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

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Federal Reserve Bank of Richmond

Disclaimer

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


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Nov. 3, 2016 7:33 p.m. ET

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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

Burning Glass Technologies (BGT): near-universe of U.S. online vacancies in 2007 and 2010–2017. Detailed descriptions of location, sector, occupation, and skill requirements for each posted position.
BGT sample JOLTS

Longitudinal Business Database (LBD): universe of U.S. employers since 1976. Contains location, sector, employment (head count), and payroll. LBD sample

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)
- $x_{\cdot t}$ can be employment, job creation, vacancies or sales
- m is sector × 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"

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

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

where $\varepsilon_S = \frac{dN}{dw}\frac{w}{N}\Big|_{N=N^*}$ is a firm's labor supply elasticity.

HHIs and markdown rates Details

→ *Do large firms have larger markdowns?*

◇ Markdown is increasing in $\frac{N_i}{N} \Leftrightarrow \varepsilon_S$ 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:

$$\frac{w'(N) \cdot N}{w(N)} + 1 = \lambda \frac{Y'(N)}{w(N)}$$

$$\underbrace{\frac{\varepsilon_S + 1}{\varepsilon_S}}_{\text{markdown}} = \underbrace{\mu^{-1}}_{\text{markup}} \cdot \underbrace{\theta_N}_{\text{output elasticity}} \cdot \underbrace{\alpha_N^{-1}}_{\text{labor share}}$$

Markdown rates in manufacturing

Markups Markdown v. markups Trend

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

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

Dependent variable: plant-level (log) markdowns		
	Cobb-Douglas	*Translog*
log firm share	**0.0292** (0.0140)	**0.0251** (0.0052)
Observations (in millions)	1.449	1.449

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

→ 1 SD ↑ in a firm's share is associated with a 3.7% ↑ in the firm's markdown rate

→ indexes based on firm-level employment shares (e.g., HHI) capture concentration as well as monopsony power

Aggregation

Two **aggregate** statistics of labor market concentration:

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

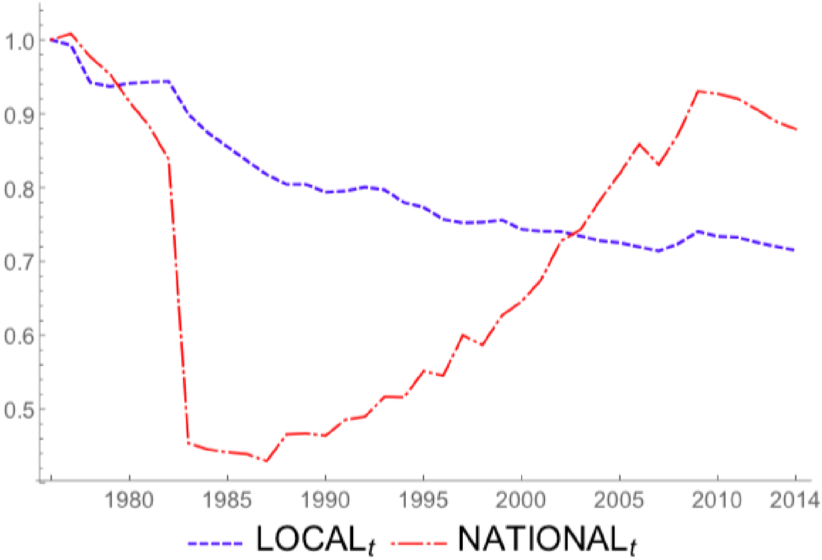
$$\text{LOCAL}_t \equiv \sum_{j \in J} \sum_{\ell \in L} \omega_{j\ell t} HHI_{j\ell t}$$

where ω_{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:

$$\begin{aligned}
\sum_{j\in J}\sum_{\ell\in L}\omega_{j\ell t} HHI_{j\ell t} &= \sum_{j\in J}\omega_{jt}\left[\sum_{\ell\in L} s^j_{\ell t} HHI_{j\ell t}\right] \\
&= \sum_{j\in J}\omega_{jt}\left[\overline{HHI}_{jt} + cov(s^j_{\ell t}, HHI_{j\ell t})\right] \\
&= \sum_{j\in J}\omega_{jt} HHI_{jt} + \sum_{j\in J}\omega_{jt} cov(s^j_{\ell t}, HHI_{j\ell t}) - \sum_{j\in J}\omega_{jt}(HHI_{jt} - \overline{HHI}_{jt}) \\
\text{LOCAL}_t &= \text{NATIONAL}_t + \text{OP}_t - \text{SPATIAL}_t
\end{aligned}$$

where:

- $s^j_{\ell t} = \frac{\omega_{j\ell t}}{\omega_{jt}}$
- $\overline{HHI}_{jt} \equiv \frac{1}{|L|}\sum_{\ell\in L} HHI_{j\ell t}$

