Employer Concentration and Outside Options

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Increased concern about employer concentration
Fact 1: Many US labor markets are highly concentrated (though most workers are in low-concentration labor markets)
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Market definition: Does this actually capture workers’ labor markets?
Fact 2: wage and concentration are strongly negatively correlated
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Endogeneity: Is this relationship causal?
Employer concentration (starting to be) considered in policy

<table>
<thead>
<tr>
<th>Hospital</th>
<th>Pre-Merger Share</th>
<th>Post-Merger Share</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hendrick</td>
<td>70.1%</td>
<td>92.6%</td>
</tr>
<tr>
<td>Abilene Regional</td>
<td>22.4%</td>
<td></td>
</tr>
<tr>
<td>Rolling Plains Memorial Hospital</td>
<td>4.9%</td>
<td>4.9%</td>
</tr>
<tr>
<td>Fisher County Hospital District</td>
<td>1.0%</td>
<td>1.0%</td>
</tr>
<tr>
<td>Anson General Hospital</td>
<td>0.8%</td>
<td>0.8%</td>
</tr>
<tr>
<td>Hanlin Memorial Hospital</td>
<td>0.8%</td>
<td>0.8%</td>
</tr>
<tr>
<td></td>
<td><strong>HHI</strong></td>
<td><strong>8,598</strong></td>
</tr>
<tr>
<td></td>
<td>Change in HHI</td>
<td>-3,149</td>
</tr>
</tbody>
</table>

Federal Trade Commission Staff Submission to Texas Health and Human Services Commission Regarding the Certificate of Public Advantage Applications of Hendrick Health System and Shannon Health System
What effect does employer concentration have on wages – and for whom does it matter?
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   - Outside-occupation options: IV approach leveraging differential local exposure to national occupation-level shocks
This paper

Findings:

- Most workers are not in highly concentrated labor markets
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• For those who are, concentration matters.
  
  • median to 95th percentile HHI $\rightarrow$ 3.5% lower wages on average
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• Much **bigger effects if it’s hard to switch** occupation:
  
  • **6%** lower wages for low mobility occupations
    (e.g. registered nurses, security guards)
  
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• Increased attention toward employer concentration justified, but important that it is targeted towards workers for whom it is a true problem.

• Policymakers can target attention based on within-occupation concentration, low outward mobility and/or poor outside-occupation job options.
Plan

Employer concentration: setting the scene

Conceptual Framework

Market definition

Empirical approach

Endogeneity and identification

Main results

Implications

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**Employer concentration**: the degree to which a given labor market is dominated by few employers.

We use the Herfindahl-Hirschman Index – the sum of squared employer shares of the labor market:

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HHI = \sum_i \sigma_i^2
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**Data:**
- **Vacancy** HHI within **occupation-by-metro area** labor market
- Calculated from Burning Glass Technologies’ database of online job postings (74m vacancies over 2013–2016: near-universe of online vacancy postings) (More)
- Previously used to calculate employer HHIs: Azar, Marinescu, Steinbaum, & Taska (2018); Hershbein, Macaluso, & Yeh (2019)
Selected Relevant Work

Employer concentration:

• **& labor market power**: Jarosch, Nimczik, and Sorkin (2019); Berger, Herkenhoff, and Mongey (2019)

• **& wages**: Azar, Marinescu, and Steinbaum (2020); Azar, Marinescu, Steinbaum, and Taska (2018); Benmelech, Bergman, and Kim (2018); Rinz (2018); Hershbein, Macaluso, and Yeh (2019); Qiu and Sojourner (2019)

• **& specific settings**: Arnold (2019); Prager and Schmitt (2019); Gibbons, Greenman, Norlander, and Sorensen (2019)

• **& policy implications**: Hemphill and Rose (2017); Naidu, Posner, and Weyl (2018); Marinescu and Hovenkamp (2019); Naidu and Posner (2020)
Selected Relevant Work

Employer concentration:

Role of outside job options:

- Beaudry, Green, and Sand (2012); Caldwell and Danieli (2018); Caldwell and Harmon (2018); Macaluso (2019); Alfaro-Urena, Manelici, and Vasquez (2020)
Selected Relevant Work

Employer concentration:

Role of outside job options:

Flow-based market definition/similarity calculation:

- Shaw (1987); Manning and Petrongolo (2017); Nimczik (2018); Neffke, Otto, and Weyh (2017); Arnold (2020)
Selected Relevant Work

Employer concentration:

Role of outside job options:

Flow-based market definition/similarity calculation:

Imperfect competition in labor markets (large literature):

- & monopsony: Robinson (1935); Boal and Ransom (1997); Manning (2003); Azar, Berry, and Marinescu (2019); Berger, Herkenoff, and Mongey (2019)

- & elasticity of labor supply to the firm: Webber (2015); Sokolova and Sorensen (2020); Hirsch and Schumacher (2005); Staiger, Spetz, and Phibbs (2010); Ransom and Sims (2010); Ashenfelter, Farber, and Ransom (2013); Matsudaira (2014); Naidu, Nyarko, and Wang (2016); Bassier, Dube, and Naidu (2019); Goolsbee and Syverson (2019); Dube, Jacobs, Naidu, and Suri (2020)

- & search and matching models: e.g. Burdett and Mortensen (1980); Pissarides (2000)
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Conceptual framework: outside options in wage determination

- Worker’s outside option
- Firm’s outside option
- Bargaining power to divide match surplus / rents
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Conceptual framework

Nash bargaining for wages:

\[ w_i = \beta p_i + (1 - \beta)oo_i \]
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**Outside option value** = expected wage if worker leaves firm \( i \)

\[ oo_i = \sum_{j \neq i} \text{Prob}(\text{match with firm } j) w_j + \left( 1 - \sum_{j \neq i} \text{Prob}(\text{match with firm } j) \right) b \]

- jobs at other firms
- unemployment

where \( h.o.t. \) = higher order terms
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**Average wage** is approximately:

\[ \bar{w} \approx (1 - (1 - \beta) HHI) \cdot \bar{p} + (1 - \beta) HHI \cdot b + h.o.t. \]

where \( h.o.t. = \text{higher order terms} \)

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Market definition

- Cashiers
- Retail salespersons
- Customer service representatives
- Waiters and waitresses
- Counter attendants
- Office clerks
Market definition
New occupational mobility data

- New occupational mobility data from Burning Glass Technologies:
  - U.S. data, 2002-2016
  - 178.5 million sequential worker-year observations.
  - Broadly representative by state and gender. Overweights young/middle-aged, and professionals.

