

Training, Offshoring, and the Job Ladder

NBER ITI meetings

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December 7, 2019

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- On-the-job training times have increased (Cairo, 2013)
- Life-cycle career trajectories have evolved very differently for different types of workers
 - job to job transitions
 - unemployment spells
 - education and on-the-job training

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 - links them to globalization and skill-biased technical change

The modeling exercise

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- Related literature. [▶ references](#)

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- Once employed, workers
 - bargain over their wages
 - improve their ability through experience
 - may also improve their ability through investments in on-the-job training.
- Over their life cycles, workers' wage growth is driven by
 - improvements in ability
 - shocks to employer profitability
 - arrival of job offers from poaching employers ("job ladder")
 - unemployment spells

- While improving productive efficiency, globalization reduces relative supply of jobs in the trade-exposed occupations.
 - Slows down turnover by limiting outside options of employees.
 - Low arrival rate of attractive job offers means
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 - College allows one to leapfrog missing rungs in the job ladder
 - At the margin, people switching to college are less qualified
- Similarly, globalization 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.

Effects of technological change

- Originate with changes in production function parameters.
- Like globalization, technological change affects task prices in equilibrium
 - Affect career paths though same mechanisms as globalization.
 - But changes in relative task prices are distinct.
 - Identification of technology effect comes from changing shares of tasks in production

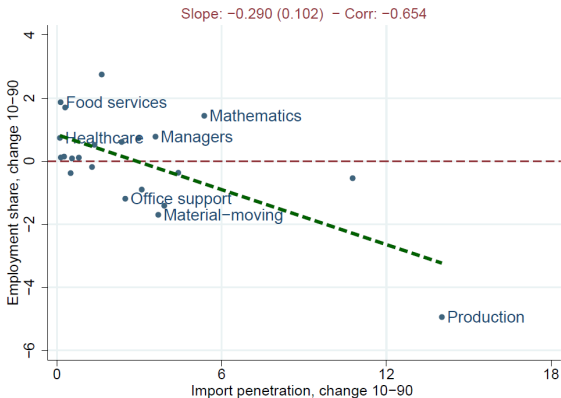
- **Data sets:**

- **Survey of Income and Program Participation (SIPP)**
nationally representative U.S. household-based survey;
continuous series of national panels, each lasting approximately
four years
- **Occupational Information Network (O*NET):** skill mix
(brain, brawn) of 4-digit occupations
- **World I-O Table (WIOT)** imports, exports and output by
sector
- **Occupational Employment Statistics (OES):** Annual
employment and wage estimates for about 800 occupations,
broken down by industry.
- **Panel Study of Income Dynamics (PSID):** Nationally
representative household survey. Series of annual waves
between 1968 and 1997; biennial thereafter. Annual earnings
and tenure by job, occupation, industry.

- **Variables:**

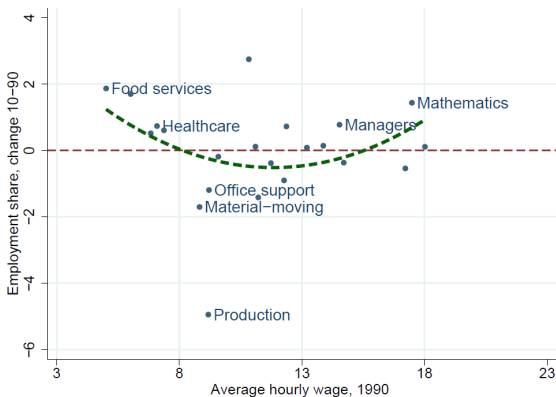
- **Job flows** employment-weighted average monthly flows by 4-digit 2002 Standard Occupational Code (SOC)
- **Employment shares** by sector (SIPP, OES)
- **Trade exposure indices:** import penetration rates, by sector (WIOT), occupation (SIPP)
- **Brain, brawn content of occupations:** based on principal components of O*NET job characteristics
- **Training indicator:** Have you received job training? (SIPP)
- **Import exposure of occupations** (OES and WIOT) employment weighted average of sectoral import penetration rates.
- **Earnings-tenure profiles** (PSID) by job, sector, and occupation.

Employment shares and import exposure, 2010 vs. 1990



- Employment shares have fallen more in sectors with growing trade exposure.
- See also: Acemoglu and Autor (2011), Autor and Dorn (2013), Autor, Dorn, Hanson (2013), Lee and Woplin (2006)

Employment shares and hourly wages, 2010 vs. 1990



- Sectors losing employment shares have tended to be in the middle of the wage distribution. (See also: Acemoglu and Autor, 2011.)