Trend in $OP_t = \sum_{j \in J} \omega_{jt} cov(s^j_{\ell t}, HHI_{j\ell t})$

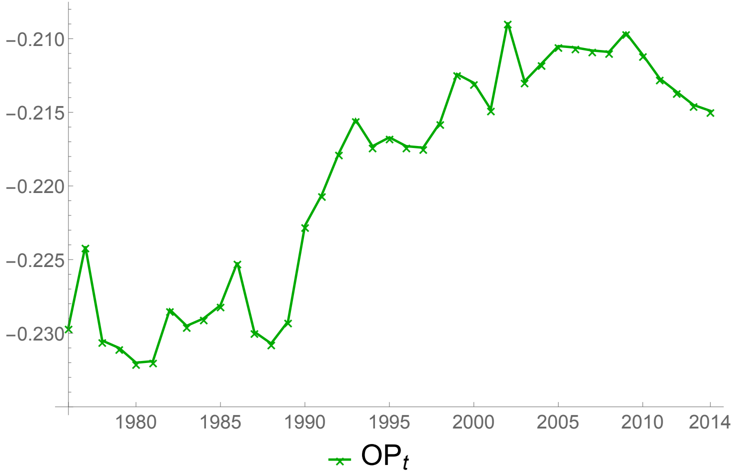


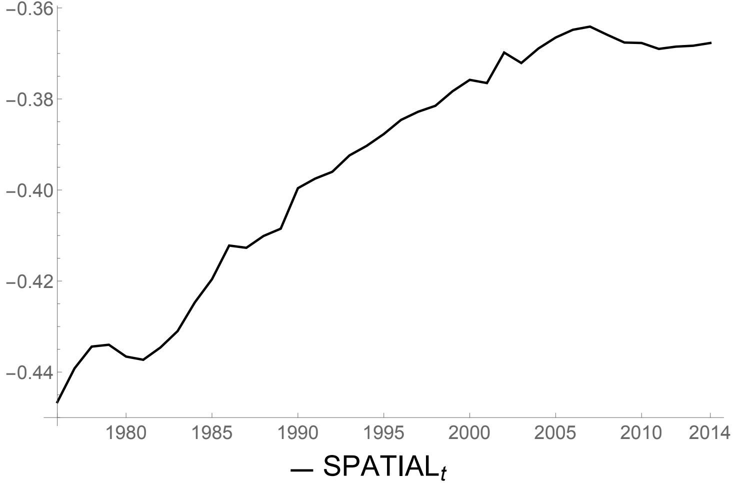
Figure 1: The OP covariance term has been increasing over time, so it cannot account for the divergence.

Interpreting the components

- ◇ 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 was 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
- $\text{SPATIAL}_t \in [-1, 1]$ (but always < 0 empirically)

- $\text{SPATIAL}_t = -1$: many "small" local monopsonists
- $\text{SPATIAL}_t = 0$: equally spaced economy
- $\text{SPATIAL}_t = 1$: industry leader is only local monopsonist

→ as $\text{SPATIAL}_t \uparrow$, locations become more and more "alike" in terms of industry and firm distribution

SPATIAL$_t$ for an industry j More formally SPATIAL=1

	firm			
		x	y	z
region	A	9	0	0
	B	0	9	0
	C	0	0	9

Table 1: "small" local monopsonies

	firm			
		x	y	z
region	A	3	3	3
	B	3	3	3
	C	3	3	3

Table 2: equally spaced economy

- $HHI_j = 3 \cdot (\frac{1}{3})^2 = \frac{1}{3}$
- $\overline{HHI}_j = \frac{1+1+1}{3} = 1$
- $\text{SPATIAL}_t = \frac{1}{3} - 1$
- as $N_f \to \infty$, $\mathbf{SPATIAL_t \to -1}$

- $HHI_j = 3 \cdot (\frac{1}{3})^2 = \frac{1}{3}$
- $\overline{HHI}_j = \frac{3 \cdot \frac{1}{3}}{3} = \frac{1}{3}$
- $\mathbf{SPATIAL_t = 0}$

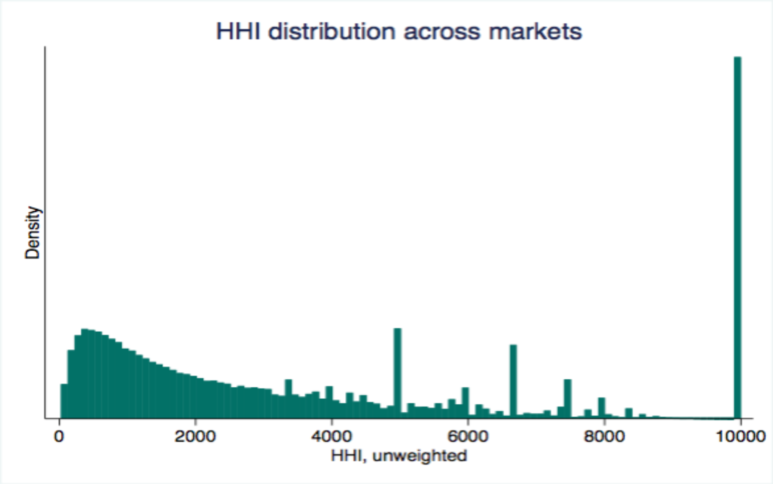
Labor market concentration in the U.S.

