Automation, Offshoring, and the Job Ladder
European Research Workshop in International Trade

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  • the types and frequency of job offers that arrive from poaching firms
  • the likelihood of being thrown into unemployment
  • lifetime earnings trajectories
Organization of the talk

- Patterns in the data
- A dynamic model
- Estimates and implications
Polarization in the U.S. employment shares

Panel A. Smoothed changes in employment by skill percentile, 1980–2005

source: Autor and Dorn, AER (2013)
Polarization in U.S. wages

Panel B. Smoothed changes in real hourly wages by skill percentile, 1980–2005

source: Autor and Dorn, AER (2013)
### Polarization in Europe (18 countries)

<table>
<thead>
<tr>
<th></th>
<th>Share of Employment</th>
<th>ΔShare, 1993-2010</th>
</tr>
</thead>
<tbody>
<tr>
<td>High-paying occupations</td>
<td>31.67</td>
<td>5.62</td>
</tr>
<tr>
<td>Middling occupations</td>
<td>46.75</td>
<td>-9.27</td>
</tr>
<tr>
<td>Low-paying occupations</td>
<td>21.56</td>
<td>3.65</td>
</tr>
</tbody>
</table>

- Source: Goos, Manning, and Salomons (*AER*, 2014)
- Data: European Labor Force Survey.
- Countries covered: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Norway, Portugal, Spain, Sweden, United Kingdom.
Possible reasons for polarization

• **Technological progress**
  • information and computer technology
    • ↓ routine office work
  • automation
    • ↓ factory floor workers, ↑ industrial robots

• **Globalization**
  • offshoring of routine tasks
    • ↓ value-added to gross output ratios
  • import competition, manufactured goods
    • ↓ gross output levels
Automation in the U.S.
automated task similarity and employment growth (1999-2019)

Source: Montobbio, et al. IZA working paper 14879 (2021)
Data: robotic patent data from USPTO; task content of occupations from ONET; wage growth from BLS
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Figure: Wage growth and ease of automation

- Source: Montobbio, et al. IZA working paper 14879 (2021)
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Trade and globalization in the U.S
Import penetration and employment share changes

- Source: SIPP, WIOD and own calculations
Earnings and globalization in the U.S.

- Source: Autor, Dorn, Hanson, Song (QJE, 2014)
- Dots show post-1991 effect of industry exposure to Chinese import competition on workers’ earnings. 75th percentile of trade exposure earned 38% less than 25th percentile after 16 years
Modeling the linkages: some structural empirical models

- **Trade and labor** (Adao, et al., 2022; Huneeus, 2022; Lee, 2020; Ferriere et al., 2020; Bellon, 2018; Burstein and Vogel, 2017; Galle, et al., 2017; Traiberman, 2017; Cosar et al., 2017; Dix-Carneiro, 2014; Artuc et al., 2010, 2015; Helpman et al., 2010, 2017)

- **Technology and labor** (Acemoglu and Restrepo, 2018, 2020; Humlum, 2019; Lee and Wolpin, 2006)

- **Trade, technology and labor** (Koch, et al., 2021; Morrow and Trefler, 2020; Burstein et al., 2019; Goos, et al., 2014; Burstein and Vogel, 2017)
Circle size reflects employment share in 1990
Data sources: ONET and Bureau of Labor Statistics
Circles reflect employment share in 1990 (blue) or 2010 (orange)

Data sources: ONET and Bureau of Labor Statistics
Change in probability of moving down/up the ladder
(2010 - 1990)

moving down:
\[ \Pr^{2010}(s_{t+1} < s_t \mid \text{move}) - \Pr^{1990}(s_{t+1} < s_t \mid \text{move}) \]

moving up:
\[ \Pr^{2010}(s_{t+1} > s_t \mid \text{move}) - \Pr^{1990}(s_{t+1} > s_t \mid \text{move}) \]

See also: Groes, et al. (2014); Keller and Utar (2021)
Change in job-to-job turnover, 2010 vs. 1990

- Each dot represents the change in J-J turnover rate for a particular occupation. (Based on SIPP.)
- Turnover has fallen more at the low end of the skill distribution. See also: Davis and Haltiwanger, 2014; Cairo et al., 2015.
Each dot gives the change in E-U rate for a particular occupation. Separations into non-employment rose at the low end of the skill distribution.
Each dot gives the change in the share of trained workers in a particular occupation.

