</td>
<td>(34.65)</td>
<td>(40.78)</td>
</tr>
<tr>
<td>log(labor force)</td>
<td>0.245</td>
<td>0.216</td>
<td>-</td>
</tr>
<tr>
<td>log(college share)</td>
<td>0.206</td>
<td>0.168</td>
<td>-</td>
</tr>
<tr>
<td>log(unempl. rate)</td>
<td>0.008</td>
<td>-0.040</td>
<td>-</td>
</tr>
<tr>
<td>market size</td>
<td>-</td>
<td>0.0001</td>
<td>0.0001</td>
</tr>
</tbody>
</table>

Employer FE ✓ ✓ ✓
Occupation FE ✓ ✓ ✓
Year FE ✓ ✓ ✓
MSA FE X X ✓

N 13,495,782 13,495,782 15,026,645
Unique employers 198,531 198,531 204,458
# clusters (MSA-SOC-year) 178,833 178,833 290,445

**Note:** t-statistics in parentheses. SE clustering: market-year.
Unweighted distribution (HHI of vacancies)


Hershbein, Macaluso and Yeh (2019)
Employment-weighted distribution (HHI of vacancies)

Source: BGT/OES 2010-17.