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.

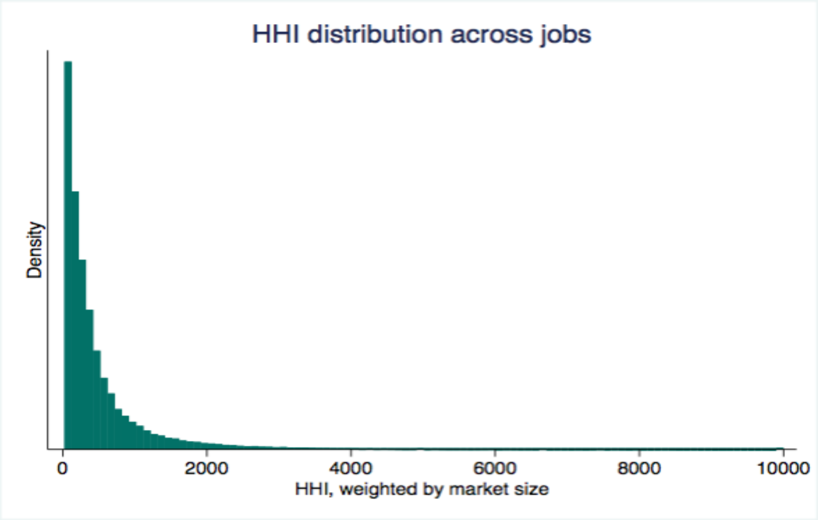
→ conclusion: the average market is moderately concentrated, but the average job is in a fairly competitive market.

Unweighted HHI distribution Maps



Source: BGT 2010-17

Weighted HHI distribution



Source: BGT/OES 2010-17

Local labor markets

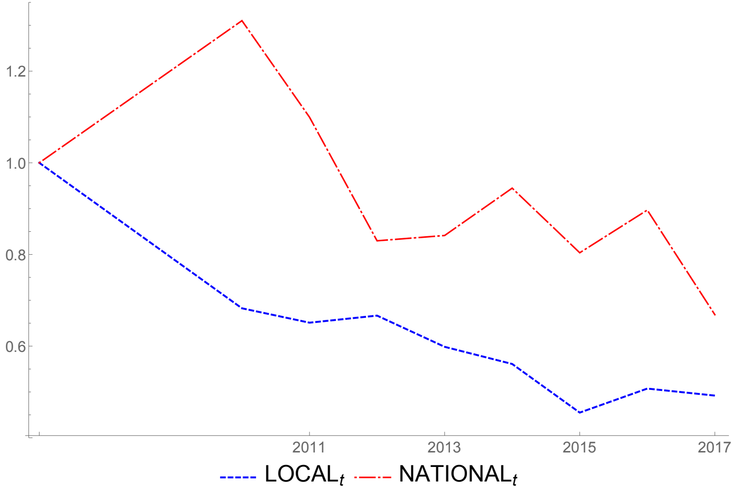
	Market's rank in concentration distribution (yearly medians)			
	1st quartile	2nd quartile	3rd quartile	4th quartile
workers per firm	<15	<15	20	30
vacancies per firm	84	125	155	173
workers per firm-county	<15	<15	<15	<15
vacancies per firm-MSA	5	5	5	5
vacancies per market	596	171	77	23
workers per market	3,200	1,500	450	200
city size	822,007	447,774	368,849	362,460
yearly income	48,000	32,000	28,600	30,000
% part-time	0.12	0.20	0.25	0.22
educ. years	15.00	13.00	13.00	13.00
unempl. rate	0.08	0.08	0.08	0.08

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

→ firms active in concentrated markets are larger *nationwide*

→ concentrated markets are smaller

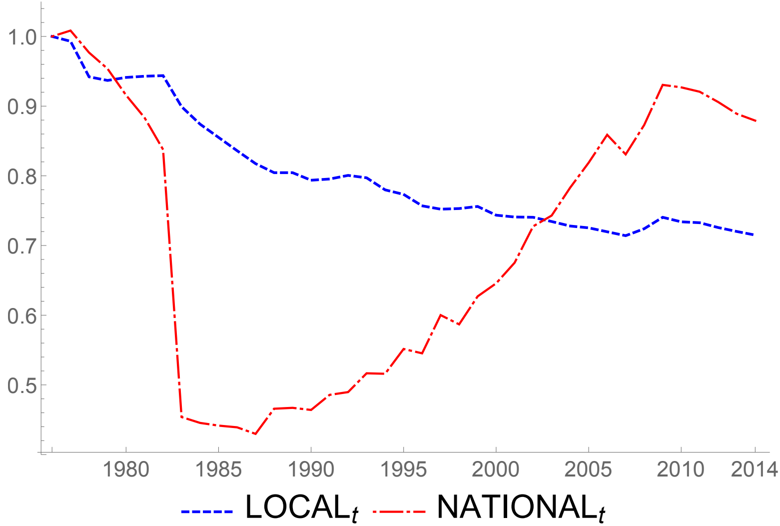
Local labor market concentration across time (BGT)