Example resume:

2003-2004 Purchasing Manager, Schubert Corp
2004-2006 Compliance Officer, Stansbury Inc
2006-2010 Compliance Officer, Taska Ltd

Calculate transition share $\pi_{o \rightarrow p}$: Probability of moving to occupation $p$ from occupation $o$ from one year to the next, conditional on leaving job in $o$. (More)
New occupational mobility data

~**16 million resumes** from Burning Glass Technologies:

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Occupational mobility is:

1. High
2. Highly heterogeneous
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Which occupations do registered nurses go to?
Facts about occupational mobility

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Occupational mobility is:

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→ administrative occupation boundaries are poor at capturing workers’ true labor markets, and differently so for different occupations
Dealing with market definition: conceptual framework

Does this matter? Yes: defining labor market as local SOC 6-digit occupation may

1. obscure **heterogeneity**
2. lead to **bias**
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**Our approach:**

- **Segment** regressions by degree of outward occupational mobility
- Control for index of the value of **outside-occupation job options** in the wage bargain
Constructing the outside-occupation option index

Empirical outside-occupation option index (occ. o, metro area k, year t):

\[
oo^\text{occs}_{o,k,t} = \sum_{p \neq o} \text{Prob}(\text{job in occ } p) \bar{w}_{p,k,t}
\]

where

- \(\bar{w}_{p,k,t}\): average hourly wage from BLS OES
- \(\pi_{o \rightarrow p}\): national average transition share from occupation o to occupation p, from Burning Glass Technologies resume data (Why transition shares?)
- \(s_{p,k,t}\): local relative employment share of occupation p, compared to national share, from BLS OES

Conceptual framework:

\[
\bar{w}_o \approx (1 - (1 - \beta) \pi_{o \rightarrow o}) \text{HHI}_o \cdot b
\]

which represents within-occ. productivity and outside-occ. options
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- $\frac{S_{p,k,t}}{S_{p,t}}$: local relative employment share of occupation $p$, compared to national share, from BLS OES

Conceptual framework: (More)

$$\bar{w}_o \approx (1 - (1 - \beta)\pi_{o \rightarrow o} HHl_o) \left( \alpha \bar{p}_o + (1 - \alpha) \text{oo}_{o,k,t} \right) + (1 - \beta)\pi_{o \rightarrow o} HHl_o \cdot b$$

\[\text{within-occ. productivity and outside-occ. options} \quad \text{unemployment}\]
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Empirical approach

Testable predictions:

1. **Employer concentration**: Higher employer concentration in workers’ own occupation reduces wages.
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**Specification:**

$$\ln \tilde{w}_{o,k,t} = \alpha + \Gamma_{o,t} + \Gamma_{k,t} + \gamma_1 \ln HHI_{o,k,t} + \gamma_2 \ln o_0^{occs} + u_{o,k,t}$$
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\ln \bar{w}_{o,k,t} = \alpha + \Gamma_{o,t} + \Gamma_{k,t} + \gamma_1 \ln HHI_{o,k,t} + \gamma_2 \ln oo_{o,k,t}^{occs} + u_{o,k,t}
\]
Empirical approach

Testable predictions:

1. **Employer concentration**: Higher employer concentration in workers’ own occupation reduces wages.

2. **Outside-occupation options**: Changes in wages in other local occupations affect local occupational wages.

3. **Heterogeneity**: Empirical relationship between wages and employer concentration (HHI) should be stronger for less mobile occupations.

4. **Bias**: HHI estimates may be biased without controlling for \( oo^{occs} \) (coefficients will be too negative)

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Estimating the effect of concentration on wages: data

Setting:
• near-universe of U.S. occupations (SOC 6-digit) within metropolitan areas
• total of c. 100,000 occupation-metro area labor markets
• annual data 2013–2016

Data:
• Average hourly wage, employment: BLS OES
• Vacancy concentration (HHI): BGT online vacancy postings
• Outside-occupation options: constructed from BLS OES and BGT resume data
Plan

Employer concentration: setting the scene

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Summary
Endogeneity
Case 1: improved local conditions cause large firms to expand, increasing concentration and productivity
Endogeneity

Case 2: local productivity decline leads to firm shrinkage/death, increasing concentration
Identification: labor market concentration

Our solution: leverage differential local-level exposure to large national firms:
Identification: labor market concentration

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Change in HHI is a function of individual firms’ growth $g_{j,o,k,t}$:

$$\Delta HHI_{o,k,t} = \sum_j \sigma^2_{j,o,k,t-1} \left( \frac{(1 + g_{j,o,k,t})^2}{(1 + g_{o,k,t})^2} - 1 \right)$$
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Instrument for HHI:

$$\Delta HHI_{o,k,t}^{inst} = \sum_j \sigma_{j,o,k,t-1}^2 \left( \frac{(1 + \tilde{g}_j,t)^2}{(1 + \tilde{g}_{o,k,t})^2} - 1 \right)$$

Instrument for local firm growth with national vacancy growth of major firms (note: $\tilde{g}_{o,k,t} = \sum_j \sigma_j \cdot \tilde{g}_{j,t}$)

Local exposure to national growth is driven by initial vacancy share of that firm in the local area

Controls for local vacancy growth $g_{o,k,t}$ and predicted vacancy growth $\tilde{g}_{o,k,t}$ (Identification conditions)
Identification: labor market concentration

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- Controls for local vacancy growth $g_{o,k,t}$ and predicted vacancy growth $\tilde{g}_{o,k,t}$
  (Identification conditions) (Example)
Identification: outside-occupation options
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Our solution: leverage differential local-level exposure to national occupational wage shocks:
Identification: outside-occupation options

Bartik-type instrument for outside-occupation options:

$$OO_{o,k}^{occ} = \sum_{p \neq o}^{N_{occ}} \pi_{o \rightarrow p} \cdot \frac{S_{p,k}}{S_p} \cdot \bar{W}_{p,k}$$
Identification: outside-occupation options

Bartik-type instrument for outside-occupation options:

\[ oo_{o,k}^{occ} = \sum_{p \neq o}^{N_{occ}} \pi_{o \rightarrow p} \cdot \frac{S_{p,k}}{S_p} \cdot \bar{W}_{p,k} \]

- Instrument for outside-option wage in each occupation \( p \) and city \( k \): national mean wage for \( p \), excluding own city \( k \)
Identification: outside-occupation options

**Bartik-type instrument for outside-occupation options:**

\[
OO_{o,k}^{occ} = \sum_{p \neq o} N_{occ} \pi_{o \rightarrow p} \cdot \frac{S_{p,k}}{S_p} \cdot \bar{W}_{p,k}
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- Instrument for outside-option wage in each occupation \( p \) and city \( k \): national mean wage for \( p \), excluding own city \( k \)
- Instrument for local relative employment share in each occupation \( p \) and city \( k \): initial employment share in that occupation and city in 1999.
Plan

