The Geography of Jobs and the Gender Wage Gap

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Gender wage gap

- Convergence of gender wage gap (Blau and Kahn, 2017)
  - Human capital gap (education, experience, etc.)
  - Discrimination

- Unexplained gap persists

- Preferences for non-pay job attributes => compensating differential (Goldin, 2014) (Wiswall et al., 2014, 2017) (Gutierrez, 2018), (Le Barbanchon et al., 2019)
  - Temporal flexibility
  - Occupations and industries

- Commuting friction

This paper
Preview:
• Large geographic variation in commuting friction due to the geography of jobs
• Commuting friction accounts for 17-20% of the remaining gender wage gap (preliminary)
Job Choice Model

Empirical Evidence

Estimating the Model

Decomposition Analysis
Job Choice Model

Empirical Evidence

Estimating the Model

Decomposition Analysis
Job choice model (1/3)

• Workers maximize following

\[ U(\tau, w) = \ln(w) - \lambda_i \tau \]

• Job choice frontier- maximum wage attainable within commuting time \( \tau \)

\[ \ln(w) = \xi_i + \beta_i \ln(\tau - \tau^{min}) \quad \text{if} \quad \tau > \tau^{min}, \]

\[ \ln(w) = \xi_i \quad \text{if} \quad \tau = \tau^{min} \]
Job choice model (2/3)

\[ U(\tau, w) = \ln(w) - \lambda_i \tau \]

\[ \ln(w) = \xi_i + \beta_i \ln(\tau - \tau^{\text{min}}) \text{ if } \tau > \tau^{\text{min}} \]
Job choice model (3/3) – smaller $\beta$

\[ U(\tau, w) = \ln(w) - \lambda_i \tau \]

\[ \ln(w) = \xi_i + \beta_i \ln(\tau - \tau^{min}) \text{ if } \tau > \tau^{min} \]
Model prediction

• Gender gap in commuting time and wage larger for workers living far from high-wage jobs (relative to low-wage jobs).
  
  • Workers living far from city centers should see larger wage and commuting gaps.
  
  • Gaps should vary more spatially for occupations in which high-wage jobs are geographically concentrated.

• Wage gap should be correlated with commuting gap.
Job Choice Model

Empirical Evidence

Estimating the Model

Decomposition Analysis
**Data**

- **American Community Survey (2013-2017)**
  - Cross-sectional earnings, hours worked and commuting time
  - Rich set of demographic variables: sex, age, marital status, children, education.
  - PUMA (Public Use Microdata Areas) geocode for each worker.
Empirical evidence (1/3): Gender gaps larger farther from city centers

Log wage gap

Residual log wage gap

Log commuting gap

Residual log commuting gap
Empirical evidence (2/3): wage gap is highly correlated with commuting gap

- Commuting gap can explain a portion of the gender wage gap
- Gender wage gap is slightly lower in places with no commuting gap. (0.1079 to \(~0.0893 \text{ – around 17\%}\)
Empirical evidence (3/3): Commuting gap unlikely driven by spatial sorting

- Management professional jobs are highly centralized
- Healthcare practitioner jobs much more decentralized

- Spatial sorting not likely drives commuting gap
Job Choice Model

Empirical Evidence

Estimating the Model

Decomposition Analysis
Estimating the Indifference curve

\[ U(\tau, w) = \ln(w) - \lambda_i \tau \]

- American Community Survey 2013-2017
- Under perfect mobility, utility U equal everywhere
  - Regress \( \ln(w) \) on \( \tau \) yield unbiased estimate of \( \lambda \)
- Simple cross-sectional regression yield biased results
  1. Location sorting by ability (demo)
  2. Random job arrival (demo)
- Identify the slope of reservation utility curve
  - Slope of the lower boundary of observed \( (\ln(w), \tau) \):
    - \( (\ln(w^R), \tau^R) \)
  - Estimator must be robust to outliers and measurement errors
  - 0.01 quantile regression on residualized \( (\ln(w), \tau) \) (simulation)
## Indifference curve: Results