Change in job turnover, 2010 vs. 1990

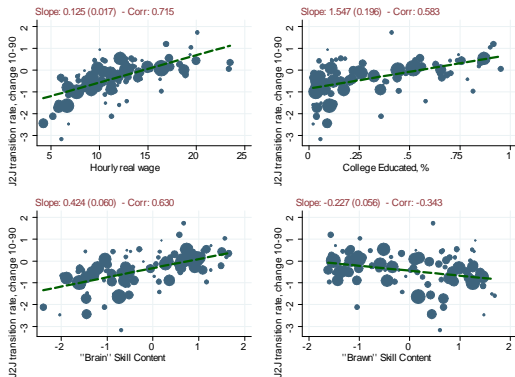


Figure: Changes in Monthly Job-to-Job Transitions

- 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

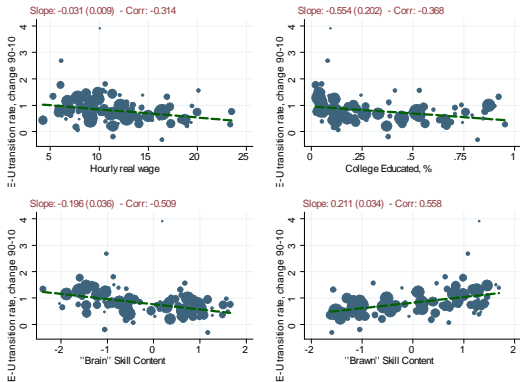


Figure: Change in Monthly E-to-U Transitions

- Separations into unemployment rose at the low end of the skill distribution.

Change in training rates, 2010 vs. 1990

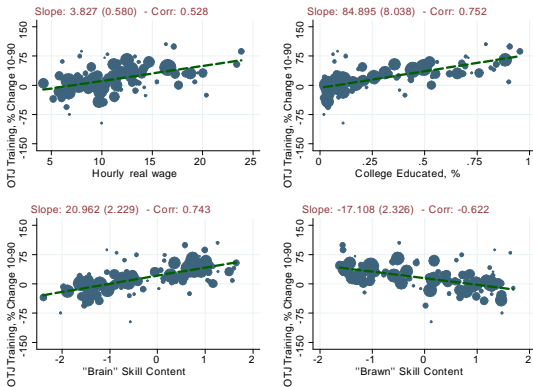


Figure: Change in the Fraction of Trained Workers

- Training has increased in most occupations, but decreased or remained stable in low-skill occupations. [▶ relation to imports](#)

Earnings-age profile: 1990 and 2010

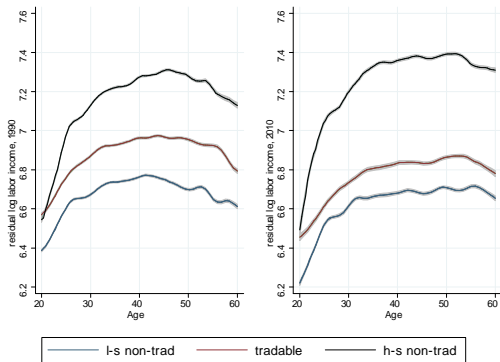


Figure: Labor Earnings by Age and Tradability of Occupations

- Profile for tradable occupations flattens relative to others.
- Transition or new steady state?

Earnings-age profile: 1990 and 2010

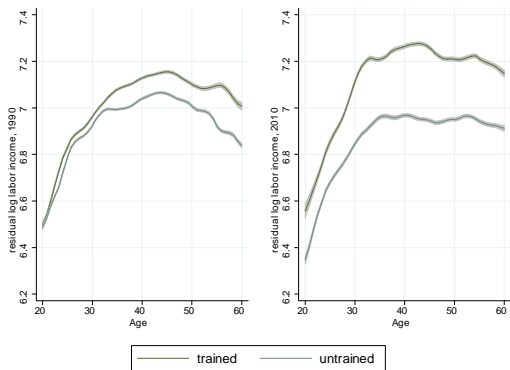
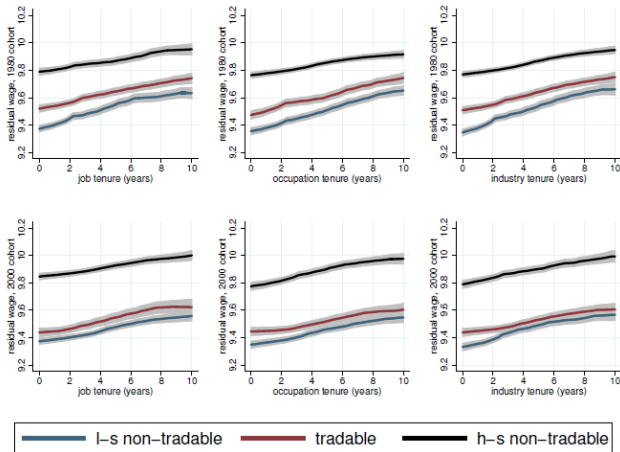