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\[ \ln \bar{w}_{o,k,t} = \alpha + \Gamma_{o,t} + \Gamma_{k,t} + \gamma_1 \ln HHI_{o,k,t} + \gamma_2 \ln oo_{o,k,t}^{occ} + u_{o,k,t} \]
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### Main results

**Dependent variable:** Log wage

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## Main results

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### 2SLS regression of wage on instrumented HHI and instrumented $oo^{occs}$

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### Predictions:

1. Concentration matters ✓
2. Outside-occ options matter ✓
3. Heterogeneity by outward mobility ✓
4. Bias w/o controlling for $oo^{occs}$ ✓
Main results

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**2SLS regression of wage on instrumented HHI and instrumented oo^{occ}**

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Predictions:

1. Concentration matters ✓
2. Outside-occ options matter ✓
3. Heterogeneity by outward mobility ✓
## Main results

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4. Bias w/o controlling for $oo^{occ}$ ✓ (previous slide)
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2SLS regression of wage on instrumented HHI and instrumented $oo^{occ}$

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Moving from median to 95th percentile HHI:
($\approx 220$ to $2,200$)
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Moving from median to 95th percentile HHI:
($\approx 220$ to $2,200$)
• → 3.5% lower wage on average
## Main results

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<td>2SLS regression of wage on instrumented HHI and instrumented ( oo_{occ} )</td>
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</tr>
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<td>Log vacancy HHI, instrumented</td>
<td>-0.015*** (0.003)</td>
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</tr>
<tr>
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* p < 0.10, ** p < 0.05, *** p < 0.01. Heteroskedasticity-robust standard errors clustered at metro area level. Units of observation: 6 digit SOC by metro area by year. (Occ-City) (First Stage)

### Moving from median to 95th percentile HHI:
\( \approx 220 \text{ to } 2,200 \)
- → 3.5% lower wage on average
- → 6% lower wage for lowest outward mobility quartile
## Main results

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<th>Dependent variable:</th>
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\( \approx 220 \text{ to } 2,200 \)

- → 3.5% lower wage on average
- → 6% lower wage for lowest outward mobility quartile
- → \textbf{No} estimated effect for highest outward mobility quartile (& confidence interval rules out anything greater than 1%)
Robustness Checks

- Control for industry Bartik shocks (see results)
- Exclude vacancy growth controls (see results)
- Include control for equal-weighted firm vacancy growth (see results)
- Include occupation-metro area fixed effects (see results)
- Employment weighted regressions (see results)
- Dropping underrepresented occupations (see results)
- Weighting by occupation represented-ness (see results)
- Weighting by metro area represented-ness (see results)
Plan

Employer concentration: setting the scene

Conceptual Framework

Market definition

Empirical approach

Endogeneity and identification

Main results

Implications

Summary
Who is most affected by employer concentration?

Estimated average wage effect, relative to $HHI = 200$:

$HHI = 200 \approx \text{median}$

\[
\Delta \log(\bar{w})_{o,k} = \left( \log(HHI_{o,k}) - \log(200) \right) \cdot \hat{\gamma}_{1|\text{quartile}(\pi_{o\rightarrow o})}
\]

- \(\Delta \log(\bar{w})_{o,k}\) is the log difference between actual HHI and 200.
- \(\hat{\gamma}_{1|\text{quartile}(\pi_{o\rightarrow o})}\) is the estimated coefficient for occ. mobility quartile.

Calculate for each occ-city labor market.
Who is most affected by employer concentration?

Estimated average wage effect, relative to $HHI = 200$:

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$$\Delta \log(\bar{w})_{o,k} = (\log(HHI_{o,k}) - \log(200)) \cdot \hat{\gamma}_1|_{\text{quartile}(\pi_{o\rightarrow o})}$$

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(Our data covers about 110m of the 120m private sector employees in the U.S. labor market in 2016).

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| Q2 mobility | (1.1m) | (1.0m) | (4.5m) | (7.0m) | (15.7m) |
| Q3 mobility | (0.9m) | (0.9m) | (3.7m) | (9.0m) | (16.3m) |
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<th>Represent- ativeness (BGT)</th>
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<td>Security guards</td>
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<td>.63</td>
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Employer concentration and inequality

Estimated wage effect of employer concentration, relative to $HHI = 200$, by hourly wage quartile:

- **Q1** $(w<13.02)$: No wage effect ($HHI<200$), Wage effect $2\%-5\%$
- **Q2** $(13.02<w<17.81)$: No wage effect ($HHI<200$), Wage effect $2\%-5\%$
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Why does targeting by occ. mobility matter?

Duluth, MN/WI:

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<th>Occupation</th>
<th>HHI</th>
<th>Occ. leave share quartile</th>
<th>Predicted wage effect</th>
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<td>1,571</td>
<td>q1/q2</td>
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<tr>
<td>Bank tellers</td>
<td>1,911</td>
<td>q4</td>
<td>?</td>
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<tr>
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<td>580</td>
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Plan

Employer concentration: setting the scene

Conceptual Framework

Market definition

Empirical approach

Endogeneity and identification

Main results

Implications

Summary
This paper

Findings:

• Most workers are not in highly concentrated labor markets

• For those who are, concentration matters.
  • median to 95th percentile HHI → 3.5% lower wages on average
  • effects at least 6x higher for low mobility than high mobility occupations

Policy implications:

• Increased attention toward employer concentration justified, but important that it is targeted towards workers for whom it is a true problem.

• Policymakers can target attention based on within-occupation concentration, low outward mobility and/or poor outside-occupation job options.

Policy response?

• Our estimates hold productivity constant: to what extent does concentration reduce wages relative to productivity?

• Antitrust/policy to reduce concentration may not always be the solution: may change both productivity and concentration

• In some cases, instead policies to provide countervailing power/raise wages for affected workers may be better.
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Thank you!

All comments and suggestions appreciated: annastansbury@g.harvard.edu
Paper available at scholar.harvard.edu/stansbury
Plan

Appendix
BGT Vacancy Data

- 40,000 websites
- 74 million unique vacancies (49m w/ employer name)
- 1.04 million employers
- 665 employers responsible for c. half of vacancies
- 75% of vacancies from firms present in all four years (2013–2016)

(Back)
Wage-HHI correlations, with fixed effects

A: Year FEs

B: CBSA-year FEs

C: Occ-year FEs

D: Occ-yr & CBSA-yr FEs
Conceptual framework

Nash bargaining for wages:

\[ w_i = \beta p_i + (1 - \beta) oo_i \]
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jobs at other firms

unemployment
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(Back)
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(Back)
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(Back)
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**Average wage** is approximately:

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\bar{w} \approx (1 - (1 - \beta)HHI) \cdot \bar{p} + (1 - \beta)HHI \cdot b + h.o.t.
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(Back)
Why transition shares?