Training rates rose at the high end of the skill distribution.
Modeling the goods markets

- Similar to Caliendo and Parro (2014), but with multiple types of labor services
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- 24 countries, each with own sector-specific productivity levels
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- 30 sectors, half are tradable
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- Each sector uses intermediate inputs obtained from cheapest source, including foreign bundles of labor services (assembly, legal, transport, etc.) and physical capital.
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  - bargain over their wages
  - improve their ability through experience
  - may also improve their ability through employer investments in on-the-job training (Flinn et al, 2016).

- Over their life cycles, workers' wage growth is driven by:
  - improvements in ability, including through training
  - shocks to employer profitability
  - arrival of job offers from poaching employers, own or neighboring occupations ("job ladder")
  - unemployment spells
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Polarization in the model

- Reduces demand for mid-skill occupations slows down turnover in adjacent occupations.
  - slows movement up job ladder
  - more likely to separate into unemployment and lose bargaining power

- Changes the incentives to invest in college degrees.
  - College allows one to leapfrog missing rungs in the job ladder
  - At the margin, people switching to college are less qualified

- Affects training incentives:
  - Those with college degrees see greater returns to on-the-job training.
  - Those without degrees are forced into jobs with little scope for training or on-the-job learning.
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Agent types: **Workers, Task Producers, and Goods Producers**
• Born with an initial ability level $a_0$ drawn from $F_{a_0}(\cdot)$

• Either invest in a college degree (become an $H$-type) or enter the labor market immediately as low-skilled ($L$-type) worker.

• Those who go to college incur a utility cost of $\kappa/a_0$

• Stochastically improve their ability level, moving up through the finite ordered set $a \in \{a^1, \ldots, a^I\}$.

• **Hazard of a one-step improvement** for a worker in state $(E, a)$ at a firm producing type-$j$ services with productivity $z$:

\[
\gamma_E(a, j, z) = \gamma_{j, E}^1 + \gamma_{j, E}^2 1^t_E(a, j, z)
\]

where $E \in \{H, L\}$ and $1^t_E(a, j, z) = 1$ if the worker and her employer have agreed to training (Flinn et al., 2017).
Service-producing firms

- Specialize in producing a particular service \( j \in \{1, \ldots, J\} \)
- One worker or vacancy per firm. Flow vacancy posting cost: \( c_v \)
- Employ workers they match with in a frictional labor market.
- May invest in the training of their employees, flow cost \( c^t \).
- Experience ongoing, idiosyncratic productivity shocks, \( z \).
- Supply output \( \ell_E(a, j, z) \) in competitive national market at price \( r_j \). Service production technology:

\[
\ell_E(a, j, z) = zs_j a \zeta_{j,E} - c^t 1^t_E(a, j, z) - c^o - \min \{0, a - \kappa_E s_j z\}^2 - \min \{0, s_j z - \iota_E a\}^2
\]

