Automation, Offshoring, and the Job Ladder

NYU Seminar

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The core question

How have globalization, computerization, and automation affected the career paths of heterogeneous workers?

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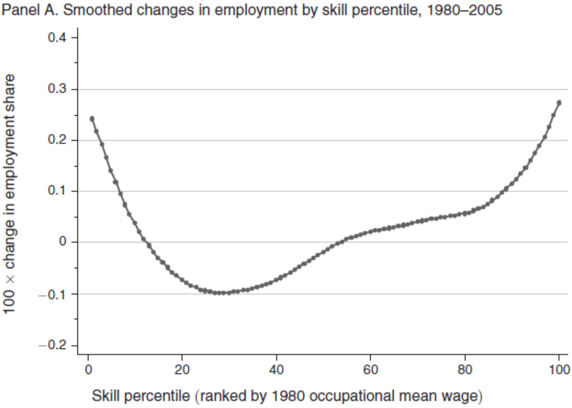
  - protectionism–selective or general
  - robot tax

Plan for the talk

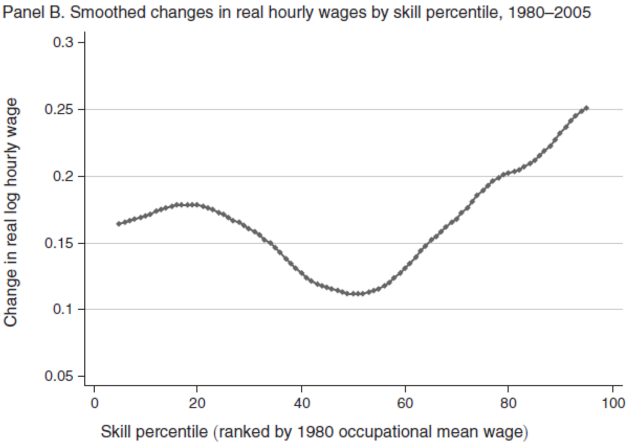
- Patterns in the data
- A dynamic model
- Estimates and implications

Polarization in the U.S. employment shares



- source: Autor and Dorn, AER (2013)

Polarization in U.S. wages



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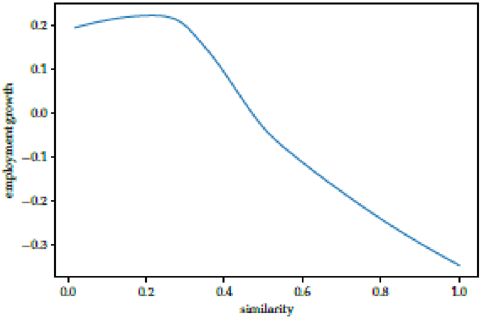
Polarization in Europe (18 countries)

	share of employment	Δ*share*, 1993-2010
High-paying occupations	31.67	5.62
Middling occupations	46.75	-9.27
Low-paying occupations	21.56	3.65

- Source: Goos, Manning, and Salomons (*American Economic Review*, 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

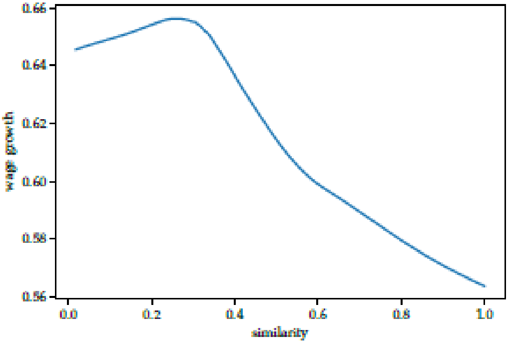
- **Technological progress**
  - information and computer technology
    - $\Downarrow$ routine office work
  - automation
    - $\Downarrow$ factory floor workers, $\Uparrow$ industrial robots
- **Globalization**
  - offshoring of routine tasks
    - $\Downarrow$ value-added to gross output ratios
  - import competition, manufactured goods
    - $\Downarrow$ gross output levels



- Source: Montobbio, et al. (2021)
- Data: robotic patent data from USPTO; task content of occupations from ONET; employment growth from BLS

Automation in the U.S.

automated task similarity and wage growth (1999-2019)



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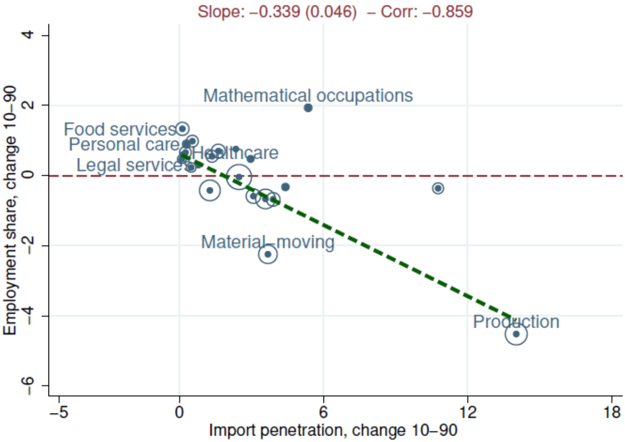
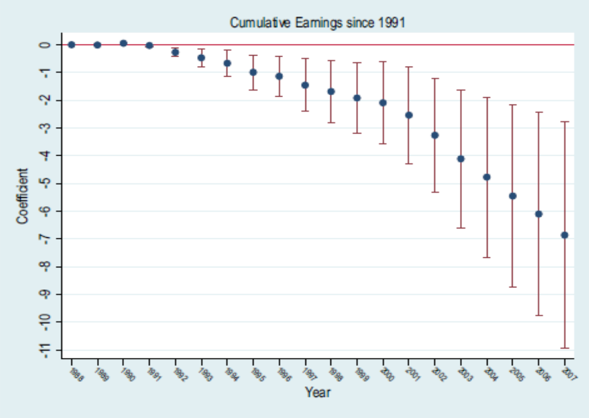
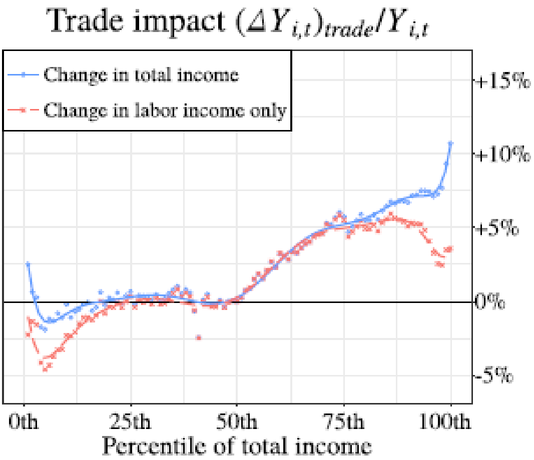