Concentration based on vacancies in BGT ($\text{LOCAL}_{2007} = 1$)

Levels

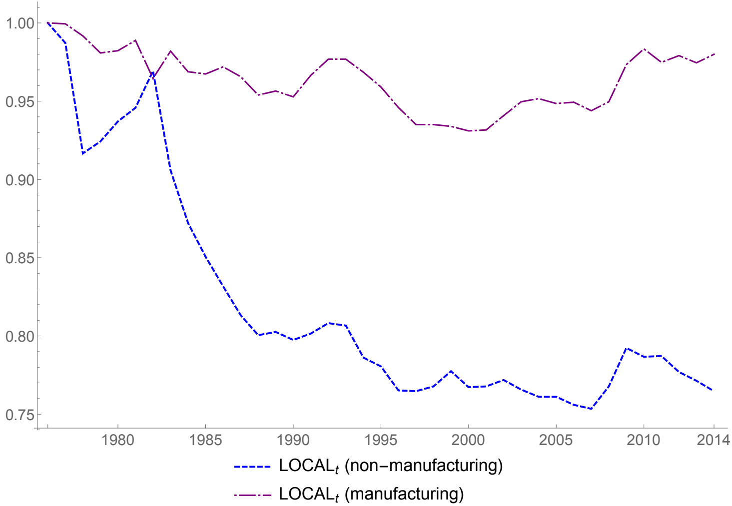
Local labor market concentration across time (LBD)



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

Levels

Manufacturing



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

Monopsony and upskilling

Concentration and wages

$$\log w_{imt} = \mu + \alpha_{o(i)} + \alpha_{c(i)} + \alpha_{j(i)} + \alpha_t + X_i\beta + \gamma \log(HHI_{mt}) + \varepsilon_{it}$$

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)

Alternative approaches

Lower wages

Comparison with estimates in literature

Table 4: Increases in the local HHI are associated with decreases in wages concentrated among college-educated workers.

log(HHI)	**-0.010**	0.014
	(0.002)	(0.006)
log(HHI)*HS	–	-0.007
		(0.007)
log(HHI)*SC	–	-0.013
		(0.007)
log(HHI)*C	–	**-0.033**
		(0.010)
log(city size)	0.758	0.253
	(0.083)	(0.091)
log(tightness)	0.335	0.312
	(0.086)	(0.073)
log(remoteness)	-0.073	-0.075
	(0.031)	(0.026)
N=3,932,553		

Source: ACS/OES/BGT 2010-17. SE clustering: city-occupation.

Concentration and skill demand

Do firms in concentrated markets demand higher-skilled workers?

- We refer to this phenomenon as **upskilling**.

$$\text{skill demand}_{fmt} = \mu + \alpha_f + \alpha_{o(m)} + \alpha_{c(m)} + \alpha_t + \gamma \log(HHI_{mt}) + \varepsilon_{fmt}$$

- $\gamma \simeq$ 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.

Skill demand in the BGT data Details

Table 5: The stated demand for various skills (number of ads mentioning skills) is positively related to local concentration.

Skill type	% of 0s	Mean	SD	γ	% of mean
Social	49	0.89	3.36	0.12	13.5
Cognitive	59	0.66	3.09	0.07	10.6
Organizational	61	0.57	2.11	0.08	14.0
Computer, gen.	76	0.30	1.42	0.05	16.6
Computer, spec.	95	0.07	1.20	0.02	28.6
Any computer	75	0.33	1.84	0.06	18.2
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.

	High-skill	*Low-skill*
Social	0.080	0.130
	(0.004)	(0.004)
Cognitive	0.041	0.092
	(0.004)	(0.003)
Organizational	0.06	0.06
	(0.002)	(0.002)
N = 15,032,577		

List of low-skill occupations

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!

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Appendix

Interpretation of covariance term

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

$$
\begin{aligned}
cov(s^j_{\ell t}, HHI_{j\ell t}) &\equiv \sum_{\ell \in L} (s^j_{\ell t} - \bar{s}^j_t)(HHI_{j\ell t} - \overline{HHI}_{jt}) \\
&= \sum_{\ell \in L} \left(s^j_{\ell t} - \frac{1}{L} \right) HHI_{j\ell t}
\end{aligned}
$$

where $s^j_{\ell t} - \frac{1}{L}$ is a deviation relative to a scenario in which employment is equally distributed across space.