Figure: Labor Earnings over the Cycle

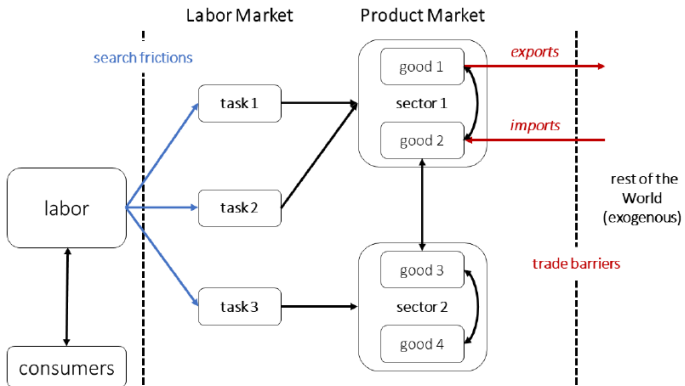
- The earnings gap between trained and untrained workers has grown.

Longitudinal earnings-tenure profiles



- Life cycle earnings profiles become flatter for low-skill and tradable workers (2000 cohort vs. 1990 cohort).

- Life-cycle human capital accumulation and college education (Bagger et al. 2014, Lise et al. 2016, Flin et al. 2016)
- Search and matching frictions, worker poaching in the labor market (Mortensen and Pissarides 1999, Mortensen 2010)
- Ricardian production and trade with sectoral linkages (Caliendo and Parro 2014)
- Three types of agents:
 - worker/consumers
 - goods producers
 - task producers [▶ why task producers?](#)



Model structure: goods producers

- Goods producers combine bundles of labor services (tasks) and bundles of product varieties to generate output. ▶ goods sector technology
 - Factor intensities (both task and intermediate bundles) vary across sectors
 - Output goes to consumers and to other producers (as intermediate inputs)
- Product markets are as in Caliendo and Parro, 2015).
 - Intermediate goods are sourced globally from their cheapest suppliers.
 - Offshoring occurs when a variety is sourced abroad.
 - Direct offshoring of labor services nested as a sector that uses no intermediates.

The environment: 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, $a \in \{a^1, \dots, a^I\}$, through on-the-job experience and (perhaps) training.
- **Hazard of a one-step improvement** for a worker in state (E, a) at a firm producing type- j services ("tasks") with productivity z :

$$\gamma_E(a, j, z) = \gamma_{j,E}^1 + \gamma_{j,E}^2 \mathbf{1}_E^t(a, j, z)$$

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

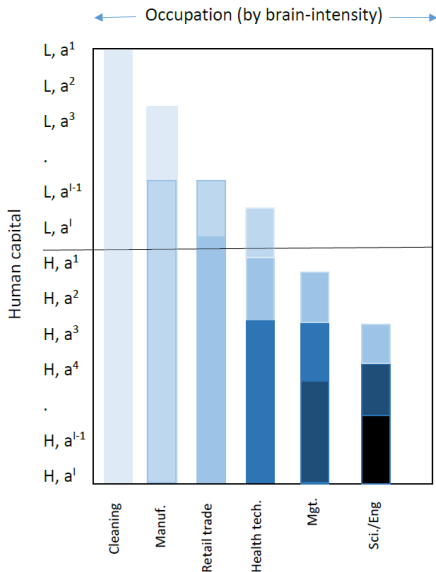
The environment: task-producing firms

- Specialize in producing a particular service ("task"), indexed by $j \in \{1, \dots, J\}$
- One worker or vacancy per firm. Flow vacancy posting cost: c_v
- Employ workers they match with in a frictional labor market.
- May or may not invest in the training of their employees.
- Experience ongoing, idiosyncratic productivity shocks, z .
- Supply output $y_E(a, j, z)$ in competitive national market at price r_j . Task production technology:

$$y_E(a, j, z) = z s_j a^{\zeta_{j,E}} - c^t \mathbf{1}_E^t(a, j, z) - c^o$$

where s_j is a productivity index for task j . and $\zeta_{j,E}$ measures return to ability for type (j, E) workers.