Slope: –0.339 (0.046) – Corr: –0.859
Mathematical occupations
Food services
Personal care
Healthcare
Legal services
Material–moving
Production
Employment share, change 10–90
Import penetration, change 10–90
4
2
0
–2
–4
–6
–5
0
6
12
18

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

Earnings and globalization in Ecuador



- Source: Adao, et al. (2022, QJE)
- Effects of exports and imports on income in Ecuador, recognizing indirect linkages

Some related trade and labor papers

- **Stylized facts, trade and labor** Jensen and Kletzer (2006); Kletzer (2007); Autor and Dorn (2013); Autor, Dorn, and Hanson (2013); Autor, Dorn, Hanson, and Song (2014); etc.
- **Structural trade and labor models** 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. (2016); Dix-Carneiro (2014); Artuc et al. (2010, 2015); Helpman et al. (2010, 2017)
- **Structural trade, technology and labor models** Koch, et al. (2021); Morrow and Trefler (2020); Burstein et al. (2019); Goos, et al. (2014); Burstein and Vogel (2017)

Some related labor papers

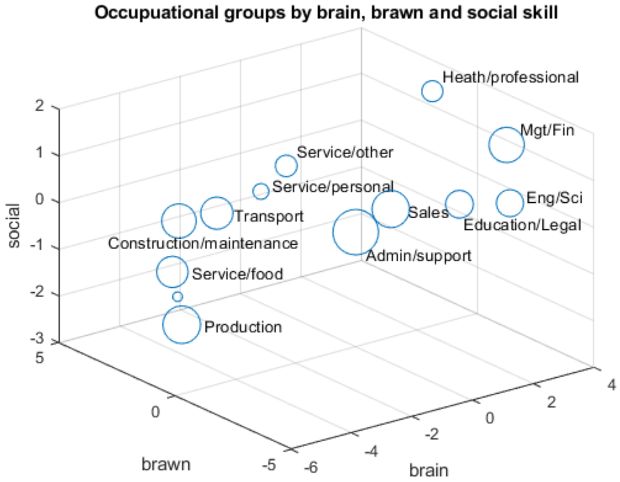
- **On-the-job search and bargaining** Postel-Vinay and Robin (2002); Mortensen (2011); Bagger, Fontaine, Postel-Vinay, and Robin (2014); Lise, Meghir and Robin (2016); Engbom (2021); and Lise and Robin (2017).

- **Life cycle earnings models with work experience and college decisions**: Lee and Wolpin (2006, 2010), Bagger et al. (2014), Kong et al. (2016); **with training**: Cairo (2013), Cairo and Kajner (2016), Flinn, Gemici, and Laufer (2017), Lentz and Roys (2015), Engbom (2022); **with task–dependent career paths:** Gathmann and Schonberg (2010).

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

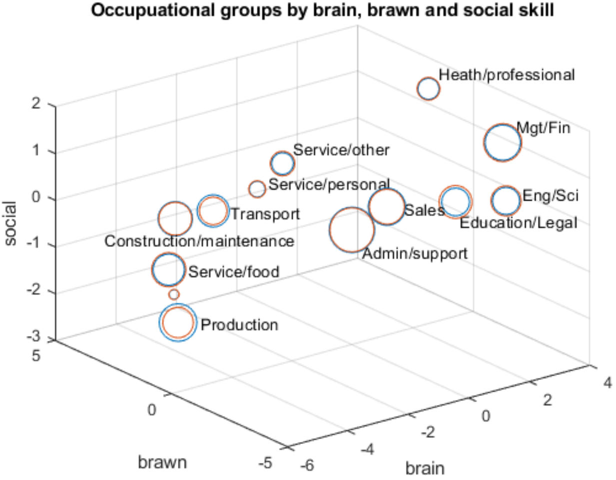
- **Stylized facts on job turnover and skill premium** Hyatt and Spletzer (2012), Decker, Haltiwanger, Engbom (2022), Jarmin and Miranda (2016), Davis and Haltiwanger (2014), Cairo and Cajner (2015), Haltiwanger, Hyatt, and McEntarfer (2017)

Occupations by skill requirements, 1990



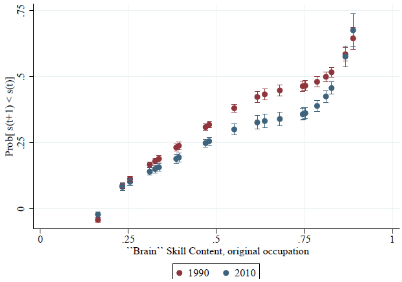
- Circle size reflects prevalence of occupation in 1990
- Data sources: ONET and Bureau of Labor Statistics

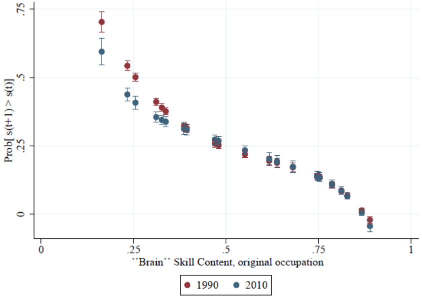
Occupations by skill requirements, 2010 vs. 1990



- Circle size reflects prevalence of occupation in 1990 (blue) and 2010 (orange)

Change in probability of moving down/up the ladder (2010 - 1990)





moving down:

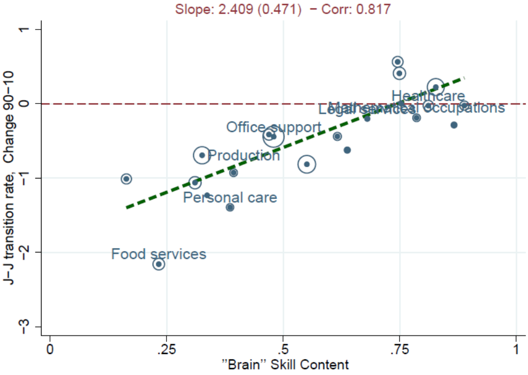
$$\Pr^{2010}(s_{t+1} < s_t | \text{move}) - \Pr^{1990}(s_{t+1} < s_t | \text{move})$$

moving up:

$$\Pr^{2010}(s_{t+1} > s_t | \text{move}) - \Pr^{1990}(s_{t+1} > s_t | \text{move})$$

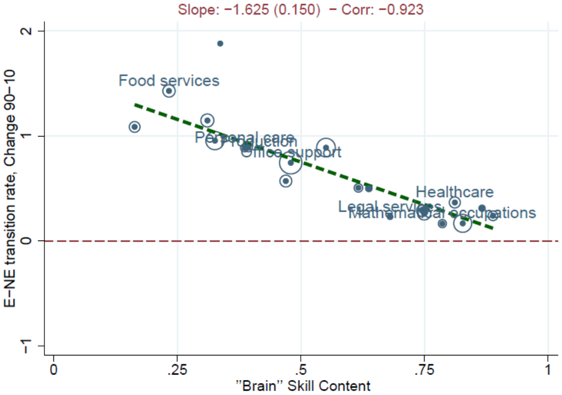
See also: Groes, et al. (2014); Keller and Utar (2021)

Change in job-to-job turnover, 2010 vs. 1990



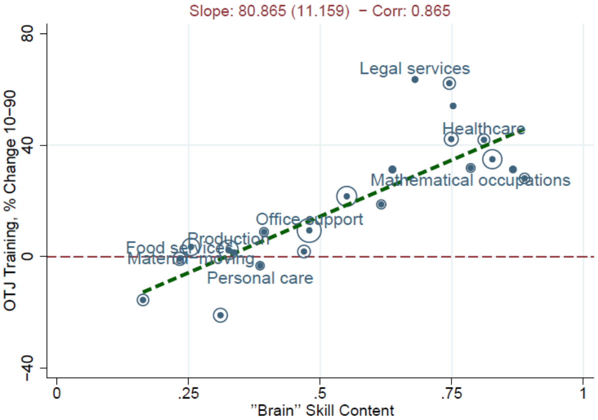
- Each dot represents the change in J-J turnover rate for a particular occupation. (Based on SIPP.)
- Turnover has fallen more at the low end of the skill distribution. See also: Davis and Haltiwanger, 2014; Cairo et al., 2015.

Change in E-to-U transition rates, 2010 vs. 1990

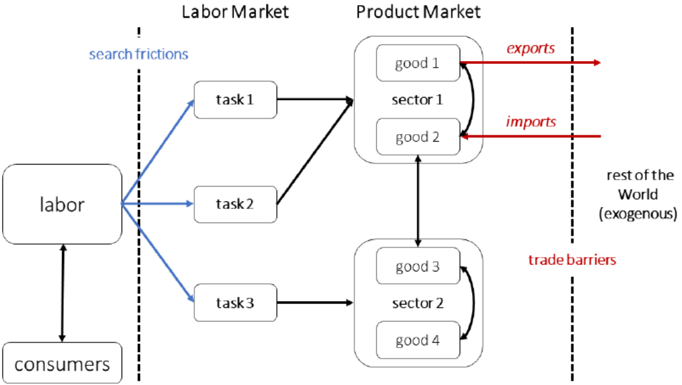


- Each dot gives the change in E-U rate for a particular occupation.
- Separations into unemployment rose at the low end of the skill distribution.

Change in training rates, 2010 vs. 1990



- Training has increased in most occupations, but decreased or remained stable in low-skill occupations.



Agents: Worker-Consumers, Task Producers, and Goods Producers

- Forward-looking heterogeneous high school graduates decide whether to attend college.

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  - arrival of job offers from poaching employers hiring "close" occupations (job ladder)
  - unemployment spells

Worker-consumers

- 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 κ / a_0
- Stochastically improve their ability level, moving up through the finite ordered set $a \in \{\mathrm{a}^1, \ldots, \mathrm{a}^I\}$.
- Hazard of a one-step improvement for a worker in state (E, a) at a firm producing type-j services with productivity z:

$$\gamma_E(a, j, z) = \gamma^1_{j,E} + \gamma^2_{j,E} \mathbf{1}^t_E(a, j, z)$$

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, indexed by $j \in \{1, .., J\}$
- One worker or vacancy per firm. Flow vacancy posting cost: c_v
- Match with employees in a frictional labor market.
- May or may not invest in the training of their employees, flow cost c^t.
- Experience ongoing, idiosyncratic productivity shocks, z.
- Supply quantity $y_E(a, j, z)$ of service j in competitive national market at price r_j. Service production technology:

$$\begin{aligned} y_E(a, j, z) \quad &= \quad \psi_j az - c^t \cdot \mathbf{1}_E^t(a, j, z) - c^o \\ &\quad - \min\left\{0, a - \kappa_E \psi_j z\right\}^2 - \min\left\{0, \psi_j z - \iota_E a\right\}^2 \end{aligned}$$

Skill-augmenting technical change is captured by changes in ψ_j values over time.

Random matching: visibility

- Service-producing firms hire both unemployed and employed workers (poaching).
- Random matching within education-specific markets. ▸ matching
- Following Traiberman (2017), Mahalanobis distances determine probability of drawing occupation j
  - $\Pr(j|\tilde{j}) = \left(\Gamma^e_{j\tilde{j}}\right)^{\zeta^e} / \sum_{i=1}^{J} \left(\Gamma^e_{i\tilde{j}}\right)^{\zeta^e}$ for employed worker currently in occupation $\tilde{j}$, where

$$\Gamma^e_{j\tilde{j}} = \frac{\sqrt{\left(\upsilon^j - \upsilon^{\tilde{j}}\right)' \Sigma^{-1} \left(\upsilon^j - \upsilon^{\tilde{j}}\right)}}{\sum_{j'} \sqrt{\left(\upsilon^{j'} - \upsilon^{\tilde{j}}\right)' \Sigma^{-1} \left(\upsilon^{j'} - \upsilon^{\tilde{j}}\right)}}$$

    and υ^j is vector of brain, brawn, and social skill indices.
  - $\Pr(j|u) = \Gamma^u_j$ for unemployed worker

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) ▸ bargaining
  - Standard Nash bargaining over match surplus
  - Renegotiation after productivity shocks
  - Renegotation after human capital shocks
  - Workers move to poaching firm when match surplus is larger there.