1. Capture *feasibility* and *desirability*
2. Reflect task, skill, amenity similarity *(More)*
3. Allow asymmetry of occupational relevance *(Back)*
Transitions reflect occupational similarity

Absolute difference

Hourly wages
Skill vector distance

**Skilled Task Intensities**
- ALM: Non-routine analyt.
- ALM: Non-routine interpers.
- ALM: Routine cognitive
- ALM: Routine manual
- ALM: Non-routine manual
- DD: Math
- DD: Routine
- DD: Social skills
- DD: Social x Math

**Amenities**
- Time pressure
- Contact with others
- Relationship building
- Structured job
- Decision-making freedom

**Leadership**
- Work style: Leadership
- Guide, Direct & Motivate
- Develop & Build Teams
- Coordinate Work & Activities
- Monitor & Control Resources
- Staff Organizational Units
- Leadership composite

(Back)
Conceptual framework: outside-occupation options

Recall our previous outside option expression for workers at firm $i$,

$$oo_i = \sum_{j \neq i} \sigma_j \cdot w_j + \sigma_i \cdot b$$

- $\sum_{j \neq i} \sigma_j \cdot w_j$: jobs in other firms
- $\sigma_i \cdot b$: unemployment
Conceptual framework: outside-occupation options

Recall our previous outside option expression for workers at firm $i$,

$$
OO_i = \sum_{j \neq i} \sigma_j \cdot w_j + \sigma_i \cdot b
$$

jobs in other firms

Segment into jobs within and outside occupation:

$$
OO_{i,o} = \pi_{o \rightarrow o} \sum_{j \neq i} \sigma_{j,o} w_{j,o} + \sum_{p \neq o}^{N_{occ}} \pi_{o \rightarrow p} \sum_{k} \sigma_{k,p} w_{k,p} + \pi_{o \rightarrow o} \sigma_i b
$$

jobs in own occ  
jobs in other occs  
unemployment
Conceptual framework: outside-occupation options

Recall our previous outside option expression for workers at firm $i$,

$$oo_i = \sum_{j \neq i} \sigma_j \cdot w_j + \underbrace{\sigma_i \cdot b}_{\text{unemployment}}$$

jobs in other firms

Segment into jobs within and outside occupation:

$$oo_{i,o} = \sum_{j \neq i} \sigma_{j,o} w_{j,o} + \sum_{p \neq o}^{\text{occs}} \pi_{o \rightarrow p} \sum_{k} \sigma_{k,p} W_{k,p} + \sum_{p \neq o}^{\text{occs}} \pi_{o \rightarrow p} \sigma_{i} b$$

jobs in own occ

jobs in other occs

unemployment
Conceptual framework: outside-occupation options

Recall our previous outside option expression for workers at firm $i$,

$$oo_i = \sum_{j \neq i} \sigma_j \cdot w_j + \sigma_i \cdot b$$

where $\sigma_j \cdot w_j$ represents jobs in other firms and $\sigma_i \cdot b$ represents unemployment.

Segment into jobs within and outside occupation:

$$oo_{i,o} = \pi_{o \rightarrow o} \sum_{j \neq i} \sigma_{j,o} w_{j,o} + \sum_{p \neq o}^{N_{occ}} \pi_{o \rightarrow p} \sum_{k} \sigma_{k,p} w_{k,p} + \pi_{o \rightarrow o} \sigma_i b$$

where $\sigma_{j,o} w_{j,o}$ represents jobs in own occupation, $\sigma_{k,p} w_{k,p}$ represents jobs in other occupations, and $\pi_{o \rightarrow o} \sigma_i b$ represents unemployment.
Conceptual framework: outside-occupation options

Recall our previous outside option expression for workers at firm $i$,

$$\text{oo}_i = \sum_{j \neq i} \sigma_j \cdot w_j + \sigma_i \cdot b$$

Segment into jobs within and outside occupation:

$$\text{oo}_{i,o} = \pi_{o \rightarrow o} \sum_{j \neq i} \sigma_{j,o} w_{j,o} + \sum_{p \neq o}^{\text{occ}s} \text{oo}_{o,k}^{\text{occ}s} + \pi_{o \rightarrow o} \sigma_i b$$
Conceptual framework: outside-occupation options

**Average wage**, taking into account outside-occupation options, is approx.: 

\[ \tilde{w}_o \approx (1 - (1 - \beta)\pi_{o \rightarrow o} HHI_o) \left( \alpha \bar{p}_o + (1 - \alpha) oo_{o, k, t}^{occ} \right) + (1 - \beta)\pi_{o \rightarrow o} HHI_o \cdot b \]

within-occ. productivity and outside-occ. options

unemployment

where \( \alpha = \frac{\beta}{1 - \pi_{o \rightarrow o}(1 - \beta)} \)

(Back)
Conceptual framework: outside-occupation options

**Average wage**, taking into account outside-occupation options, is approx.:

\[
\tilde{w}_o \approx (1 - (1 - \beta)\pi_{o \to o} HHI_o) \left( \alpha \bar{p}_o + (1 - \alpha) oo_{o, k, t}^{occ} \right) + (1 - \beta)\pi_{o \to o} HHI_o \cdot b
\]

where \( \alpha = \frac{\beta}{1 - \pi_{o \to o}(1 - \beta)} \)

(Back)
**Conceptual framework: outside-occupation options**

**Average wage**, taking into account outside-occupation options, is approx.:

\[ \bar{w}_o \approx (1 - (1 - \beta)\pi_o \rightarrow o HHI_o) \left( \alpha \bar{p}_o + (1 - \alpha) oo^{ocs}_{o, k, t} \right) + (1 - \beta) \pi_o \rightarrow o HHI_o \cdot b \]

where \( \alpha = \frac{\beta}{1 - \pi_o \rightarrow o (1 - \beta)} \)

(Back)
Conceptual framework: outside-occupation options

**Average wage**, taking into account outside-occupation options, is approx.:

\[
\tilde{w}_o \approx (1 - (1 - \beta)\pi_o \to oHHI_o) \left( \alpha \bar{p}_o + (1 - \alpha) oocso_{o,k,t} \right) + (1 - \beta)\pi_o \to oHHI_o \cdot b
\]

where \( \alpha = \frac{\beta}{1 - \pi_o \to o(1 - \beta)} \)

(Back)
Conceptual framework: outside-occupation options

**Average wage**, taking into account outside-occupation options, is approx.:

\[
\bar{w}_o \approx (1 - (1 - \beta)\pi_{o\to o} HHI_o) \left( \alpha \bar{p}_o + (1 - \alpha) o_{occ}^{occ_{o,k,t}} \right) + (1 - \beta)\pi_{o\to o} HHI_o \cdot b
\]

where \( \alpha = \frac{\beta}{1 - \pi_{o\to o}(1 - \beta)} \)