Skill-augmenting technical change is captured by changes in \( s_j \) values over time.
• Within sector $k$, firms that supply quantity $q_{k\omega}$ of variety $\omega \in \Omega_k$ do so using the following technology:

\[
q_{k\omega} = e_{k\omega} (\bar{y}_{k\omega})^{\alpha_k} \prod_{\tilde{k}=1}^{K} \left(x_{k\omega}^{\tilde{k}}\right)^{(1-\alpha_k)\theta_{k\tilde{k}}}, \text{ where}
\]

\[
\bar{y}_{k\omega} = \left(\prod_{j=1}^{J} \left(\ell_{j_{k\omega}}^j\right)^{\mu_j^j_k}\right)^{s_L^L} \left(h_{k\omega}\right)^{1-s_L^L},
\]

\[
x_{k\omega}^{\tilde{k}} = \left[\int_{\tilde{\omega} \in \Omega_{\tilde{k}}} \left(x_{k\omega}^{\tilde{\omega}}\right)^{\eta_{k-1}} d\tilde{\omega}\right]^{\frac{\eta_k}{\eta_{k-1}}}
\]

• Here $x_{k\omega}^{\tilde{k}\tilde{\omega}}$ is intermediate usage of variety $\tilde{\omega}$, good $\tilde{k}$,

• $\ell_{j_{k\omega}}^j$ is usage of occupational service $j$, and

• $h_{k\omega}$ is usage of capital services.
Goods producers: Technology

• Production function (from previous slide):

\[ q_{k\omega} = e_{k\omega} (\bar{y}_{k\omega})^{\alpha_k} \prod_{\tilde{k}=1}^{K} (x_{k\omega}^{\tilde{k}})^{(1-\alpha_k)\theta_{k\tilde{k}}}) \]

• In country \( n \), \( e_{k\omega} \) draws are distributed Fréchet with location parameter \( T_n \) and dispersion parameter \( \theta_k \).

• Factor-augmenting technical progress (relative to U.S.) is reflected in changes in \( T_n \).

• Automation is reflected in changes in labor’s share in value added \( s_k^L \) and factor service weights \( \mu_k^j \), as in Acemoglu and Restrepo (2018).

• Globalization is reflected in changes in iceberg costs and tariffs.
Market clearing

- Standard income equation, generalized to include return on capital stocks:

\[
Y^n = \sum_{j=1}^{J} r_j^n L_j^n + (1 - \Psi) \sum_{k=1}^{K} \alpha_k (1 - s_L^k) X_k^n,
\]

- \(L_j^n\) is total usage of type-\(j\) occupational services—matches supply in equilibrium.

- \(\Psi\) is share of spending on capital goods that goes to replacement of depreciated capital.

- \(X_k^n = \int_{\omega \in \Omega_k} p_{k\omega}^n q_{k\omega}^n \, d\omega\) is total value of \(k\)-type bundles supplied by country \(n\).

- Standard global product market clearing conditions, generalized to incorporate spending on replacement capital (trade frictions enter here.)
Random matching: visibility

- Service-producing firms hire both unemployed and employed workers (poaching).

- Random matching within education-specific markets.

- Workers relatively likely to encounter jobs similar to the ones they hold. Probability of drawing occupation $j$ :
  - $\Gamma^u_j$ for unemployed worker
  - $\Gamma^\ell_{\tilde{j}j}$ for employed worker currently in occupation $\tilde{j}$, where

$$
\Gamma^\ell_{\tilde{j}j} = \frac{\sqrt{\left(\mathbf{v}_j - \mathbf{v}_{\tilde{j}}\right)' \sum^{-1} \left(\mathbf{v}_j - \mathbf{v}_{\tilde{j}}\right)}}{\sum_{j'} \sqrt{\left(\mathbf{v}_{j'} - \mathbf{v}_{\tilde{j}}\right)' \sum^{-1} \left(\mathbf{v}_{j'} - \mathbf{v}_{\tilde{j}}\right)}}
$$

and $\mathbf{v}_j$ is vector of brain, brawn, and social skill indices.
Wage setting and career paths

• Wage setting with on-the-job search is based on Mortensen (2011). (Alternatives: Bagger et al., 2014; Lise et al., 2016)
  • Standard Nash bargaining over match surplus
  • Renegotiation after productivity shocks
  • Renegotiation after human capital shocks
  • Workers move to poaching firm when match surplus is larger.