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

Polarization in the model

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  - slows movement up job ladder
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  - Gives one access to a job ladder without "missing" rungs
  - 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 on-the-job learning.

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Goods markets

Generalized Caliendo-Parro (2015)

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    - bundles of (replacement) capital goods

Goods producers

- Within sector k, firms that supply quantity $q_{k\omega}$ of variety $\omega \in \Omega_k$ do so using the following technology:

$$
\begin{aligned}
q_{k\omega} &= e_{k\omega}\left(\bar{y}_{k\omega}\right)^{\alpha_k}\prod_{\tilde{k}=1}^{K}\left(x_{k\omega}^{\tilde{k}}\right)^{(1-\alpha_k)\vartheta_{k\tilde{k}}}, \text{ where} \\
x_{k\omega}^{\tilde{k}} &= \left[\int_{\tilde{\omega}\in\Omega_{\tilde{k}}}\left(x_{k\omega}^{\tilde{k}\tilde{\omega}}\right)^{\frac{\eta_k-1}{\eta_k}} d\tilde{\omega}\right]^{\frac{\eta_k}{\eta_k-1}}, \\
\bar{y}_{k\omega} &= \left(\prod_{j=1}^{J}\left(\ell_{k\omega}^{j}\right)^{\mu_k^j}\right)^{s_k^L}\left(h_{k\omega}\right)^{1-s_k^L}
\end{aligned}
$$

- $e_{k\omega}$ is a Frechet productivity shock
- $x_{k\omega}^{\tilde{k}\tilde{\omega}}$ is intermediate usage of variety $\tilde{\omega}$, good $\tilde{k}$,
- $\ell_{k\omega}^{j}$ is usage of occupational service j, and
- $h_{k\omega}$ is usage of capital services.

- Production function (from previous slide):

$$q_{k\omega} = e_{k\omega} \left(\bar{y}_{k\omega}\right)^{\alpha_k} \prod_{\tilde{k}=1}^{K} \left(x_{k\omega}^{\tilde{k}}\right)^{(1-\alpha_k)\vartheta_{k\tilde{k}}}$$

- In country n, $e_{k\omega}$ draws are distributed Fréchet with location parameter T_k^n and dispersion parameter θ_k.

- Factor-augmenting technical progress (relative to U.S.) is reflected in changes in T_k^n

- Automation is reflected in changes in labor's share in value added s_k^L and factor service weights μ_k^j, as in Acemoglu and Restrepo (2018).

- Globalization is reflected in changes in iceberg costs and tariffs, as usual.

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

$$Y^n = \sum_{j=1}^{J} r_j^n L_j^n + (1-\Psi) \sum_{k=1}^{K} \alpha_k (1 - s_k^L) X_k^n,$$

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

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 contiuation 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 in each occupation and unemployed states
  - task producers of each type of labor service
- Free entry condition holds for task producing firms

Preliminary Calibration

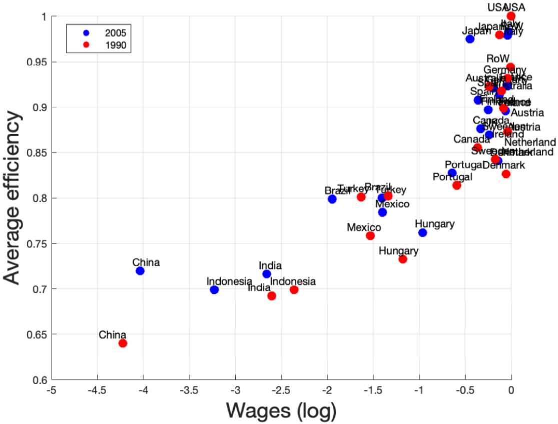
- Baseline period: 2005-2008
- Countries: 23 + ROW ▸ details
- Industries: 30 ISIC Rev.3.1 (15 tradable) ▸ details
- Occupations: 12 SOC 2-digit ▸ details
- Model numeraire: monthly labor income per employee (USD 3,700)

- The economy is assumed to be in steady state with free entry ▸ details

Identification: goods market parameters

- Skill-augmenting technical change: ψ_j values are chosen to match observed employment levels by occupation, each year.
- Factor-augmenting technical progress: T_k^n values are imputed from bilateral trade flows and wages using Bolatto's methodology
- Automation: s_k^L and μ_k^j are taken directly from year-specific factor shares.
- Globalization effects tariffs ($\tau_k^{n\tilde{n}}$) from data, iceberg costs ($\kappa_k^{n\tilde{n}}$) imputed using Bolatto's approach.
- Non U.S., labor markets treated as competitive
  - no intra-country, cross-sectoral variation in occupational bundling weights.
  - ψ_j^n values are therefore absorbed by T_k^n, $n \neq U.S.$, as are automation levels.

Estimated productivity measures



- Calculations based on bilateral trade flows, Bolatto's (2013) methodology.

Identification: goods market parameters

Parameter description		Informative moment
Training costs	c_t	training shares, L and E
Efficiency labor market low educated (L)	A_L	N2E, L
Efficiency labor market high educated (H)	A_H	N2E, H
Jump size, productivity shock	Δ_z	wage dispersion, J2J rate
Hazard, productivity shock	γ_z	wage dispersion, J2J rate
Visibility employed, low educated	λ_L	N2E vs. E2E rate, L
Visibility employed, high educated	λ_E	N2E vs. E2E rate, H
Cost of education parameter	κ	college shares, by occup.
Hazard, ability jump, L	γ_L^1	wage growth by tenure, L
Hazard, ability jump, H	γ_H^1	wage growth by tenure, H
Hazard, ability jump w/ OTJ training, L	γ_L^2	wage growth training prem., L
Hazard, ability jump w/ OTJ training, H	γ_H^2	wage growth training prem., H
Hazard, skill depreciation	γ^0	life cycle earnings profiles
Exogeneous separation low educated	δ_L	E2N, by occup., L
Exogeneous separation high educated	δ_H	E2N, by occup., H