Worker productivity by human capital and occupation



- Darker shades reflect higher productivity.
- Workers increase wages by improving ability (downward movement) or moving across employers, occupations (rightward movement).
- Workers care about market thickness, not just wages

- Total measure of vacant jobs in occupation j : V_j

- Measure of jobs seekers' visibility to type- j employers:

$$Z_j = \lambda_0^L U_L + \lambda_0^H U_H + \sum_{\tilde{j}} \lambda_{j,\tilde{j}} N_{\tilde{j}} \quad \text{where}$$

- U_H and U_L are masses of low- and high-education unemployed workers, respectively
- $N_{\tilde{j}}$ is the mass of employed workers in occupation \tilde{j}
- $\lambda_{j,\tilde{j}}$ controls the visibility of a worker currently producing task \tilde{j} to a type- j task-producing firm

- **Matching function:**

$$m(V_j, Z_j) = \frac{V_j Z_j}{(V_j^\chi + Z_j^\chi)^{\frac{1}{\chi}}}$$

- **Visibility function:**

$$\lambda_{j\tilde{j}} = \frac{\lambda}{[1 + d(j, \tilde{j})]^\xi}$$

where

$$d(j, \tilde{j}) = \sqrt{(v^j - v^{\tilde{j}})' \Sigma^{-1} (v^j - v^{\tilde{j}})},$$

v^j is vector of brain and brawn indices.

- Wage setting with on-the-job search based on Mortensen (2011).
(Alternatives: Bagger et al., 2014; Lise et al., 2016) ▶ bargaining
 - Negotiation with unemployed workers
 - Renegotiation after outside offers
 - Renegotiation after productivity shocks
 - Renegotiation after human capital shocks

- Value of employment reflects: ▶ value function
 - flow earnings
 - capital loss from death shock
 - capital gain/loss from productivity shock, recognizing quit option
 - capital gain/loss from ability shock, recognizing quit option.
 - size and likelihood of outside offers

- Value of an active job reflects: ▶ value function
 - exogenous separation hazards
 - expected capital gains/losses from productivity shocks
 - expected capital gains/losses from worker ability shocks
 - expected capital losses due to poachers

- Let $\Pi^v(j, z)$ be value of unfilled vacancy. Task producer **free entry condition**.

$$\sum_{z \in \mathcal{Z}} \Pi^v(j, z) \Gamma(z) \geq 0 \quad \forall j \in \Omega$$

- **College decision** depends on initial ability, a_0 :

$$\mathbf{E}(a_0) = \begin{cases} H & \text{if } \frac{k}{a_0} \leq J_H^u(a_0) - J_L^u(a_0) \\ L & \text{otherwise} \end{cases}$$

- **Training decisions** maximize the joint surplus of each match:

$$\mathbf{1}_E^t(a, j, z) = \begin{cases} 1 & \text{if } S_E(a, j, z; \mathbf{1}^t(a, j, z, E) = 1) \\ & \geq S_E(a, j, z; \mathbf{1}^t(a, j, z, E) = 0) \\ 0 & \text{otherwise} \end{cases}$$

- Baseline period: 2005-2008
- Countries: 30 + ROW [▶ details](#)
- Industries: 30 ISIC Rev.3.1 (15 tradable) [▶ details](#)
- Occupations: 5 SOC 1-digit [▶ details](#)
- Model numeraire: monthly labor income per employee (USD 3,700)

- The economy is assumed to be in steady state [▶ details](#)
- Production function parameters calibrated directly from expenditure shares in production data

- Initial distribution of human capital assumed to be Beta with shape parameters α_{a_0} and β_{a_0}
- Task-producing technology: $y_E(j, z, i) = z s_j a_i^{\zeta_{j,E}} - c^o$
- Permanent productivity assumed to be increasing in skill content:

$$s_j = (1 + \Delta_s)^{\text{brain}_j}, \quad \text{brain}_j \in (0, 1)$$

- Productivity shocks assumed following the Poisson jump process with hazard φ and realization equal to:

$$z' = \begin{cases} z + \Delta_z \\ z - \Delta_z \\ \text{other} \end{cases} \text{ with probability } \begin{cases} \frac{1}{2} \left(1 - \frac{z}{n\Delta_z} \right) \\ \frac{1}{2} \left(1 + \frac{z}{n\Delta_z} \right) \\ 0 \end{cases} .$$

along the support $Z \equiv \{-n\Delta_z, -(n-1)\Delta_z, \dots, 0, \dots, n\Delta_z\}$ and $n = 100$