• Wage setting, in combination with the visibility function and labor market tightness, (probabilistically) determines the career paths of different types of workers
Steady state equilibrium

- Product and factor markets clear

- Workers and firms maximize their expected present values
  - Firms enter when they expect positive net returns and shut down when continuation values are negative
  - Firms make optimal training choices (i.e., maximize match surplus)
  - Workers make optimal college decisions, given their initial abilities
  - Workers accept job offers that improve their continuation values.

- Inflows match outflows for
  - each type of labor service/occupations and unemployed states
  - task producers of each type of labor service

- Free entry condition holds for task producing firms
Preliminary Calibration

- Baseline period: 2010-2013
- Countries: 23 + ROW
- Industries: 30 ISIC Rev.3.1 (15 tradable)
- Occupations: 12 SOC 2-digit

- The economy is assumed to be in steady state with free entry
- Estimation: simulated method of moments
• **Skill-augmenting technical change**: $s_j$ values are chosen to match observed employment levels by occupation, each year.

• **Factor-augmenting technical progress**: $T^n_k$ values are imputed as in Bolatto (2013).

• **Automation**: $s^L_k$ and $\mu^j_k$ are taken directly from year-specific factor shares.

• **Globalization effects**: tariffs ($\tau^n_k$) from data, iceberg costs ($\kappa^n_{k}$) imputed as in Anderson and van Wincoop’s (2003).

• **Non U.S., labor markets treated as competitive**
  • no intra-country, cross-sectoral variation in occupational bundling weights.
  • $s^L_k$ and $\mu^j_k$ are therefore absorbed by $T^n_k$, $n \neq U.S.$
Estimated productivity measures

- Calculations based on bilateral trade flows as in Bolatto (2013)
Some targeted moments (labor markets)

<table>
<thead>
<tr>
<th>Selected moments</th>
<th>Data</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Labor income</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average college premium</td>
<td>0.509</td>
<td>0.420</td>
</tr>
<tr>
<td>Std. dev., non-college</td>
<td>0.605</td>
<td>0.620</td>
</tr>
<tr>
<td>Std. dev., college</td>
<td>0.622</td>
<td>0.517</td>
</tr>
<tr>
<td>Avg. income growth, non-college</td>
<td>0.331</td>
<td>0.235</td>
</tr>
<tr>
<td>Avg. income growth, college</td>
<td>0.503</td>
<td>0.430</td>
</tr>
<tr>
<td>5 yr. income growth, trained</td>
<td>0.318</td>
<td>0.515</td>
</tr>
<tr>
<td>5 yr. income growth, non-trained</td>
<td>0.273</td>
<td>0.331</td>
</tr>
</tbody>
</table>
## Targeted moments (continued)

<table>
<thead>
<tr>
<th>Selected moments, continued</th>
<th>Data</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Labor market flows</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>E-NE transition, intercept (brain content)</td>
<td>2.110</td>
<td>2.002</td>
</tr>
<tr>
<td>E-NE transition, slope (brain content)</td>
<td>-0.581</td>
<td>-0.157</td>
</tr>
<tr>
<td>E-NE rate, college</td>
<td>1.610</td>
<td>1.421</td>
</tr>
<tr>
<td>E-NE rate, non-college</td>
<td>2.536</td>
<td>2.306</td>
</tr>
<tr>
<td>J-J rate, intercept (brain content)</td>
<td>1.472</td>
<td>1.537</td>
</tr>
<tr>
<td>J-J rate, slope (brain content)</td>
<td>-0.185</td>
<td>-0.169</td>
</tr>
<tr>
<td>J-J rate, college</td>
<td>1.263</td>
<td>0.844</td>
</tr>
<tr>
<td>J-J rate, non-college</td>
<td>1.430</td>
<td>1.540</td>
</tr>
<tr>
<td><strong>Education</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>College share</td>
<td>0.251</td>
<td>0.276</td>
</tr>
<tr>
<td>Training share</td>
<td>0.392</td>
<td>0.076</td>
</tr>
<tr>
<td>Trained share, employed</td>
<td>0.390</td>
<td>0.130</td>
</tr>
<tr>
<td>Trained share, non-employed</td>
<td>0.173</td>
<td>0.043</td>
</tr>
</tbody>
</table>
Automation shock
Average changes in occupational shares