Identification: goods market parameters

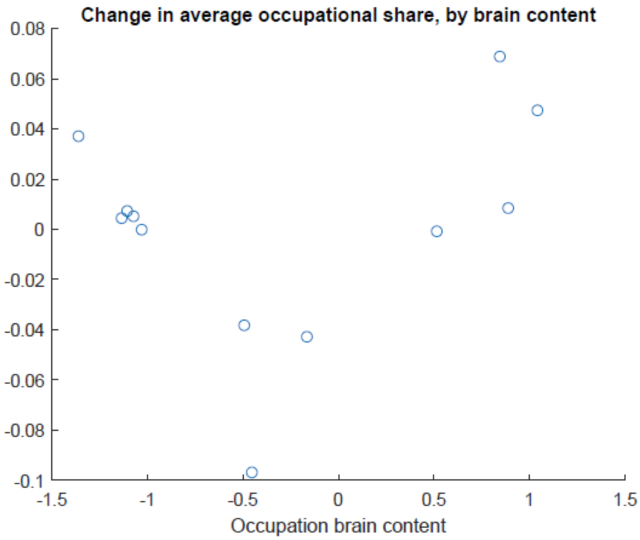
Parameter description		**Informative moment**
Occup. distance logit parameter, L	ζ^u	N2O transition patterns
Occup. distance logit parameter, H	ζ^e	O2O transition patterns
Cost of being underskilled, L	κ_L	J2N by age, L
Cost of being underskilled, H	κ_E	J2N by age, H
Cost of being overskilled, L	ι_L	J2N by age, L
Cost of being overskilled, H	ι_E	J2N by age, H
Cost of operation	c^o	minimum earnings
Occupational productivity intercept	ψ_0	avg. wage, by occup.
Occupation productivity slope	Δ_ψ	wage-brain gradient
Pareto scale - initial human capital		wage dist., entrants
Pareto shape - initial human capital		wage dist., entrants

- parameter estimates details

Selected moments, continued	Data	Model
Labor market flows		
E-NE transition, intercept (brain content)	2.11	2.00
E-NE transition, slope (brain content)	-0.58	-0.157
E-NE rate, college	1.610	1.421
E-NE rate, non-college	2.536	2.306
J-J rate, intercept (brain content)	1.472	1.537
J-J rate, slope (brain content)	-0.185	-0.069
J-J rate, college	1.263	0.844
J-J rate, non-college	1.430	1.540
Education		
College share	0.251	0.276
Training share	0.392	0.076
trained share, employed	0.390	0.130
trained share, non-employed	0.173	0.043

Some targeted moments (continued)

Selected moments	**Data**	**Model**
Labor income		
Average college premium	0.509	0.420
Std.dev., non-college	0.605	0.620
Std. dev., college	0.622	0.517
avg. income growth, non-college	0.331	0.430
avg. income growth, college	0.503	0.235
5 yr. income growth, trained	0.318	0.515
5 yr. income growth, non-trained	0.273	0.331


Change in average occupational share, by brain content
0.08
0.06
0.04
0.02
0
-0.02
-0.04
-0.06
-0.08
-0.1
-1.5
-1
-0.5
0
0.5
1
1.5
Occupation brain content

Change with automation shock	
E2N transition, intercept (brain content)	-0.025
E2N transition, slope (brain content)	-0.083
E2N transition, college	-0.020
E2N transition, non-college	0.038
J2J rate, intercept (brain content)	0.092
J2J rate, slope (brain content)	-0.024
J2J rate, college	0.140
J2J rate, non-college	-0.011

Counterfactual patterns of heterogeneity

▸ observed changes, training ▸ observed changes, life cycle

Change with automation shock	
College share	0.043
Training share	0.032
trained share, college	0.042
trained share, non-college	0.033
Std.dev. income, non-college	0.024
Std. dev. income, college	0.020
life cycle income growth, non-college	0.022
life cylce income growth, college	0.098

▸ occupation-specific results

Concluding remarks

- Model calibration and simulations very preliminary.
- Version in progress:
  - partial human capital depreciation with job switching, depending on occupational distance.
  - separate occupational distance matrices for college and non-college workers.
- Meant to provide a way of thinking about effects in play; not final word on quantitative outcomes.
- Ultimately model will provide a basis for analysis of impact of various policies on the way different types of people experience the labor market
  - protectionism
  - tax on automation (Acemoglu, Humlum)

Data sources

- **Survey of Income and Program Participation (SIPP)** nationally representative U.S. household-based survey; continuous series of national panels, each lasting approximately four years (1984-1993, 1996, 2001, 2004, 2008, 2012).
- **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

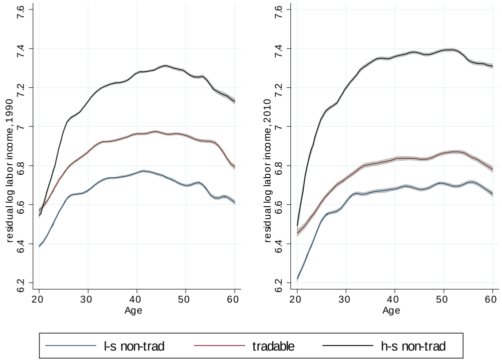
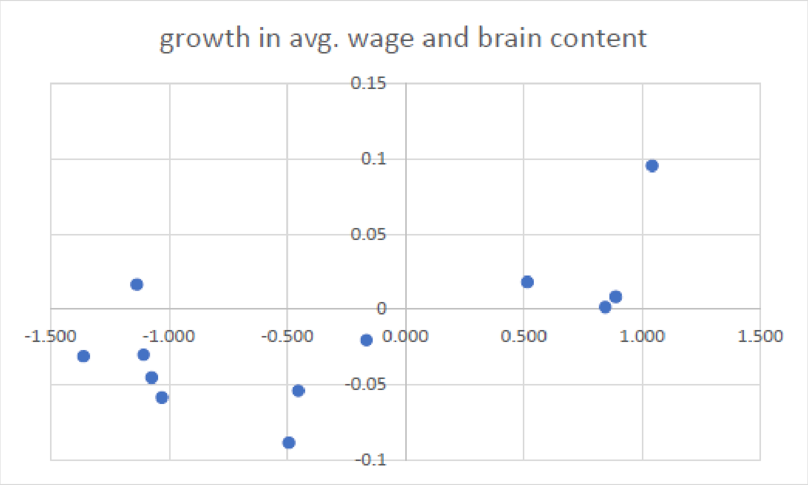