Back

Interpretation of covariance term (2)

- Alternative decomposition:

$$\begin{aligned}\sum_{j\in J}\sum_{\ell\in L}\omega_{j\ell t}HHI_{j\ell t} &= \overline{HHI}_t + cov(\omega_{j\ell t}, HHI_{j\ell t}) \\ &= \sum_{j\in J}\omega_{jt}HHI_{jt} - \sum_{j\in J}\omega_{jt}(HHI_{jt} - \overline{HHI}_{jt}) \\ &+ cov(\omega_{j\ell t}, HHI_{j\ell t}) - \sum_{j\in J}\left(\omega_{jt} - \tfrac{1}{|J|}\right)\overline{HHI}_{jt}\end{aligned}$$

- Then, the OP term from original decomposition satisfies:

$$\begin{aligned}\mathrm{OP}_t &\equiv \sum_{j\in J}\omega_{jt}cov(s^j_{\ell t}, HHI_{j\ell t}) \\ &= cov(\omega_{j\ell t}, HHI_{j\ell t}) - \sum_{j\in J}\left(\omega_{jt} - \tfrac{1}{|J|}\right)\overline{HHI}_{jt}\end{aligned}$$

Back

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: $\text{emp}_{f\ell t} = \frac{1}{|L|}\text{emp}_{ft}$.

$$
\begin{aligned}
HHI_{jt} &= \left(\frac{1}{\text{EMP}_{jt}}\right)^2 \sum_{f\in F(j)} \text{emp}_{ft}^2 \\
&= \left(\frac{1}{|L|\cdot \text{EMP}_{j\ell t}}\right)^2 \sum_{f\in F(j)} \left(|L|\cdot \text{emp}_{f\ell t}\right)^2 \\
&= \frac{1}{|L|}\sum_{\ell\in L}\sum_{f\in F(j)}\left(\frac{\text{emp}_{f\ell t}}{\text{EMP}_{j\ell t}}\right)^2 \\
&= \frac{1}{|L|}\sum_{\ell\in L} HHI_{j\ell t} \equiv \overline{HHI}_{jt}
\end{aligned}
$$

Back

Sales HHI v. employment HHI

- Generalized, monopolistically competitive environment à la Arkolakis *et al.* (2018)
    - Demand curve $q_\nu(\mathbf{p}, I) = Q(\mathbf{p}, I) D\left(\frac{p(\nu)}{P(\mathbf{p}, I)}\right)$
    - 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

Sales HHI v. employment HHI (2)

- Let $v = P(\mathbf{p}, I)/c(\nu)$ denote relative efficiency, then we have:

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

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

- 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.

Back

Markup rates in US Manufacturing

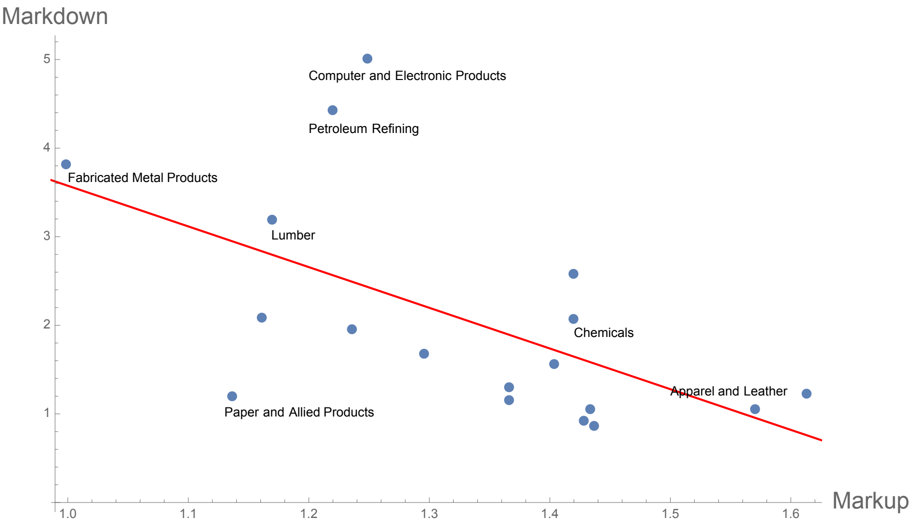
Back to markdowns

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

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

Markdown v. markup rates

Back to markdowns

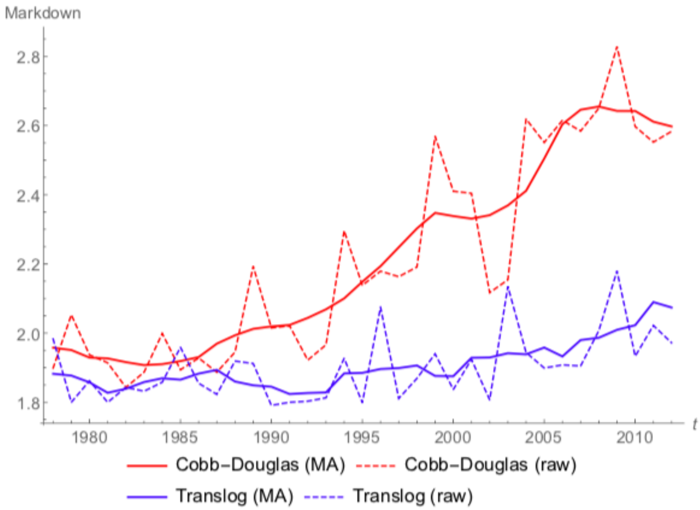


Note: CRS estimates from ASM 1976-2014.