Change in average occupational share, by brain content

Occupation brain content
### Change with automation shock

| Transition Type                        | Value  
|---------------------------------------|--------
| E-NE transition, intercept (brain content) | 0.025  
| E-NE transition, slope (brain content)   | -0.083 
| E-NE transition, college               | -0.020 
| E-NE transition, non-college           | 0.038  
| J-J rate, intercept (brain content)    | -0.092 
| J-J rate, slope (brain content)        | 0.024  
| J-J rate, college                      | 0.140  
| J-J rate, non-college                  | -0.011 

Counterfactual patterns of heterogeneity

<table>
<thead>
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<tbody>
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<td>College share</td>
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<tr>
<td>Training share</td>
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<td>Life-cycle income growth, non-college</td>
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<td>Life-cycle income growth, college</td>
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observed changes, life cycle  ▶ occupation-specific results
Concluding remarks

- Model calibration and simulations very preliminary:
  - extend the model to account for limited portability of human capital.
- Meant to provide a way of thinking about effects in play; not final word on quantitative outcomes.
- Adding in trade shocks will enrich the analysis, but some limitations will remain:
  - doesn’t describe outcomes during transition to polarized world
  - presumes passive adjustments in capital stocks
- The model will provide a basis for analysis of heterogeneous impact of various policies on workers
  - protectionism
  - tax on automation (Acemoglu, Humlum)

• **Occupational Information Network (O*NET)**: Skill mix (brain, brawn, social) of 4-digit occupations

• **Occupational Employment Statistics (OES)**: Annual employment and wage estimates for about 800 occupations, broken down by industry.
Earnings-age profile: 1990 and 2010

Imputed life-cycle profiles, SIPP

- Profile for tradable occupations flattens relative to others.
Automation shock
change in avg. occupational wages

growth in avg. wage and brain content
Automation shock
change in college degree rates, by occupation

![Graph showing change in college shares and brain content](image-url)
Automation shock
change in training rates, by occupation

change in trained shares and brain content

Figure
• **Why have a service producing sector?**
  
  • Need poaching and search frictions to help drive wage trajectories.

  • If goods producers hired multiple types of workers directly, wage bargaining would become impossibly complex.

  • Competitive markets for occupational services divorce effects of hiring frictions from producers’ factor proportions decisions.
Matching

• Aggregate measure of job seekers, market $E$:

$$K_E = U_E + \lambda_E N_E \quad \forall E \in \{L, H\}$$

• The volume of matches in market $E$ is:

$$m_E(V_E, K_E) = A_E K_E^\chi V_E^{1-\chi}$$

where $V_E$ is vacancies posted and $A_E$ and $\chi$ are parameters.

• Once in contact, each worker-vacancy pair randomly draws an occupation $j$ and productivity $z$.
  • Probability of a type-$j$ job is $\Gamma^\ell_j$ or $\Gamma^u_j$, depending upon worker’s status.
  • Productivity draws are from $\Lambda^0(z)$

• If the draws generate positive match surplus, the match is consummated.
• Wage setting with on-the-job search related to Mortensen (2010), Bagger et al. (2014), Lise et al. (2016)

• Define:
  • $S_E(a, j, z)$: match surplus when a type-$(E, a)$ worker meets a type-$j$ firm in productivity state $z$
  • $J_E^e(w_u, a, j, z)$: value of the job to the worker
  • $J_E^u(a)$: value of unemployed state.