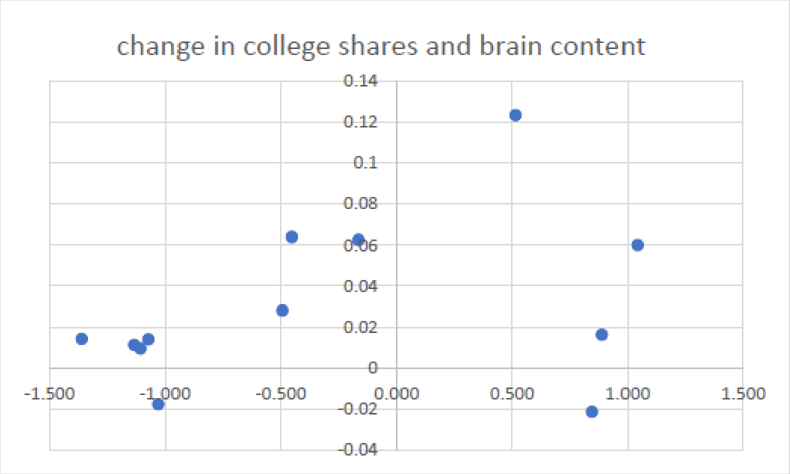
Figure: Labor Earnings by Age and Tradability of Occupations

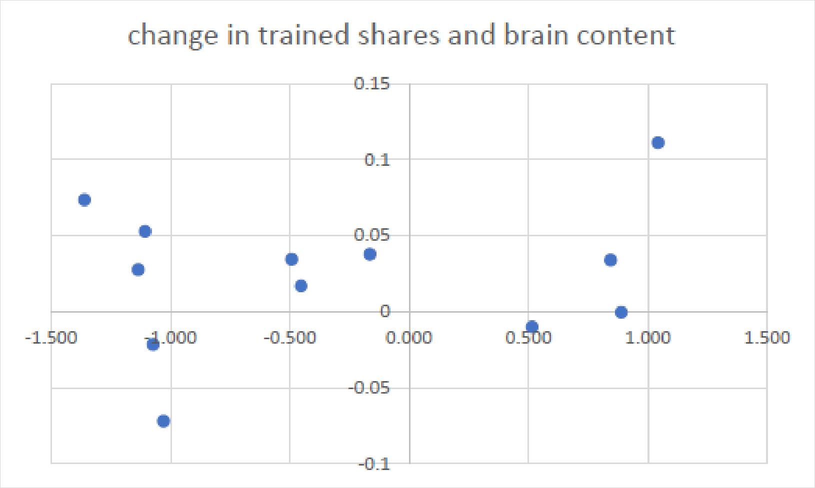
- Profile for tradable occupations flattens relative to others. back


growth in avg. wage and brain content
0.15
0.1
0.05
0
-0.05
-0.1
-1.500
-1.000
-0.500
0.000
0.500
1.000
1.500

Automation shock

change in college degree rates, by occupation




change in trained shares and brain content
0.15
0.1
0.05
0
-0.05
-0.1
-1.500
-1.000
-0.500
0.000
0.500
1.000
1.500

- **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.
  - Competititve markets for occupational services divorce effects of hiring frictions from producers' factor proportions decisions.

- 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 χ are parameters.
- Once in contact, each worker-vacancy pair randomly draws an occupation j and productivity z.
  - Probability of a type-j job is $\Gamma^{\ell}_{j\tilde{j}}$ or Γ^{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

- 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.
- For 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 vacancy at a type-$(\widetilde{j}, \widetilde{z})$ firm. Possible outcomes:

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

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

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

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

$$w = w_o$$

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

$$w = b_E$$

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

$$w = b_E$$

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

$$J^e_E(w, a, j, z') - J^u_E(a) = \beta S_E(a, j, z')$$

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

$$w = b_E$$

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

$$J_E^e(w, a, j, z') - J_E^u(a) = \beta S_E(a, j, z')$$

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

$$w = b_E$$

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

$$w = b_E$$

Ability shocks

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

$$w = b_E$$

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

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

Value of job to worker

$$[\rho + \delta_\ell] J_E^e(w, a, j, z) =$$

$$w + \delta_f \left[J_E^u(i) - J_E^e(a, j, z) \right]$$

$$+ \varphi \sum_{\tilde{z} \in \mathcal{Z}} \max\{ J_E^e(w_\varphi, a, j, \tilde{z}) - J_E^e(w, a, j, z), \\ J_E^u(a) - J_E^e(w, a, j, z) \} \Lambda(\tilde{z} | z)$$

$$+ \gamma_E(a, j, z) \max\{ J_E^e(w_\gamma, a', j, z) - J_E^e(w, a, j, z), \\ J_E^u(a') - J_E^e(w, a, j, z) \}$$

$$+ \phi_{1E}^\ell \sum_{\tilde{j} \in \mathcal{J}} \sum_{\tilde{z} \in \mathcal{A}_E(a,j,z|\tilde{j})} [J_E^e(w_o, a, \tilde{j}, \tilde{z}) - J_E^e(w, a, j, z)] \Lambda^o(\tilde{z}) \Gamma_{j\tilde{j}}^e$$

$$[\rho + \delta_f]\Pi_E^e(w, a, j, z) =$$

$$r_j y_E(a, j, z) - w + \delta_\ell[\Pi^v(j, z) - \Pi_E^e(w, a, j, z)]$$

$$+ \varphi \sum_{\tilde{z} \in \mathcal{Z}} \max\{\Pi_E^e(w_\varphi, a, j, \tilde{z}) - \Pi_E^e(w, a, j, z), \\ \Pi^v(j, \tilde{z}) - \Pi_E^e(w, a, j, z)\}\Lambda(\tilde{z}|z)$$