(Back)
The HHI instrument: conditions for identification

✓: can capture average effects of such variation across large share of U.S. labor markets; does not require specific local/contextual knowledge

X: ‘black box’
The HHI instrument: conditions for identification

✓: can capture average effects of such variation across large share of U.S. labor markets; does not require specific local/contextual knowledge

X: ‘black box’

Identifying assumptions for HHI instrument:

\[(1) \quad \text{Cov} \left[ u_{o,k,t}, \sum_{j} \sigma_{j,o,k,t-1}^2 \left( \frac{(1 + \tilde{g}_{j,t})^2}{(1 + \tilde{g}_{o,k,t})^2} - 1 \right) \right] \mid \Gamma_{o,t}, \Gamma_{k,t}, \tilde{g}_{o,k,t} \rightarrow 0\]

Sufficient:

(1) large firms’ national vacancy growth is orthogonal to local demand/supply conditions in any specific occupation-metro area labor market (controlling for metro area-year and occ-year fixed effects)

(2) large number of independent shocks to national firms’ hiring
The HHI instrument: conditions for identification

✓: can capture average effects of such variation across large share of U.S. labor markets; does not require specific local/contextual knowledge

X: ‘black box’

Identifying assumptions for HHI instrument:

\[
\begin{align*}
(1) & \quad \text{Cov} \left[ u_{o,k,t}, \sum_j \sigma^2_{j,o,k,t-1} \left( \frac{(1 + \tilde{g}_{j,t})^2}{(1 + \tilde{g}_{o,k,t})^2} - 1 \right) \right. \\
& \quad \quad \left. \left| \Gamma_{o,t}, \Gamma_{k,t}, \tilde{g}_{o,k,t} \right] \to 0
\end{align*}
\]

Sufficient:

(1) large firms’ national vacancy growth is orthogonal to local demand/supply conditions in any specific occupation-metro area labor market (controlling for metro area-year and occ-year fixed effects)

(2) large number of independent shocks to national firms’ hiring

\[
\begin{align*}
(2) & \quad \text{Cov} \left[ \text{HHI}_{o,k,t}, \sum_j \sigma^2_{j,o,k,t-1} \left( \frac{(1 + \tilde{g}_{j,t})^2}{(1 + \tilde{g}_{o,k,t})^2} - 1 \right) \right. \\
& \quad \quad \left. \left| \Gamma_{o,t}, \Gamma_{k,t}, \tilde{g}_{o,k,t} \right] > 0
\end{align*}
\]

Sufficient:

large firms’ national (relative) vacancy growth is correlated with their (relative) vacancy growth in individual occupation-metro area labor markets
The HHI instrument: Amazon example

**Focus:** Order clerks; Stock clerks and order fillers; Production, planning, and expediting clerks; Purchasing agents, except wholesale, retail, and farm products; Laborers and freight, stock, and material movers.

Check 1: higher initial Amazon ‘exposure’ \(ightarrow\) higher HHI as Amazon grows (conditional on initial HHI)

Coefficient: 0.88; std. error: 0.25
The HHI instrument: Amazon example

Focus: Order clerks; Stock clerks and order fillers; Production, planning, and expediting clerks; Purchasing agents, except wholesale, retail, and farm products; Laborers and freight, stock, and material movers.

Check 1: higher initial Amazon ‘exposure’ \( \rightarrow \) higher HHI as Amazon grows (conditional on initial HHI)

Coefficient: 0.88; std. error: 0.25
The HHI instrument: Amazon example

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The HHI instrument: Amazon example

**Focus:** Order clerks; Stock clerks and order fillers; Production, planning, and expediting clerks; Purchasing agents, except wholesale, retail, and farm products; Laborers and freight, stock, and material movers.

**Check 2:** higher initial Amazon ‘exposure’ $\rightarrow$ higher HHI instrument

![Binned scatter plot](image)

*Coefficient: 0.52; std. error: 0.06*

(Back)
The HHI instrument: Amazon example

**Focus:** Order clerks; Stock clerks and order fillers; Production, planning, and expediting clerks; Purchasing agents, except wholesale, retail, and farm products; Laborers and freight, stock, and material movers.

Check 3: effect of HHI on wages for Amazon-exposed occupations

Coefficient on 2SLS IV regression: -0.037; std. error: 0.018

(Back)
The HHI instrument: Amazon example

Focus: Order clerks; Stock clerks and order fillers; Production, planning, and expediting clerks; Purchasing agents, except wholesale, retail, and farm products; Laborers and freight, stock, and material movers.

Check 3: effect of HHI on wages for Amazon-exposed occupations

Coefficient on 2SLS IV regression: -0.037; std. error: 0.018

(Back)
Regressions by occupation group

$$\ln \bar{w}_{o,k,t} = \alpha + \Gamma_{o,t} + \Gamma_{k,t} + \gamma_1 \ln HHI_{o,k,t} + \gamma_2 \ln \text{occs}_{o,k,t} + u_{o,k,t}$$

Coefficient plot shows coefficient $\gamma_1$, the estimated coefficient on the log of the HHI.
## Summary Stats

### Table: Summary statistics: main data set

<table>
<thead>
<tr>
<th>Percentile</th>
<th>1</th>
<th>5</th>
<th>10</th>
<th>25</th>
<th>50</th>
<th>75</th>
<th>90</th>
<th>95</th>
<th>99</th>
</tr>
</thead>
<tbody>
<tr>
<td>HHI</td>
<td>35</td>
<td>97</td>
<td>166</td>
<td>388</td>
<td>955</td>
<td>2,222</td>
<td>5,000</td>
<td>7,222</td>
<td>10,000</td>
</tr>
<tr>
<td>HHI (emp-wt)</td>
<td>10</td>
<td>22</td>
<td>33</td>
<td>80</td>
<td>219</td>
<td>534</td>
<td>1,348</td>
<td>2,245</td>
<td>5,556</td>
</tr>
</tbody>
</table>

### Panel A: Employer concentration HHI (2016)

### Panel B: Outside-occupation option index $oo^{occs}$ (2016)

<table>
<thead>
<tr>
<th>$oo^{occs}$ (2016)</th>
<th>1.4</th>
<th>2.1</th>
<th>2.6</th>
<th>3.5</th>
<th>4.8</th>
<th>6.6</th>
<th>8.8</th>
<th>10.6</th>
<th>16.1</th>
</tr>
</thead>
<tbody>
<tr>
<td>$oo^{occs}$ <em>wage</em></td>
<td>0.03</td>
<td>0.06</td>
<td>0.09</td>
<td>0.15</td>
<td>0.23</td>
<td>0.34</td>
<td>0.45</td>
<td>0.53</td>
<td>0.74</td>
</tr>
<tr>
<td>$oo^{occs}$ <em>wage</em>, emp-wt</td>
<td>0.06</td>
<td>0.11</td>
<td>0.15</td>
<td>0.23</td>
<td>0.34</td>
<td>0.45</td>
<td>0.55</td>
<td>0.63</td>
<td>0.77</td>
</tr>
</tbody>
</table>