• **Workers hired out of unemployment**: the negotiated wage solves:

$$J_E^e(w_u, a, j, z) - J_E^u(a) = \beta S_E(a, j, z)$$
Encounters with potential poachers

Suppose type-$(E, a)$ worker at a type-$(j, z)$ firm discovers a vacandy at a type-$(\tilde{j}, \tilde{z})$ firm. Possible outcomes:

- **Surplus bigger at potential poaching firm:** $S_E(a, \tilde{j}, \tilde{z}) \geq S_E(a, j, z)$. Worker moves and receives wage that solves

  $$J_E^e(w_o, a, \tilde{j}, \tilde{z}) - J_E^u(a) = \beta S_E(a, \tilde{j}, \tilde{z})$$

- **Surplus less at potential poaching firm:** $S_E(a, \tilde{j}, \tilde{z}) < S_E(a, j, z)$. Poaching firm has no effect on worker’s wage:

  $$w_o = w$$
Productivity shocks

- **Productivity shock destroys match surplus:** \( S_E(a, j, z') < 0 \). Worker reverts to unemployed state:

  \[
  w_\varphi = b_E
  \]

- **Productivity shock doesn’t destroy match surplus:** \( S_E(a, j, z') \geq 0 \). Worker renegotiates wage:

  \[
  J^e_E(w_\varphi, a, j, z') - J^u_E(a) = \beta S_E(a, j, z')
  \]

- **Exogenous separation shock:** Worker reverts to unemployed state:

  \[
  w_\varphi = b_E
  \]
• **Shock destroys match surplus:** $S_E(a', j, z) < 0$. Worker reverts to unemployed state:

$$w_\varphi = b_E$$

• **Shock doesn’t destroy match surplus:** $S_E(a', j, z) \geq 0$. Worker renegotiates wage:

$$J^e_E(w_\varphi, a', j, \tilde{z}) - J^u_E(a') = \beta S_E(a', j, \tilde{z})$$
Value of being employed:

\[ [\rho + \delta \ell] J_E^e(w, a, j, z) = w + \delta f [J^u_E(a) - J^e_E(w, a, j, z)] + \phi \sum_{\tilde{z} \in \mathcal{Z}} \left[ \max \{ J^e_E(w, a, j, \tilde{z}), J^u_E(a) \} - J^e_E(w, a, j, z) \right] \Lambda(\tilde{z} | z) + \gamma_E(a, j, z) \left[ \max \{ J^e_E(w, a', j, z), J^u_E(a') \} - J^e_E(w, a, j, z) \right] + \phi_{1E} \sum_{\tilde{j} \in \mathcal{J}} \sum_{\tilde{z} \in \mathcal{A}_E(a, j, z | \tilde{j})} \left[ J^e_E(w, a, j, \tilde{z}) - J^e_E(w, a, j, z) \right] \Lambda^o(\tilde{z}) \Gamma^e_{\tilde{j} \tilde{z}} \]
Values of producer

Value of a job:

\[
[\rho + \delta_f] \Pi_E^e (w, a, j, z)
= r_j y_E (a, j, z) - w + \delta_\ell [\Pi^v_E - \Pi_E^e (w, a, j, z)]
+ \phi \sum_{\tilde{z} \in \mathbb{Z}} \left[ \max \{ \Pi_E^e (w_\varphi, a, j, \tilde{z}), \Pi^v_E \} - \Pi_E^e (w, a, j, z) \right] \Lambda (\tilde{z} | z)
+ \gamma_E (a, j, z) \left[ \max \{ \Pi_E^e (w_\gamma a', j, z), \Pi^v_E \} - \Pi_E^e (w, a, j, z) \right]
+ \phi^l \sum_{\tilde{j} \in S} \sum_{\tilde{z} \in A_E (h, j, z | \tilde{j})} \left[ \Pi^v_E - \Pi_E^e (w, a, j, z) \right] \Lambda^o (\tilde{z}) \Gamma^e_{\tilde{j}}.
\]
Value of unemployment, vacancy