$$+ \gamma_E(a, j, z) \max\{\Pi_E^e(w, a', j, z) - \Pi_E^e(w, a, i, z), \\ \Pi^v(j, z) - \Pi_E^e(w, a, j, z)\}$$

$$+ \phi_{1E}^\ell \sum_{\tilde{j} \in \mathcal{S}} \sum_{\tilde{z} \in \mathcal{A}_E(h_i, j, z|\tilde{j})} [\Pi^v(j, z) - \Pi_E^e(w, a, j, z)]\Lambda^o(\tilde{z})\Gamma_{\tilde{j}j}^e$$

value of being unemployed:

$$
\begin{aligned}
[\rho + \delta_\ell + \delta_u^E] J_E^u(a) \quad = \quad & b_E + \beta \phi_{0E}^f \sum_{j \in \mathcal{J}} \sum_{z \in \mathcal{Z}} \max\{S_E(a,j,z), 0\} \Lambda^o(z) \Gamma_j^u \\
& + \delta_u^E J_E^u(a').
\end{aligned}
$$

value of vacancy:

$$
\begin{aligned}
& (\rho + \delta_f) \Pi_E^v \\
& = -c_E^v + (1-\beta)\phi_{0E}^f \sum_{j \in \mathcal{J}} \sum_{z \in \mathcal{Z}} \sum_{a \in \mathcal{A}} \max\{S_E(a,j,z), 0\} g_E(a) \Lambda^o(z) \Gamma_j^u \\
& + (1-\beta)\phi_{1E}^f \sum_{j \in \mathcal{J}} \sum_{z \in \mathcal{Z}} \sum_{a \in \mathcal{A}} \sum_{\tilde{j} \in \mathcal{J}} \sum_{\tilde{z} \in \mathcal{A}_E(a,j,z|\tilde{j})} S_E(a,j,z) f_E(a, \tilde{z}|\tilde{j}) \Lambda^o(z) \Gamma_{\tilde{j}j}^e
\end{aligned}
$$

- Clearing in product markets:

$$\begin{aligned}
X_k^n &= \sum_{\tilde{k}=1}^{K} \left[(1-\alpha_{\tilde{k}})\vartheta_{\tilde{k}k} + \Psi \xi_{\tilde{k}k} \alpha_{\tilde{k}} (1 - s_{\tilde{k}}^L) \right] \sum_{\tilde{n}=1}^{N} \frac{\pi_{\tilde{k}}^{\tilde{n}n} X_{\tilde{k}}^{\tilde{n}}}{1+\tau_{\tilde{k}}^{\tilde{n}n}} + \iota_n^k I_n \\
I^n &= Y^n + G^n + D^n \\
G^n &= \sum_{k=1}^{K} \sum_{\tilde{n}=1}^{N} \frac{\pi_k^{n,\tilde{n}}}{1+\tau_k^{n,\tilde{n}}} \tau_k^{n,\tilde{n}} X_k^n \\
D^n &= \sum_{k=1}^{K} \sum_{\tilde{n}=1}^{N} \frac{\pi_k^{n,\tilde{n}}}{1+\tau_k^{n,\tilde{n}}} X_k^n - \sum_{k=1}^{K} \sum_{\tilde{n}=1}^{N} \frac{\pi_k^{n,\tilde{n}}}{1+\tau_k^{n,\tilde{n}}} X_k^{\tilde{n}}
\end{aligned}$$

- Clearing in labor services markets:

$$Y^n = \underbrace{\sum_{k=1}^{K} \mu_{jk}^n \frac{\bar{r}_k}{r_j} \frac{s_k^n \alpha_k^n}{\bar{r}_k} X_k^n}_{\text{demand}} = \underbrace{N_j \sum_{E \in \{L,H\}} \sum_{i \in \mathcal{I}} \sum_{z \in \mathcal{Z}} y_E(j,z,i) f_E(j,z,i)}_{\text{supply}}$$

- Free entry condition for service-producing firms

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

- Flow balance of service-producing firms across states

$$\underbrace{F_{jz}\left[\delta_f + \varphi \sum_{\tilde{z} \in \mathcal{Z}/z} \Lambda(\tilde{z}|z)\right]}_{\text{outflows + exit}} = \underbrace{\varphi \sum_{\tilde{z} \in \mathcal{Z}} \Lambda(z|\tilde{z}) F_{j\tilde{z}}}_{\text{inflows}} + \underbrace{\Lambda^e(z) F_j^e}_{\text{new entrants}} \quad \forall z \in \mathcal{Z}, \forall j \in \mathcal{J}$$

Flows of service-producing firms-workers matches

$$\underbrace{\gamma_E(j,z,i-1)N_{Ej}f_E(j,z,i-1)}_{\text{inflows due to training updates}} + \underbrace{\varphi \sum_{\tilde{z}\in\mathcal{Z}} \Lambda(z|\tilde{z})N_{Ej}f_E(j,\tilde{z},i)}_{\text{inflows due to productivity change}}$$

$$+\underbrace{\left[\tilde{\phi}_{0j}U_E u_E(i) + \sum_{\tilde{j}\in\mathcal{S}} \tilde{\phi}_{\tilde{j}j} N_{E\tilde{j}} \sum_{\tilde{z}\in\mathcal{C}_1(\tilde{j},z,i|j)} n_E(\tilde{j},\tilde{z},i)\right] v_{Ej}(z) =}_{\text{inflows due to new hirings}}$$

$$\underbrace{\left[\delta_w + \delta_f + \varphi \sum_{\tilde{z}\in\mathcal{Z}/z} \Lambda(\tilde{z}|z) + \gamma_E(j,z,i) + \sum_{\tilde{j}\in\mathcal{S}} \tilde{\phi}_{j,\tilde{j}} \sum_{\tilde{z}\in\mathcal{C}_2(j,z,i|\tilde{j})} v_{E\tilde{j}}(\tilde{z})\right] N_{Ej}f_E(j,z,i}_{\text{outflows}}$$

$$\underbrace{U_{Ei}[\delta_w + \sum_{j \in \mathcal{J}} \tilde{\phi}_{0,j} \sum_{z \in \mathcal{Z}} \mathbf{1}_{\{S_E(j,z,i) \geq 0\}} v_{Ej}(z)]}_{\text{outflows from unemployment}}$$

$$= \underbrace{\delta_f \sum_{j \in \mathcal{J}} \sum_{z \in \mathcal{Z}} N_{Ejzi} + \varphi \sum_{j \in \mathcal{S}} \sum_{z \in \mathcal{Z}} N_{Ejzi} \sum_{\tilde{z} \in \mathcal{Z}} \mathbf{1}_{\{S_E(j,\tilde{z},i) < 0\}} \Lambda(\tilde{z}|z)}_{\text{inflows to unemployment}} + \underbrace{L^e_{Ei}}_{\text{new entrants}}$$

List of countries

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.