<table>
<thead>
<tr>
<th></th>
<th>All (1)</th>
<th>Single no children (2)</th>
<th>Single w/ children (3)</th>
<th>Married no children (4)</th>
<th>Married w/ children (5)</th>
<th>College (6)</th>
<th>&lt; College (7)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>$\lambda_m$</strong></td>
<td>0.379***</td>
<td>0.408***</td>
<td>0.322***</td>
<td>0.467***</td>
<td>0.297***</td>
<td>0.330***</td>
<td>0.386***</td>
</tr>
<tr>
<td></td>
<td>(0.0119)</td>
<td>(0.0266)</td>
<td>(0.064)</td>
<td>(0.0253)</td>
<td>(0.0174)</td>
<td>(0.0197)</td>
<td>(0.0159)</td>
</tr>
<tr>
<td><strong>$\lambda_f$</strong></td>
<td>0.506***</td>
<td>0.357***</td>
<td>0.382***</td>
<td>0.616***</td>
<td>0.588***</td>
<td>0.491***</td>
<td>0.501***</td>
</tr>
<tr>
<td></td>
<td>(0.0144)</td>
<td>(0.0291)</td>
<td>(0.0377)</td>
<td>(0.0312)</td>
<td>(0.0267)</td>
<td>(0.0231)</td>
<td>(0.0199)</td>
</tr>
<tr>
<td><strong>$\lambda_f - \lambda_m$</strong></td>
<td>0.127***</td>
<td>-0.051</td>
<td>0.0598</td>
<td>0.149***</td>
<td>0.29***</td>
<td>0.161***</td>
<td>0.116***</td>
</tr>
<tr>
<td></td>
<td>(0.0187)</td>
<td>(0.0395)</td>
<td>(0.0743)</td>
<td>(0.0401)</td>
<td>(0.0319)</td>
<td>(0.0303)</td>
<td>(0.0255)</td>
</tr>
<tr>
<td><strong>Observations</strong></td>
<td>5,022,015</td>
<td>1,167,374</td>
<td>386,044</td>
<td>983,149</td>
<td>1,699,917</td>
<td>1,844,513</td>
<td>2,949,877</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Residence</th>
<th>NY (1)</th>
<th>Chicago (2)</th>
<th>SF (3)</th>
<th>Boston (4)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>$\lambda_m$</strong></td>
<td>0.379***</td>
<td>0.347***</td>
<td>0.475***</td>
<td>0.464***</td>
</tr>
<tr>
<td></td>
<td>(0.0439)</td>
<td>(0.0652)</td>
<td>(0.101)</td>
<td>(0.0704)</td>
</tr>
<tr>
<td><strong>$\lambda_f$</strong></td>
<td>0.429***</td>
<td>0.592***</td>
<td>0.660***</td>
<td>0.508***</td>
</tr>
<tr>
<td></td>
<td>(0.0467)</td>
<td>(0.0807)</td>
<td>(0.0827)</td>
<td>(0.105)</td>
</tr>
<tr>
<td><strong>$\lambda_f - \lambda_m$</strong></td>
<td>0.050</td>
<td>0.245***</td>
<td>0.185</td>
<td>0.0444</td>
</tr>
<tr>
<td></td>
<td>(0.0641)</td>
<td>(0.1037)</td>
<td>(0.131)</td>
<td>(0.126)</td>
</tr>
<tr>
<td><strong>Observations</strong></td>
<td>309,236</td>
<td>137,728</td>
<td>80,582</td>
<td>82,712</td>
</tr>
</tbody>
</table>
Measuring the Job choice set frontier

\[ \ln(w) = \xi_i + \beta_i \ln(\tau - \tau^{min}) \text{ if } \tau > \tau^{min} \]

- Simulate spatial distribution of jobs with wages for each occupation and residential PUMA
  - Mean and sd of residual wages - ACS 2013-2017 Place-of-Work PUMA (PWPUMA)
  - Zip Code Business Patterns (zip code level job count)
  - Google distance API
- Frontier estimator (Cazals et al. 2002) to pin down \( \beta \) (estimator)

Financial manager – Northern suburbs, NY  
Financial manager – Midtown Manhattan, NY
Job choice set frontier: Results

β distribution

β wrt. distance to downtown

β wrt. distance to downtown (Financial manager vs. physicians)
Job Choice Model

Empirical Evidence

Estimating the Model

Decomposition Analysis
Model prediction vs. data

\[
\ln(\tau^*_m) - \ln(\tau^*_f) = \frac{\beta_i (\lambda_f - \lambda_m)}{\lambda_m (\beta_i + \lambda_m \tau_{min})}
\]

\[
\ln(w^*_m) - \ln(w^*_f) = \frac{\beta_i (\lambda_f - \lambda_m)}{\lambda_m}
\]

- Predicted log wage gap is 0.01386 log gap (0.07038 actual gap) – 19.69%
- Predicted log commuting gap is 0.03365 log gap (0.0243 actual gap) – 138%
Counterfactual: increasing travel speed

- Reduce commuting time
- Re-compute $\beta$

Two effects
- Smooth existing trade-off ($\beta \downarrow$)
- Jobs previously too far may enter trade-off ($\beta \uparrow$)
- Nonlinear

<table>
<thead>
<tr>
<th>Reducing Commute Time by</th>
<th>0%</th>
<th>20%</th>
<th>50%</th>
<th>80%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Observed gap in log wage</td>
<td>0.07038</td>
<td>0.07038</td>
<td>0.07038</td>
<td>0.07038</td>
</tr>
<tr>
<td>Model explained gap</td>
<td>0.01386</td>
<td>0.01355</td>
<td>0.01297</td>
<td>0.00775</td>
</tr>
<tr>
<td>Fraction explained</td>
<td>19.69%</td>
<td>19.25%</td>
<td>18.43%</td>
<td>11.01%</td>
</tr>
</tbody>
</table>
Conclusion

• We analyze the role of commuting friction in the remaining gender wage gap

• Use a job choice model to illustrate that differential preferences for commuting and returns to commuting lead to wage differentials between genders

• Strong empirical support in the data

• Estimate the model: the indifference curve and job choice frontier

• Commuting friction explains a portion (17-20%) of the gender wage gap (preliminary)
Appendix
Log wage gap and log commuting gap
Sorting by ability
Random job arrival
Identification (1/2)
Identification (2/2)
Frontier estimator

• Cazals et al. (2002)

\[
\hat{\phi}_{m,n} (\ln(\tilde{\tau} - \tau_{\text{min}})) = \ln \left( w_{(1)}^{\tilde{\tau}} \right) + \sum_{j=1}^{n(\tilde{\tau})-1} \left[ \frac{n(\tilde{\tau}) - j}{n(\tilde{\tau})} \right]^{m} \left( \ln \left( w_{(j+1)}^{\tilde{\tau}} \right) - \ln \left( w_{(j)}^{\tilde{\tau}} \right) \right)
\]

\[
\ln \left( w_{(1)}^{\tilde{\tau}} \right) > \ln \left( w_{(2)}^{\tilde{\tau}} \right) > \ldots > \ln \left( w_{n(\tilde{\tau})}^{\tilde{\tau}} \right)
\]

• M=500

• n(\tau) is the number of observations less than \tau

• Robust to outliers

• Estimate the maximum log wage within certain log commuting time threshold