Parameters taken from the literature

Parameter	Description	Value	Source
ρ	Discount factor	0.0033	4% yearly
δ_w	Retirement rate	0.0023	ages 25-60
δ_f	Firm exit rate	0.0045	BLS 2005
β	Bargaining power	0.50	Pissarides (2009)
χ	Matching function	0.45	Den Haan et al (2006)
(b_L, b_H)	Home production	(0.31, 0.52)	ACS 2005
c_v	Cost of vacancy	0.29	Abowd and Kramarz (2003)
c_t	Cost of training	0.16	Abowd and Kramarz (2003)
$(\alpha_{a_0}, \beta_{a_0})$	Distribution of a_0	(2.11, 2.45)	AFQT test distribution
(φ, Δ_z)	Productivity shock	(1.57, 0.24)	Lee and Mukoyama (2015)

Parameters from literature, continued

Parameters	Description	Source
Taken from the literature		
η	Elasticity of substitution between varieties ω	Broda and Weinstein (2006)
$\tau_k^{n\bar{n}}$	Bilateral tariffs (countries $n-\bar{n}$, sector k)	Caliendo and Parro (2015)
θ_k	Dispersion Frchet (sector k)	Caliendo and Parro (2015)
Estimated		
ν_k^n	Consumption elasticity of product k (country n)	WIOD-IOT (2013)
$\theta_{k\bar{k}}^n$	Output elasticity of product \bar{k} (country n , sector k)	WIOD-IOT (2013)
α_k^n	Output elasticity of labor tasks (country n , sector k)	KLEMS (2017)
μ_{kj}^n	Labor tasks elasticity of task j (country n , industry k)	OES (2017)

Moments	Data (2005)	Model
<i>Labor income</i>		
College premium	0.557	0.491
St.Dev., non-college	0.605	0.375
St.Dev., college	0.735	0.641
45-25 y.o. premium, non-college	0.191	0.144
45-25 y.o. premium, college	0.382	0.376
Training premium	0.356	0.103
Brain-skill premium	0.337	0.199
<i>Labor market flows</i>		
NE-E rate	0.022	0.016
E-NE rate	0.023	0.025
J-J rate	0.019	0.022
<i>Shares</i>		
College share	0.281	0.310
Training share	0.392	0.304

$$\theta = \left\{ \underbrace{\kappa}_{\text{education}}, \underbrace{\Delta_s, \zeta^E, c^o}_{\text{production (4)}}, \underbrace{\gamma_E^1, \gamma_E^2}_{\text{training (4)}}, \underbrace{\lambda_0, \lambda_1, \zeta}_{\text{visibility (3)}} \right\}.$$

Parameters based on moment vector

Parameter	Description	Value
κ	Cost of college education	181.02
c^o	Cost of operating	1.18
Δ_s	Permanent productivity	0.64
λ_0	Visibility, unemployed	0.032
(λ_1, ξ)	Visibility, employed	(0.038, 0.02)
(ζ_0^L, ζ_0^H)	Return from human capital	(0.09, 0.24)
(γ_0^L, γ_0^H)	Experience, hazard rate	(0.03, 0.05)
(γ_1^L, γ_1^H)	Training, hazard rate	(0.06, 0.15)

Task prices and labor market dynamics

- Suppose something changes task prices—either trade shock or a technology shock—in a way consistent with observed data. What happens to labor market dynamics?
- Proxy changes in prices of tasks, Δr_j , using changes in wages by occupations (between 1990 and 2005)

	Imputed task prices				
tasks j	1	2	3	4	5
1-digit SOC	51-53	45-49	31-39	41-43	11-29
Brain-content	0	0.056	0.134	0.236	1
	0.767	0.845	1.106	0.872	1.592
$\Delta r_j, \%$	+3.55	- 4.14	-1.62	-2.43	+10.12

Counterfactual outcomes

tasks j	1	2	3	4	5
1-digit SOC	51-53	45-49	31-39	41-43	11-29
Brain-content	0	0.056	0.134	0.236	1
Employment share, $\Delta\%$	+0.9	-1.5	-0.8	-0.7	+2.1
J-J rate, $\Delta\%$	-1.06	-0.57	-0.43	-0.48	0.02
E-NE rate, $\Delta\%$	+0.01	+0.60	+0.40	+0.07	-0.05
Training share, $\Delta\%$	-1.03	-27.23	-15.39	-11.20	+12.54
Labor income, avg. %	+2.61	-4.12	-3.12	-1.04	+6.01
Labor income growth, 45-25 y.o. %	+0.02	-5.32	-3.45	-0.95	+7.32