Value of being unemployed:

\[
[\rho + \delta_\ell + \delta^E_u] J^u_E(a) = b_E + \beta \phi_{0E}^\ell \sum_{j \in J} \sum_{z \in Z} \max\{S_E(a, j, z), 0\} \Lambda^o(z) \Gamma^u_j + \delta^E_u J^u_E(a')
\]

Value of an open vacancy:

\[
(\rho + \delta_f) \Pi^\nu_E
\]

\[
= -c^\nu_E + (1 - \beta) \phi_{0E}^f \sum_{j \in J} \sum_{z \in Z} \sum_{a \in A} \max\{S_E(a, j, z), 0\} g_E(a) \Lambda^o(z) \Gamma^u_j
\]

\[
+ (1 - \beta) \phi_{1E}^f \sum_{j \in J} \sum_{z \in Z} \sum_{a \in A} \sum_{j' \in J} \sum_{\tilde{z} \in A_E(a, j, z)} S_E(a, j, z) f_E(a, \tilde{z}|j') \Lambda^o(z) \Gamma^e_{jj'}
\]
Market clearing conditions

- Clearing in product markets:

\[ X^n_k = \sum_{\tilde{k}=1}^{K} \left[ (1 - \alpha_{\tilde{k}}) \theta_{\tilde{k}k} + \Psi \zeta_{\tilde{k}k} \alpha_{\tilde{k}}(1 - s_{\tilde{k}k}^L) \right] \sum_{\tilde{n}=1}^{N} \frac{\pi_{\tilde{n}} \tilde{n} \alpha_{\tilde{k}}}{1 + \tau_{\tilde{n}} \tilde{n}} X^n_{\tilde{n}} + v^n_k I_n \]

\[ I^n = Y^n + G^n + D^n \]

\[ G^n = \sum_{k=1}^{K} \sum_{\tilde{n}=1}^{N} \frac{\pi^n_k \tilde{n} X^n_k}{1 + \tau^n_k} \]

\[ D^n = \sum_{k=1}^{K} \sum_{\tilde{n}=1}^{N} \frac{\pi^n_k \tilde{n} X^n_k}{1 + \tau^n_k} - \sum_{k=1}^{K} \sum_{\tilde{n}=1}^{N} \frac{\pi^n_k \tilde{n} X^n_{\tilde{n}}}{1 + \tau^n_k} \]

- Clearing in labor services markets:

\[ Y^n = \sum_{k=1}^{K} \mu^n_{jk} \frac{s^n_k \alpha^n_k}{\bar{r}_k} X^n_k = N_j \sum_{E \in \{L, H\}} \sum_{i \in I} \sum_{z \in Z} y_E(j, z, i) f_E(j, z, i) \]

\[ \text{demand} \quad \text{supply} \]
• Free entry condition for service-producing firms

\[ \sum_{z \in Z} \Pi^v(j, z) \Lambda^e(z) \leq 0, \quad F_j \geq 0, \quad \forall j \in J \]

• Flow balance of service-producing firms across states

\[ F_{jz} \left[ \delta_f + \varphi \sum_{\tilde{z} \in Z / z} \Lambda(\tilde{z} | z) \right] = \varphi \sum_{\tilde{z} \in Z} \Lambda(z | \tilde{z}) F_{j\tilde{z}} + \Lambda^e(z) F^e_j \quad \forall z \in Z, \forall j \in J \]
Flows of service-producing firms-workers matches