### Panel C: Occupation-city wages and employment (2016)

<table>
<thead>
<tr>
<th>Employment</th>
<th>30</th>
<th>40</th>
<th>50</th>
<th>90</th>
<th>220</th>
<th>670</th>
<th>1,980</th>
<th>3,920</th>
<th>14,410</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean hourly wage</td>
<td>9.05</td>
<td>10.50</td>
<td>11.94</td>
<td>15.40</td>
<td>21.42</td>
<td>31.08</td>
<td>44.07</td>
<td>53.68</td>
<td>90.50</td>
</tr>
<tr>
<td>Wage, emp-wt</td>
<td>8.97</td>
<td>9.94</td>
<td>10.99</td>
<td>13.39</td>
<td>18.33</td>
<td>30.28</td>
<td>45.10</td>
<td>56.42</td>
<td>80.50</td>
</tr>
</tbody>
</table>

### Panel D: national hourly wage distribution (2016) from BLS OES

<table>
<thead>
<tr>
<th>Hourly wage</th>
<th>–</th>
<th>–</th>
<th>9.27</th>
<th>11.60</th>
<th>17.81</th>
<th>28.92</th>
<th>45.45</th>
<th>–</th>
<th>–</th>
</tr>
</thead>
</table>
Baseline OLS regressions

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Log wage</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(a) All quartiles</td>
</tr>
</tbody>
</table>

**Panel A: OLS regression of wage on HHI**

<p>| | | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Log HHI</td>
<td>-0.011***</td>
<td>-0.016***</td>
<td>-0.009***</td>
<td>-0.007***</td>
<td>-0.006***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Observations</td>
<td>212,417</td>
<td>58,788</td>
<td>56,862</td>
<td>55,917</td>
<td>40,850</td>
</tr>
</tbody>
</table>

**Panel B: OLS regression of wage on HHI and \( oo^{occs} \)**

<p>| | | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Log HHI</td>
<td>-0.007***</td>
<td>-0.013***</td>
<td>-0.006***</td>
<td>-0.002*</td>
<td>-0.002</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Log outside-occ. options</td>
<td>0.101***</td>
<td>0.089***</td>
<td>0.080***</td>
<td>0.110***</td>
<td>0.141***</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.011)</td>
<td>(0.009)</td>
<td>(0.009)</td>
<td>(0.011)</td>
</tr>
<tr>
<td>Observations</td>
<td>212,417</td>
<td>58,788</td>
<td>56,862</td>
<td>55,917</td>
<td>40,850</td>
</tr>
</tbody>
</table>

Notes: Heteroskedasticity-robust standard errors clustered at the city level shown in parentheses. Significance levels: * \( p<0.10 \), ** \( p<0.05 \), *** \( p<0.01 \).
## HHI regression: First stage

**Table: First-stage regressions**

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Log wage</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Full sample</td>
<td>Q1</td>
<td>Q2</td>
<td>Q3</td>
<td>Q4</td>
</tr>
<tr>
<td></td>
<td>All quartiles</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Panel A: Dependent variable is log vacancy HHI</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log vacancy HHI, instrument</td>
<td>0.107*** (0.004)</td>
<td>0.110*** (0.005)</td>
<td>0.106*** (0.004)</td>
<td>0.099*** (0.005)</td>
<td>0.108*** (0.006)</td>
</tr>
<tr>
<td>Log outside-occ. options, instrument</td>
<td>-0.723*** (0.044)</td>
<td>-0.651*** (0.052)</td>
<td>-0.763*** (0.053)</td>
<td>-0.771*** (0.050)</td>
<td>-0.816*** (0.052)</td>
</tr>
<tr>
<td><strong>Observations</strong></td>
<td>212,417</td>
<td>58,788</td>
<td>56,862</td>
<td>55,917</td>
<td>40,850</td>
</tr>
<tr>
<td><strong>Panel B: Dependent variable is log outside-occ. options</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log outside-occ. options, instrument</td>
<td>0.775*** (0.018)</td>
<td>0.685*** (0.017)</td>
<td>0.808*** (0.018)</td>
<td>0.804*** (0.021)</td>
<td>0.799*** (0.022)</td>
</tr>
<tr>
<td>Log vacancy HHI, instrument</td>
<td>-0.002*** (0.000)</td>
<td>-0.002*** (0.000)</td>
<td>-0.001*** (0.001)</td>
<td>-0.002*** (0.000)</td>
<td>-0.001*** (0.000)</td>
</tr>
<tr>
<td><strong>Observations</strong></td>
<td>212,417</td>
<td>58,788</td>
<td>56,862</td>
<td>55,917</td>
<td>40,850</td>
</tr>
</tbody>
</table>

Notes: Heteroskedasticity-robust standard errors clustered at the city level shown in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.
Robustness check: occ-city fixed effects

### Table: Robustness check

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Log wage</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Full sample</td>
</tr>
<tr>
<td></td>
<td>All quartiles</td>
</tr>
<tr>
<td>Baseline specification – 2SLS regression of wage on instrumented HHI and instrumented $o^cocc$</td>
<td></td>
</tr>
<tr>
<td>Log HHI, instrumented</td>
<td>-0.009</td>
</tr>
<tr>
<td>(0.007)</td>
<td>(0.010)</td>
</tr>
<tr>
<td>Log outside-occ. options, instrumented</td>
<td>0.009</td>
</tr>
<tr>
<td>(0.008)</td>
<td>(0.012)</td>
</tr>
<tr>
<td>Vacancy growth</td>
<td>-0.001</td>
</tr>
<tr>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Predicted vac. growth</td>
<td>-0.030**</td>
</tr>
<tr>
<td>(0.014)</td>
<td>(0.025)</td>
</tr>
<tr>
<td>Observations</td>
<td>185,746</td>
</tr>
<tr>
<td>Fixed effects</td>
<td>Occ-City</td>
</tr>
<tr>
<td>Year</td>
<td>Year</td>
</tr>
</tbody>
</table>

* p < 0.10, ** p < 0.05, *** p < 0.01

Heteroskedasticity-robust standard errors clustered at the city level shown in parentheses. Units of observation are 6 digit SOC by city by year.
Robustness check: w/ industry Bartik control