- Use full range of occupations and sectors, and calibrate more seriously
- Using only changes in openness, ask how well the model predicts:
 - job turnover slowdown at each skill level
 - shifts in training and education patterns
 - changes in wages
- Explore added contribution of skill-biased technological change.
- Consider counterfactual policy experiments with commercial policy, education subsidies, training subsidies

- **On-the-job search and bargaining with ex ante heterogeneous workers and firms:** Postel-Vinay and Robin (2002); Bagger, Fontaine, Postel-Vinay, and Robin (2014); Lise, Meghir and Robin (2016); and Lise and Robin (2017).
- **Job and worker turnover decisions interdependent with training investments:** Cairo (2013); Cairo and Kajner (forthcoming); Flinn, Gemici, and Laufer (2017); Lentz and Roys (2015)
- **Stylized facts on job turnover, skill premium, relation to tradability of products:** Hyatt and Spletzer (2012); Decker, Haltiwanger, Jarmin, and Miranda (2016); Davis and Haltiwanger (2014); Cairo and Cajner (2015); Haltiwanger, Hyatt, and McEntarfer (2017); Autor and Dorn (2013); Jensen and Kletzer (2006); Kletzer (2007); Autor, Dorn, and Hanson (2013); Autor, Dorn, Hanson, and Song (2014); etc..

- **Output producers bundle specific tasks, some of which can be accomplished offshore and embodied in intermediate goods trade:** Grossman and Rossi-Hansberg (2008); Eaton, Kortum, and Kramartz (2017).
- **Product market shocks partly transmitted through global intermediate input markets.** Caliendo and Parro (2015).
- **Globalization affects the skill distribution by changing the worker-specific returns to human capital investment:** Cosar (2013); Davidson and Sly (2014); and Blanchard and Willmann (2016).
- **Random search processes empirically link openness with job turnover and unemployment:** Cosar, Guner, and Tybout (2016); Helpman, Itskhoki, Muendler, and Redding. (2017); and Fajgelbaum (2017), Carrère, Grujovic, and Robert-Nicoud (2017).

- **Quantify barriers to worker mobility across sectors and/or occupations:** Lee and Wolpin (2006, 2010); Cosar (2013); Artuc, Chaudhuri, and McClaren (2014, 2016); Dix-Carneiro (2014); Caliendo, Dvorkin, and Parro (2016); Lee (2016); and Traiberman (2017).
- **Life cycle earnings trajectories:** Cosar (2013), Autor, Dorn and Hanson (2015), Kong, Ravikumar and Vandenbroucke (2018), Lagakos, Moll, Porzio, Qian, and Schoellman (2018)

▶ back

J2J transitions and import penetration

$$\mathbf{1}_{it}^{j2j} = \beta \cdot \mathit{imp}_{o(it)} + \delta \cdot \mathit{brain}_{o(it)} + \zeta \cdot X_{it} + \eta_t + v_{s(it)} + \epsilon_{it}$$

	Time period			
	89-95	96-03	04-07	08-13
$\mathit{imp}_{o(it)}$	-0.004*** (0.001)	-0.009*** (0.001)	-0.0128*** (0.004)	-0.0131*** (0.002)
Observations	1,577,329	1,215,022	408,378	996,730

$\mathit{imp}_{o(it)}$: employment share-weighted import penetration rate,
occupation o

X_{it} : gender, race, married, state, metropolitan city, # kids,
disability, union affiliation, multiple jobs

$\eta_t, v_{s(it)}$ time and sector fixed effects

Occupation-specific changes in training rates

1990-2000 and 2000-2010

$$\Delta train_{jt} = \beta \cdot \Delta imp_{jt} + \zeta \cdot X_{jt} + \eta_j + v_t + \epsilon_{jt}$$

	(1)	(2)	(3)
Δimp_{jt}	-4.96** (0.78)	-8.93** (2.29)	-4.14** (1.87)
occupation FE	no	yes	yes
controls	no	no	yes
R^2	0.19	0.43	0.66
Observations	198	198	198

imp_{jt} : employment share-weighted import penetration rate, occup. j

X_{jt} : share female, share white, share college-educated,
brain indicies, brawn indicies

- **Why have a task 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 market for tasks divorces effects of hiring frictions from producers' factor proportions decisions.
- **Think of human resource departments as independent task-producing firms**
 - View the earnings of human resource personnel as reflective of the vacancy posting costs incurred by task-producing firms.
 - View profits of the task-producing firms as the operating profits of goods producers in excess of capital costs. (No product market mark-ups.)
 - Similar in spirit to literature linking labor's share to employer's monopsony power.