Markdown trend

Back to markdowns

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.

Adjustment cost | Production function estimation | Back

Markdowns with adjustment cost (1)

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

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

- 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: $\simeq 20\%$.
- Markdowns need to be adjusted by (at most):

$$\frac{A'(N)\cdot N}{A(N)} \cdot \alpha_{A(N)} \cdot \alpha_N^{-1} \simeq 1 \times 1.01\% \times \frac{1}{20\%} = 5.05\%$$

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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:

$$\begin{aligned} y_{it} &= f(\mathbf{x}_{it};\beta) + p_{it} + \varepsilon_{it} \\ &= f(k_{it}, \ell_{it}, m_{it}, e_{it}; \beta) + p_{it} + \varepsilon_{it}. \end{aligned}$$

- 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 $y_{it} = \phi(k_{it}, \ell_{it}, m_{it}, e_{it}) + \varepsilon_{it}$.
  - Estimate output non-parametrically and obtain $\widehat{\varphi}_{it} = \widehat{\phi}(k_{it}, \ell_{it}, m_{it}, e_{it})$ and $\widehat{\varepsilon}_{it}$.

Estimation procedure (2)

- Unobserved productivity $p_{it}(\beta)$ satisfies $p_{it}(\beta) = \widehat{\varphi}_{it} - \mathbf{x}'_{it}\beta$.
- 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 β only.
- Identifying moments:

$$\mathbb{E}\left(\xi_{it}(\beta)\mathbf{z}_{it}\right) = \mathbf{0}_{B\times 1}$$

  where $\mathbf{z}_{it}$ are instruments and $B = \dim(\beta)$.
- Capital k_{it} is predetermined as of time t.
- **Identifying assumption**. Tomorrow's innovation to productivity is orthogonal to today's input decisions.

$\Rightarrow$ Cobb-Douglas production: $\mathbf{z}_{it} = (k_{it}, \ell_{it-1}, m_{it-1}, e_{it-1})'$.

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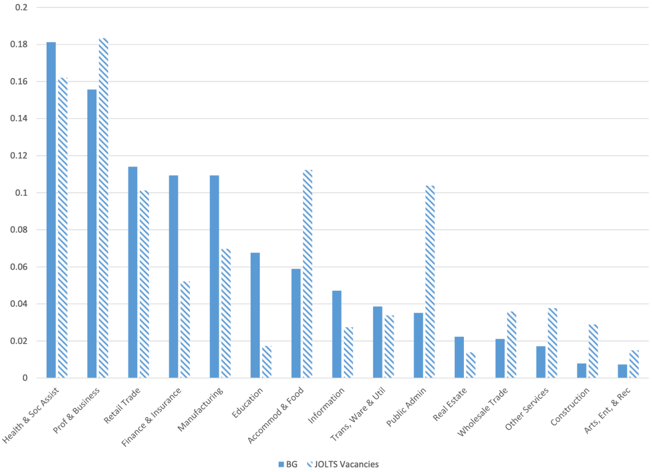
Our sample (BGT)

- 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)

Back

Representativeness of BGT

- Comparison between BGT and JOLTS (based on industry)



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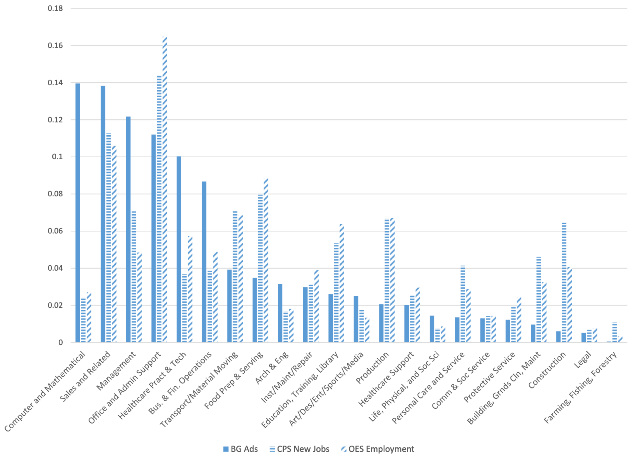
Representativeness of BGT (2)

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



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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)

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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:

$\Rightarrow$ (BGT) Kalamazoo, MI - Physical Scientists

$\Rightarrow$ (LBD) Kalamazoo county, MI - Professional, Scientific, and Technical Services

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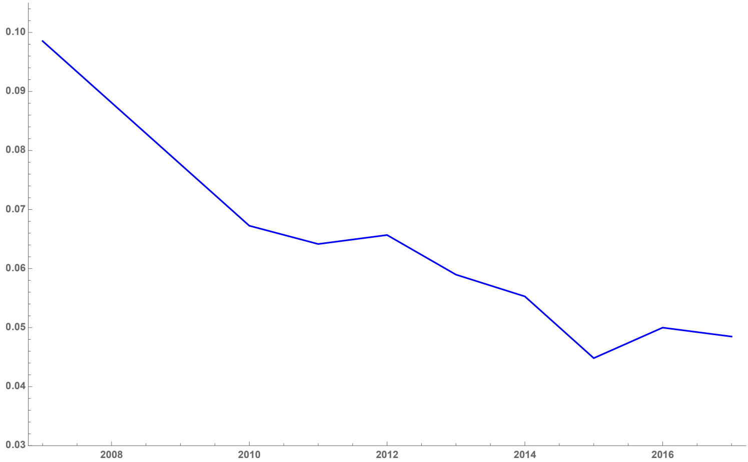
Local concentration: BGT