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Log wage</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Full sample</td>
</tr>
<tr>
<td></td>
<td>All quartiles</td>
</tr>
<tr>
<td>Baseline specification – 2SLS regression of wage on instrumented HHI and instrumented occs</td>
<td></td>
</tr>
<tr>
<td>Log HHI, instrumented</td>
<td>-0.014*** (0.003)</td>
</tr>
<tr>
<td>Log outside-occ. options, instrumented</td>
<td>0.079*** (0.009)</td>
</tr>
<tr>
<td>Vacancy growth</td>
<td>-0.016*** (0.004)</td>
</tr>
<tr>
<td>Predicted vac. growth</td>
<td>0.010 (0.018)</td>
</tr>
<tr>
<td>Industry Bartik</td>
<td>0.129*** (0.013)</td>
</tr>
<tr>
<td>Observations</td>
<td>196,189</td>
</tr>
<tr>
<td>Fixed effects</td>
<td>Occ-Year</td>
</tr>
<tr>
<td></td>
<td>City-Year</td>
</tr>
</tbody>
</table>

* p < 0.10, ** p<0.05, *** p<0.01

Heteroskedasticity-robust standard errors clustered at the city level shown in parentheses. Units of observation are 6 digit SOC by city by year.
**Robustness check: employment-weighting**

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Log wage</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Full sample</strong></td>
<td><strong>By quartile of outward occupational mobility</strong></td>
</tr>
<tr>
<td><strong>All</strong></td>
<td>Q1</td>
</tr>
<tr>
<td>Log HHI, instrumented</td>
<td>-0.028***</td>
</tr>
<tr>
<td>(0.006)</td>
<td>(0.008)</td>
</tr>
<tr>
<td>Log outside-occ. options, instrumented</td>
<td>0.103***</td>
</tr>
<tr>
<td>(0.026)</td>
<td>(0.022)</td>
</tr>
<tr>
<td><strong>Observations</strong></td>
<td>212,289</td>
</tr>
<tr>
<td><strong>Fixed effects</strong></td>
<td>Occ-Year</td>
</tr>
<tr>
<td>City-Year</td>
<td>City-Year</td>
</tr>
</tbody>
</table>

* p < 0.10, ** p < 0.05, *** p < 0.01. Heteroskedasticity-robust standard errors clustered at metro area level. Units of observation: 6 digit SOC by metro area by year, employment-weighted.

(Back)
Robustness check: w/o vacancy growth controls

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Log wage</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Full sample</td>
</tr>
<tr>
<td></td>
<td>All</td>
</tr>
<tr>
<td>2SLS regression of wage on instrumented HHI and instrumented $\text{oo}^{\text{occ}}$</td>
<td></td>
</tr>
<tr>
<td>Log HHI, instrumented</td>
<td>-0.015*** (0.003)</td>
</tr>
<tr>
<td>Log outside-occ. options, instrumented</td>
<td>0.087*** (0.009)</td>
</tr>
<tr>
<td>Observations</td>
<td>212,417</td>
</tr>
<tr>
<td>Fixed effects</td>
<td>Occ-Year</td>
</tr>
<tr>
<td></td>
<td>City-Year</td>
</tr>
</tbody>
</table>

* p < 0.10, ** p<0.05, *** p<0.01. Heteroskedasticity-robust standard errors clustered at metro area level. Units of observation: 6 digit SOC by metro area by year.
Robustness check: equal-weighted vacancy growth control

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Log wage</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Log wage</td>
</tr>
<tr>
<td></td>
<td>Full sample</td>
</tr>
<tr>
<td></td>
<td>All</td>
</tr>
<tr>
<td>2SLS regression of wage on instrumented HHI and instrumented ( oo_{occ} )</td>
<td></td>
</tr>
<tr>
<td>Log HHI, instrumented</td>
<td>-0.015***</td>
</tr>
<tr>
<td>(0.003)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>Log outside-occ. options, instrumented</td>
<td>0.086***</td>
</tr>
<tr>
<td>(0.009)</td>
<td>(0.014)</td>
</tr>
<tr>
<td>Vacancy growth</td>
<td>-0.001</td>
</tr>
<tr>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Predicted vac. growth</td>
<td>0.000</td>
</tr>
<tr>
<td>(0.000)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Equal-weighted vac. growth</td>
<td>0.001</td>
</tr>
<tr>
<td>(0.001)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Observations</td>
<td>212,417</td>
</tr>
<tr>
<td>Fixed effects</td>
<td>Occ-Year</td>
</tr>
<tr>
<td>City-Year</td>
<td>City-Year</td>
</tr>
</tbody>
</table>

* * p < 0.10, ** p < 0.05, *** p < 0.01. Heteroskedasticity-robust standard errors clustered at metro area level. Units of observation: 6 digit SOC by metro area by year.
Robustness check: excluding underrepresented occupations in vacancy data

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Log wage</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Full sample</td>
</tr>
<tr>
<td></td>
<td>All</td>
</tr>
<tr>
<td>2SLS regression of wage on instrumented HHI and instrumented ( oo^{occ} )</td>
<td></td>
</tr>
<tr>
<td>Log HHI, instrumented</td>
<td>-0.014***</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
</tr>
<tr>
<td>Log outside-occ. options, instrumented</td>
<td>0.088***</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
</tr>
<tr>
<td>Observations</td>
<td>153,927</td>
</tr>
<tr>
<td>Fixed effects</td>
<td>Occ-Year</td>
</tr>
<tr>
<td></td>
<td>City-Year</td>
</tr>
</tbody>
</table>

* \( p < 0.10, ** p < 0.05, *** p < 0.01 \). Heteroskedasticity-robust standard errors clustered at metro area level. Units of observation: 6 digit SOC by metro area by year.

(Back)
Robustness check: weighting by occupation represented-ness in BGT vacancy data

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Log wage</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Full sample</td>
</tr>
<tr>
<td></td>
<td>All</td>
</tr>
<tr>
<td>2SLS regression of wage on instrumented HHI and instrumented $oo^{occs}$</td>
<td></td>
</tr>
<tr>
<td>Log HHI, instrumented</td>
<td>-0.019***</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
</tr>
<tr>
<td>Log outside-occ. options, instrumented</td>
<td>0.092***</td>
</tr>
<tr>
<td></td>
<td>(0.010)</td>
</tr>
<tr>
<td>Observations</td>
<td>212,289</td>
</tr>
<tr>
<td>Fixed effects</td>
<td>Occ-Year</td>
</tr>
<tr>
<td></td>
<td>City-Year</td>
</tr>
</tbody>
</table>

* p < 0.10, ** p < 0.05, *** p < 0.01. Heteroskedasticity-robust standard errors clustered at metro area level. Units of observation: 6 digit SOC by metro area by year.