\[
\begin{align*}
\gamma_E(j, z, i - 1) N_{Ej} f_E(j, z, i - 1) &+ \varphi \sum_{\tilde{z} \in \mathcal{Z}} \Lambda(z|\tilde{z}) N_{Ej} f_E(j, \tilde{z}, i) \\
+ \left[ \tilde{\phi}_{0j} U_E u_E(i) + \sum_{\tilde{j} \in S} \tilde{\phi}_{jj} N_{E\tilde{j}} \sum_{\tilde{z} \in \mathcal{C}_1(\tilde{j}, z, i|j)} n_E(\tilde{j}, \tilde{z}, i) \right] v_{Ej}(z) = & \\
\delta_w + \delta_f + \varphi \sum_{\tilde{z} \in \mathcal{Z}/z} \Lambda(\tilde{z}|z) + \gamma_E(j, z, i) + \sum_{\tilde{j} \in S} \tilde{\phi}_{j\tilde{j}} \sum_{\tilde{z} \in \mathcal{C}_2(j, z, i|\tilde{j})} v_{E\tilde{j}}(\tilde{z}) & N_{Ej} f_E(j, z, i)
\end{align*}
\]
Flows of workers across states

\[ U_{Ei}[\delta_w + \sum_{j \in J} \tilde{\phi}_{0,j} \sum_{z \in Z} 1\{S_E(j,z,i) \geq 0\} V_{Ej}(z)] \]

\[ = \delta_f \sum_{j \in J} \sum_{z \in Z} N_{Ejzi} + \varphi \sum_{j \in S} \sum_{z \in Z} N_{Ejzi} \sum_{\tilde{z} \in Z} 1\{S_E(j,\tilde{z},i) < 0\} \Lambda(\tilde{z}|Z) + L^e_{Ei} \]

outflows from unemployment

inflows to unemployment

new entrants

back
Australia, Austria, Brazil, Canada, Chile, China, Denmark, Finland, France, Germany, Greece, Hungary, India, Indonesia, Ireland, Italy, Japan, Korea, Mexico, Netherlands, New Zealand, Norway, Portugal, South Africa, Spain, Sweden, Turkey, UK, USA, ROW.
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<td>Brain</td>
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Distance measures

Distance matrix for 1-digit 2002 SOC occupations

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<th>31-39</th>
<th>41-43</th>
<th>45-49</th>
<th>51-53</th>
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<td>3.26</td>
<td>5.96</td>
<td>0.75</td>
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</table>

\[
d(j, \tilde{j}) = \sqrt{(v^j - v^{\tilde{j}})^\top \Sigma^{-1} (v^j - v^{\tilde{j}})}
\]
• Productivity:

\[
\log \frac{T_n^k}{T_i^k} = \log \frac{X_{nn}^k}{X_{ni}^k} - \theta_k \alpha_k \log \left( \frac{\bar{r}_i^k}{\bar{r}_n^k} \right) - \\
\theta_k (1 - \alpha_k) \sum_{l=1}^K \lambda_{kl} \left[ -\frac{1}{\theta_l} \log \frac{X_{nn}^l}{X_{ni}^l} + \log \kappa_{ni}^l + \frac{1}{\theta_l} \log \left( \frac{X_{nn}^l}{X_{nn}^i} / \frac{X_{ni}^l}{X_{ni}^i} \right) \right] \\
- \theta_k \log \kappa_{ni}^k
\]

• Iceberg costs:

\[
\log \kappa_{ni}^k = -\frac{1}{2} \left[ \log(\pi_{ni}^k) - \log(\pi_{nn}^k) + \log(\pi_{in}^k) - \log(\pi_{ii}^k) \right] \frac{1}{\theta_k} \\
- \frac{1}{2} \log(1 + \tau_{ni}^k) - \frac{1}{2} \log(1 + \tau_{in}^k)
\]
## Parameter estimates

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<td>Pareto scale - initial human capital</td>
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<td>Pareto shape - initial human capital</td>
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<td>Visibility employed, low educated</td>
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<td>$\bar{s}$</td>
<td>0.5042</td>
</tr>
<tr>
<td>Occupation specific productivity slope</td>
<td>$\Delta_s$</td>
<td>0.1384</td>
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