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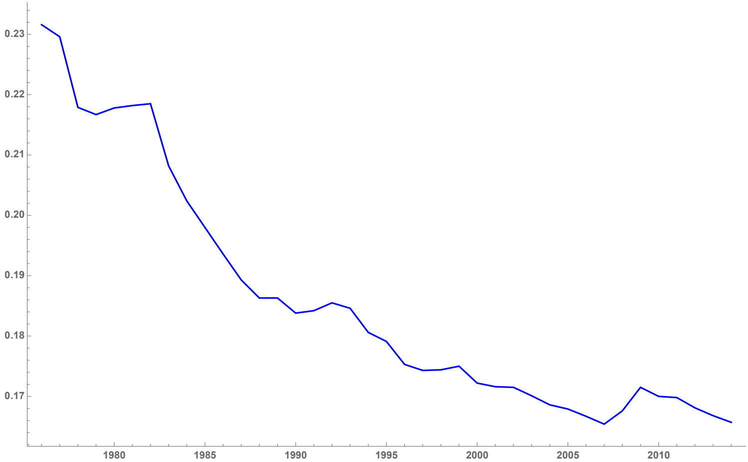
Local concentration: LBD



Back

Boundaries of a local labor market

- Skill remoteness by Macaluso (2017): outside options are governed by skill distances and specialization patterns.
  - ◇ $\texttt{remoteness}_{oct} = \sum_k \omega_{kct} d_{ok}$
- 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: $\sum_{\ell' \neq \ell} \omega^{-\ell}_{j\ell' t} HHI_{j\ell' t}$

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SPATIAL=1 case Back

Table 7: SPATIAL=1: the industry leader is the only local monopsony.

		firm		
region		x	y	z
	A	23	0	0
	B	0	1	1
	C	0	1	1

Table 8: industry leader is only local monopsony

- $HHI_j \approx 1$
- $\overline{HHI}_j = \frac{1+2\cdot\frac{1}{2}}{3} = \frac{2}{3}$
- $\text{SPATIAL}_t = 1 - \frac{2}{3}$
- as $N_x \to \infty$, $\mathbf{SPATIAL_t \to 1}$

Details on SPATIAL limiting values Back

Small local monopsonies: each firm operates as a local monopsonist. However, none of the monopsonists is large relative to the aggregate.

Region/Firm	1	2	...	$n-1$	n
1	a	0	...	0	0
2	0	a	...	0	0
$\vdots$	0	0	$\ddots$	$\vdots$	$\vdots$
$m-1$	0	0	...	a	0
m	0	0	...	0	a

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

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

$$\lim_{n \to +\infty} \text{SPATIAL}_j = \lim_{n \to +\infty} \left(\frac{1}{n} - 1 \right) = -1$$

Details on SPATIAL limiting values Back

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.

Region/Firm	1	2	...	$n-1$	n
1	a	a	...	a	a
2	a	a	...	a	a
$\vdots$	a	a	$\ddots$	$\vdots$	$\vdots$
$m-1$	a	a	...	a	a
m	a	a	...	a	a

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

$$\overline{HHI}_j = \frac{1}{m} \sum_{i=1}^{m} \frac{a}{n \cdot a} = \frac{1}{n}$$

$$\text{SPATIAL}_j = 0, \text{ for all } n > 1$$

Details on SPATIAL limiting values Back

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 α 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 Back

Region/Firm	K	1	2	$\dots$	$n-1$	n
r	a	0	0	$\dots$	0	0
1	0	1	1	$\dots$	1	1
2	0	1	1	$\dots$	1	1
$\vdots$	$\vdots$	1	1	$\ddots$	$\vdots$	$\vdots$
$m-1$	0	1	1	$\dots$	1	1
m	0	1	1	$\dots$	1	1

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

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

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

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

$$\lim_{m,n\to+\infty}\text{SPATIAL}_j = \left(\frac{\alpha}{1+\alpha}\right)^2 \qquad \Longrightarrow \lim_{m,n,a\to+\infty}\text{SPATIAL}_j = +1$$

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).

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Concentration and the demand for various skills

- Results are not driven by high-level concentration markets.