(Back)
Robustness check: weighting by metro area represented-ness in BGT vacancy data

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Log wage</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Full sample</td>
</tr>
<tr>
<td></td>
<td>All</td>
</tr>
<tr>
<td>2SLS regression of wage on instrumented HHI and instrumented $oo^{occs}$</td>
<td></td>
</tr>
<tr>
<td>Log HHI, instrumented</td>
<td>-0.014***</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
</tr>
<tr>
<td>Log outside-occ. options, instrumented</td>
<td>0.083***</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
</tr>
<tr>
<td>Observations</td>
<td>212,289</td>
</tr>
<tr>
<td>Fixed effects</td>
<td>Occ-Year</td>
</tr>
<tr>
<td></td>
<td>City-Year</td>
</tr>
</tbody>
</table>

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Heteroskedasticity-robust standard errors clustered at metro area level. Units of observation: 6 digit SOC by metro area by year.
Relationship between HHI and HHI instrument
Heterogeneity by HHI

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Log wage</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Full sample</td>
</tr>
<tr>
<td></td>
<td>All quartiles</td>
</tr>
<tr>
<td>Log HHI, instrumented</td>
<td>-0.015***</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
</tr>
<tr>
<td>Log outside-occ. options, instrumented</td>
<td>0.087***</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
</tr>
<tr>
<td>Observations</td>
<td>212,417</td>
</tr>
<tr>
<td>F-stat</td>
<td>338</td>
</tr>
</tbody>
</table>

Panel B: HHI first stage

<table>
<thead>
<tr>
<th></th>
<th>Log HHI instrument</th>
<th>Log outside-occ. options instrument</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.107***</td>
<td>-0.723***</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.044)</td>
</tr>
<tr>
<td></td>
<td>0.075***</td>
<td>-0.602***</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.059)</td>
</tr>
<tr>
<td></td>
<td>0.030***</td>
<td>-0.165***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.018)</td>
</tr>
<tr>
<td></td>
<td>0.028***</td>
<td>-0.106***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.014)</td>
</tr>
<tr>
<td></td>
<td>0.034***</td>
<td>-0.201***</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.024)</td>
</tr>
<tr>
<td>Observations</td>
<td>212,417</td>
<td>53,106</td>
</tr>
</tbody>
</table>

Notes: Heteroskedasticity-robust standard errors clustered at the city level shown in parentheses. Quartile boundaries for the average HHI in the occupation-city labor market over 2013–2016 are 302 (p25), 678 (p50), and 1,442 (p75). Significance levels: * p<0.10, ** p<0.05, *** p<0.01.
Heterogeneity by occupational wage quartile

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Log wage</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>By quartile of occupation's avg wage, 2016</td>
</tr>
<tr>
<td></td>
<td>Q1</td>
</tr>
</tbody>
</table>

**Panel A: 2SLS IV regression**

<p>| | | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Log HHI,</td>
<td>-0.011**</td>
<td>-0.013***</td>
<td>-0.003</td>
<td>-0.017***</td>
<td>-0.008</td>
</tr>
<tr>
<td>instrumented</td>
<td>(0.005)</td>
<td>(0.004)</td>
<td>(0.005)</td>
<td>(0.005)</td>
<td>(0.006)</td>
</tr>
<tr>
<td>Log outside-occ. options,</td>
<td>0.059***</td>
<td>0.072***</td>
<td>0.059***</td>
<td>0.098***</td>
<td>0.079***</td>
</tr>
<tr>
<td>instrumented</td>
<td>(0.022)</td>
<td>(0.014)</td>
<td>(0.012)</td>
<td>(0.011)</td>
<td>(0.013)</td>
</tr>
<tr>
<td>Observations</td>
<td>20,687</td>
<td>45,440</td>
<td>76,569</td>
<td>69,715</td>
<td>56,663</td>
</tr>
<tr>
<td>F-stat</td>
<td>120</td>
<td>204</td>
<td>261</td>
<td>295</td>
<td>307</td>
</tr>
</tbody>
</table>

**Panel B: HHI first stage**

<p>| | | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Log HHI instrument</td>
<td>0.096***</td>
<td>0.119***</td>
<td>0.097***</td>
<td>0.104***</td>
<td>0.094***</td>
</tr>
<tr>
<td>(0.006)</td>
<td>(0.006)</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>Log outside-occ. options instrument</td>
<td>-0.540***</td>
<td>-0.512***</td>
<td>-0.705***</td>
<td>-0.635***</td>
<td>-0.610***</td>
</tr>
<tr>
<td>(0.070)</td>
<td>(0.055)</td>
<td>(0.043)</td>
<td>(0.047)</td>
<td>(0.044)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>20,687</td>
<td>45,440</td>
<td>76,569</td>
<td>69,715</td>
<td>56,663</td>
</tr>
</tbody>
</table>

Notes: Heteroskedasticity-robust standard errors clustered at the city level shown in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.
New occupational mobility data

Figure: Black indicates transition probability of 1% or greater conditional on leaving a job. Transitions to own occupation are excluded. Source: BGT data, 2002-2015.
1. Occupational mobility is high


Mean = 23%
2. Mobility is highly heterogeneous

<table>
<thead>
<tr>
<th>Occupation</th>
<th>Leave share (%)</th>
<th>Main target occ.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dental hygienists</td>
<td>6</td>
<td>Dental assistants</td>
</tr>
<tr>
<td>Nurse practitioners</td>
<td>9</td>
<td>Registered nurses</td>
</tr>
<tr>
<td>Pharmacists</td>
<td>9</td>
<td>Medical &amp; health svc mgrs.</td>
</tr>
<tr>
<td>Firefighters</td>
<td>10</td>
<td>EMTs &amp; paramedics</td>
</tr>
<tr>
<td>Self-enrichment educ. teachers</td>
<td>10</td>
<td>Teachers/instructors, all other</td>
</tr>
<tr>
<td>Bill and account collectors</td>
<td>32</td>
<td>Customer service rep.</td>
</tr>
<tr>
<td>Tellers</td>
<td>32</td>
<td>Customer service rep.</td>
</tr>
<tr>
<td>Machine setters, operators</td>
<td>32</td>
<td>Production workers, other</td>
</tr>
<tr>
<td>&amp; tenders (metal &amp; plastic)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Telemarketers</td>
<td>36</td>
<td>Customer service rep.</td>
</tr>
<tr>
<td>Food servers, nonrestaurant</td>
<td>45</td>
<td>Waiters and waitresses</td>
</tr>
</tbody>
</table>

'Leave share' is the number of people observed in occupation i in year T who are observed in any other occupation in year T + 1, as a share of all job switchers, ‘02-‘15.
3. Mobility is not well captured by SOC hierarchy


Mean = 86%
By metro area

Concentration affects wages most in smaller metro areas

Concentration affects wages most in lower-wage metro areas

(Back)