Code	ISIC Rev.3.1	Description	Import Penetration	Tradable
1	AtB	Agriculture, forestry and fishing	11.421	yes
2	C	Mining and Quarrying	51.757	yes
3	15t16	Food, Beverages and Tobacco	7.366	yes
4	17t19	Textiles, Textile Products, Leather and Footwear	138.992	yes
5	20	Wood and Product of Wood and Cork	18.645	yes
6	21t22	Pulp, Paper, Printing and Publishing	7.814	yes
7	23	Coke, Refined Petroleum and Nuclear Fuel	12.067	yes
8	24	Chemicals and Chemical Products	27.391	yes
9	25	Rubber and Plastics	17.987	yes
10	26	Other Non-Metallic Minerals	18.199	yes
11	27t28	Basic Metals and Fabricated Metals	22.139	yes
12	29	Machinery, Nec	44.211	yes
13	30t33	Electrical and Optical Equipment	81.201	yes
14	34t35	Transport Equipment	41.497	yes
15	36t37	Manufacturing, Nec; Recycling	59.991	yes
16	E	Electricity, Gas and Water Supply	0.942	no
17	F	Construction	0.102	no
18	50	Sale, Maintenance and Repair of Motor Vehicles	0.189	no
19	51	Wholesale Trade, Except of Motor Vehicles	1.092	no
20	52	Retail Trade, Except of Motor Vehicles	0.458	no
21	H	Hotels and Restaurants	0.182	no
22	60t63	Transportation	5.907	no
23	64	Post and Telecommunications	0.208	no
24	J	Financial Intermediation	1.501	no
25	70	Real Estate Activities	0.077	no
26	71t74	Renting and Other Business Activities	5.472	no
27	L	Public Admin and Defence; Compulsory Social Security	0.065	no
28	M	Education	0.601	no
29	N	Health and Social Work	0.048	no
30	OtP	Other Community, Social, Personal Services	0.907	no

	SOC	Occupation	Share	Brain
1	11-13	Management, Business, and Fin.	0.138	0.800
2	15-19	Computer, Engineering, and Sci.	0.069	0.850
3	21-27	Education, Legal, Arts, Media	0.081	0.721
4	29	Healthcare and Technical	0.041	0.814
5	31-39	Service n.e.c.	0.162	0.324
6	41	Sales and Related	0.101	0.560
7	43	Office and Administrative Support	0.158	0.482
8	45	Farming, Fishing, and Forestry	0.008	0.337
9	47	Construction and Extraction	0.056	0.314
10	49	Installation, Maint., and Repair	0.042	0.470
11	51	Production Occupations	0.080	0.327
12	53	Transport and Material Moving	0.064	0.260

$$
\begin{aligned}
\log \frac{T_n^k}{T_i^k} &= \log \frac{X_{nn}^k}{X_{ni}^k} - \theta_k \alpha_k \left[\log \left(\frac{\bar{r}_i^k}{\bar{r}_n^k} \right) + \log \frac{\left(R\bar{p}_i^H \right)^{1-s_L^{k,i}}}{\left(R\bar{p}_n^H \right)^{1-s_L^{k,n}}} \right] - \theta_k \log d_{ni}^k \\
&\quad -\theta_k (1-\alpha_k) \sum_{l=1}^{K} \upsilon_{kl} \left[-\frac{1}{\theta_l} \log \frac{X_{nn}^l}{X_{ni}^l} + \log d_{ni}^l + \frac{1}{\theta_l} \log \left(\frac{X_{nn}^l / X_n^l}{X_{ii}^l / X_i^l} \right) \right] \\
\log \kappa_{ni}^k &= -0.5 \left[\frac{\left[\log(\pi_{ni}^k) - \log(\pi_{nn}^k) + \log(\pi_{in}^k) - \log(\pi_{ii}^k) \right]}{\theta_k} \right] \\
&\quad -0.5 \left[\log(1+\tau_{ni}^k) + \log(1+\tau_{in}^k) \right]
\end{aligned}
$$

κ_{ni}^k unit costs of shipping good k from i to n

$\bar{r}_i^k$ costs of a unit bundle of primary inputs for good k in country i

$\bar{p}_i^H$ unit cost of replacement capital (can be expressed in terms of observables)

Parameter estimates

Training costs	c_t	448.63
Efficiency labor market low educated	A_L	0.3868
Efficiency labor market high educated	A_H	0.1436
Pareto scale - initial human capital		0.6566
Pareto shape - initial human capital		1.0475
Jump size, productivity shock	Δ_z	0.2082
Hazard, productivity shock	γ_z	0.0059
Visibility employed, low educated	λ_L	0.5924
Visibility employed, high educated	λ_E	0.6885
Cost of education parameter	κ	0.9617
Hazard, ability jump, tenure, low ed.	γ_L^1	0.0356
Hazard, ability jump, tenure, high ed.	γ_H^1	0.0359
Hazard, ability jump, OTJ training low ed.	γ_L^2	0.0069
Hazard, ability jump OTJ training high ed.	γ_H^2	0.0064
Hazard, skill depreciation	γ^0	0.0024
Exogeneous separation low educated	δ_L	0.0194
Exogeneous separation high educated	δ_H	0.009

logit coef., occupational distance, emp.	ζ^e	0.7391
Cost of being underskilled - low educated	κ_L	3.7703
Cost of being underskilled - high educated	κ_E	1.0669
Cost of being overskilled - low educated	ι_L	0.5927
Cost of being overskilled - high educated	ι_E	0.6299
Cost of operation	c^o	111.1792
Occupation specific productivity shifter	ψ_0	0.5042
Occupation specific productivity slope	Δ_ψ	0.1384