	Social		Cogn.		Org.	
log(HHI)	0.12	0.12	0.07	0.07	0.08	0.08
	(40.8)	(38.7)	(26.5)	(24.6)	(36.8)	(35.2)
	Comp. (g)		Comp. (s)		Any comp.	
log(HHI)	0.05	0.05	0.02	0.02	0.06	0.06
	(32.0)	(30.3)	(4.3)	(4.1)	(15.3)	(14.4)
High HHI?	Y	N	Y	N	Y	N
N	15,026,645					
Employers	204,458					
#clusters	290,445					

Note: t-statistics in parentheses. Each coefficient is from a separate regression.

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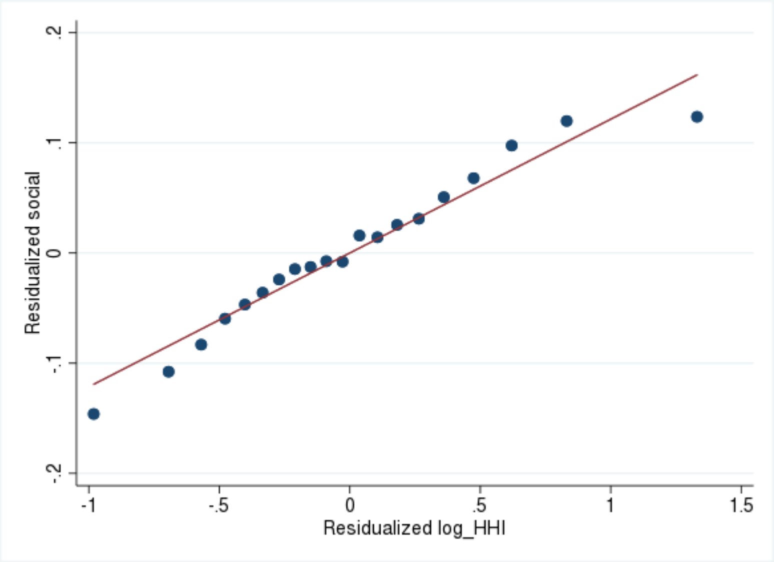
An example of upskilling Back



Skill group: **social**.

List of low-skill occupations

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

Back

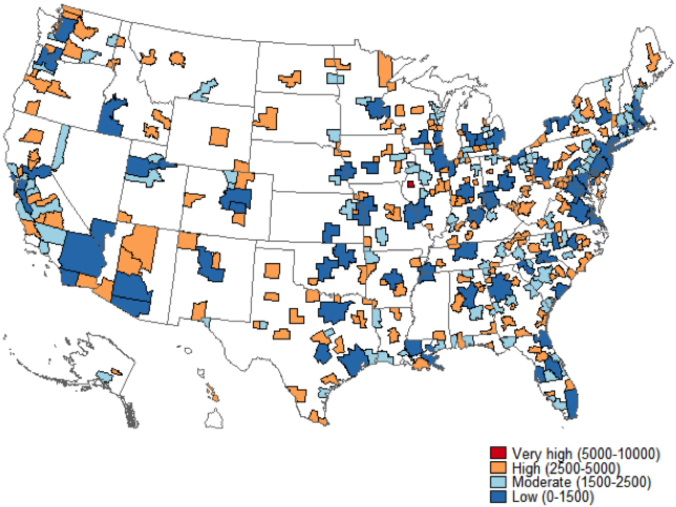
An example of upskilling Graph

Demand for **social** skills

log(HHI)	**0.101**	**0.104**	**0.117**
	(28.74)	(34.65)	(40.78)
log(labor force)	0.245	0.216	–
	(60.32)	(38.65)	
log(college share)	0.206	0.168	–
	(24.61)	(21.51)	
log(unempl. rate)	0.008	-0.040	–
	(1.30)	(-6.73)	
market size	–	0.0001	0.0001
		(8.49)	(8.46)
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

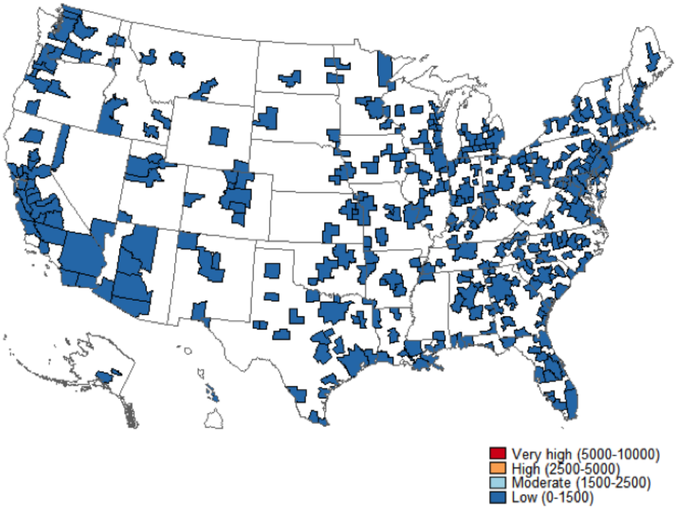
Note: t-statistics in parentheses. SE clustering: market-year.

Unweighted distribution (HHI of vacancies) Back



Source: BGT 2010-2017.

Employment-weighted distribution (HHI of vacancies)



Source: BGT/OES 2010-17.