The environment: goods producing firms

- Each produces a product variety ω specific to sector k : $\omega \in \Omega_k$, $k \in \{1, \dots, K\}$
- Combines bundles of labor services (\bar{y}_ω^k) and bundles of product varieties ($x_{k,\omega}^{\tilde{k}}$) to generate output (q_ω^k).

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

- Bundles of labor services and of varieties $\tilde{\omega} \in \Omega_{\tilde{k}}$ are CES aggregations.

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

$$\bar{y}_{k,\omega} = \prod_{j=1}^J \left(\frac{y_{k,\omega}^j}{\mu_k^j} \right)^{\mu_k^j}, \quad \mu_k^j \geq 0, \quad \sum_j \mu_k^j = 1$$

- 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- (\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

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

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

$$w_\varphi = b_E$$

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 $S_E(a, j, z') \geq 0$. Worker renegotiates wage:

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- **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:

$$w_\varphi = b_E$$

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

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

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

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

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

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

$$+ \sum_{\tilde{j} \in \mathcal{J}} \phi_{j\tilde{j}}^\ell \sum_{\tilde{z} \in \mathcal{A}_E(j, z, i|\tilde{j})} [J_E^e(a, \tilde{j}, \tilde{z}) - J_E^e(a, j, z)] v_j(\tilde{z})$$

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

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

$$+ \varphi \sum_{\tilde{z} \in \mathcal{Z}} \max\{\Pi_E^e(a, j, \tilde{z}) - \Pi_E^e(a, j, z),$$

$$\Pi^v(j, \tilde{z}) - \Pi_E^e(a, j, z)\} \Lambda(\tilde{z}|z)$$

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

$$\Pi^v(j, z) - \Pi_E^e(a, j, z)\}$$

$$+ \sum_{\tilde{j} \in \mathcal{S}} \phi_{j\tilde{j}}^\ell \sum_{\tilde{z} \in \mathcal{A}_E(j, z, i|\tilde{j})} [\Pi^v(j, z) - \Pi_E^e(a, j, z)] v_j(\tilde{z})$$

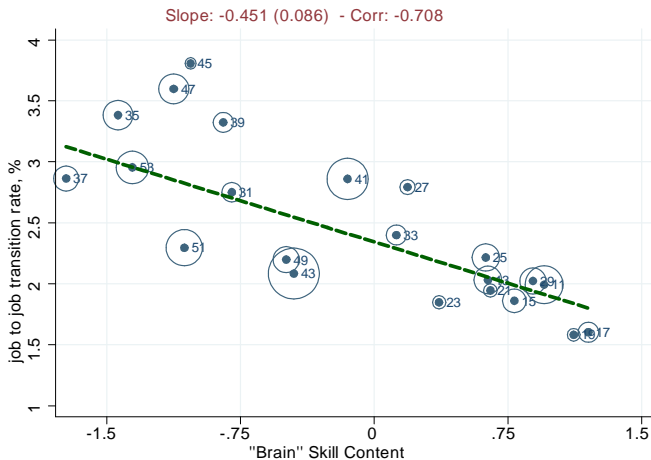
value of being unemployed:

$$[\rho + \delta_\ell] J_E^u(a) = b_E + \beta \sum_{j \in \mathcal{S}} \phi_{j,0}^\ell \sum_{z \in \mathcal{Z}} \max\{S_E(a, j, z), 0\} v_j(z).$$

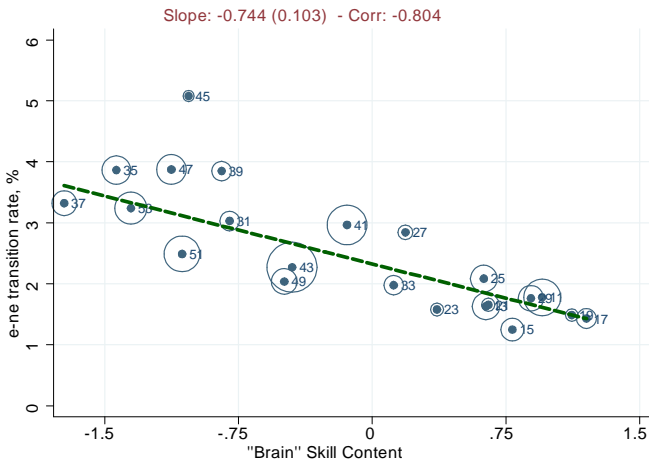
value of vacancy:

$$\begin{aligned} & (\rho + \delta_f) \Pi^v(j, z) \\ &= -c^v + (1 - \beta) \phi_{j,0}^f \sum_{E \in \{L, H\}} \sum_{a \in \mathcal{H}} \max\{S_E(a, j, z), 0\} g_E(a) \\ &+ (1 - \beta) \sum_{E \in \{L, H\}} \sum_{a \in \mathcal{H}} \sum_{\tilde{j} \in \mathcal{S}} \phi_{\tilde{j},j}^f \sum_{\tilde{z} \in \mathcal{A}_E(j, z, i|\tilde{j})} S_E(a, j, z) n_{E\tilde{j}}(a, \tilde{z}) \end{aligned}$$

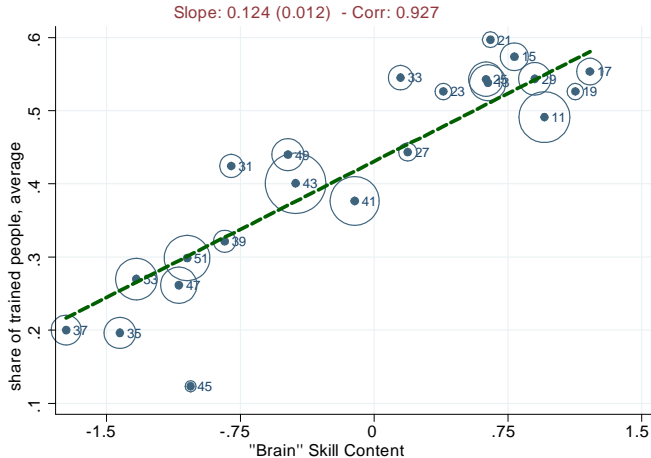
J-to-J by brain skill (Data)



E-to-U by brain skill (Data)



Share trained, by brain skill (Data)



- Clearing in product markets:

$$X_k^n = \sum_{\tilde{k}=1}^K (1 - \alpha_{\tilde{k}}^n) \theta_{\tilde{k}k}^n \sum_{\tilde{n}=1}^N \frac{\pi_{\tilde{k}}^{\tilde{n},n} X_{\tilde{k}}^{\tilde{n}}}{1 + \tau_{\tilde{k}}^{\tilde{n},n}} + v_k I^n$$

$$I^n = Y^n + T^n + D^n$$

$$T^n = \sum_{k=1}^K \sum_{\tilde{n}=1}^N \frac{\pi_k^{n,\tilde{n}}}{1 + \tau_k^{n,\tilde{n}}} \tau_k^{n,\tilde{n}} X_k^n$$

$$D^n = \sum_{k=1}^K \sum_{\tilde{n}=1}^N \frac{\pi_k^{n,\tilde{n}}}{1 + \tau_k^{n,\tilde{n}}} X_k^n - \sum_{k=1}^K \sum_{\tilde{n}=1}^N \frac{\pi_k^{n,\tilde{n}}}{1 + \tau_k^{n,\tilde{n}}} X_{\tilde{k}}^{\tilde{n}}$$

- Clearing in task markets:

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

- Free entry condition for task-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 task-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 task-producing firms-workers matches

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

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

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

Flows of workers across states

$$\begin{aligned}
 & \underbrace{U_{Ei} [\delta_w + \sum_{j \in \mathcal{J}} \tilde{\phi}_{0,j} \sum_{z \in \mathcal{Z}} \mathbf{1}_{\{S_E(j,z,i) \geq 0\}} v_{Ej}(z)]}_{\text{outflows from unemployment}} \\
 = & \underbrace{\delta_f \sum_{j \in \mathcal{J}} \sum_{z \in \mathcal{Z}} N_{Ejzi} + \varphi \sum_{j \in \mathcal{S}} \sum_{z \in \mathcal{Z}} N_{Ejzi} \sum_{\tilde{z} \in \mathcal{Z}} \mathbf{1}_{\{S_E(j,\tilde{z},i) < 0\}} \Lambda(\tilde{z}|z)}_{\text{inflows to unemployment}} + \underbrace{L_{Ei}^e}_{\text{new entrants}}
 \end{aligned}$$

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

Table: List of 1-digit SOC occupations

Code	1-digit SOC	Description	Brain-content
1	51-53	Production, Transportation, and Material Moving Occupations	0
2	45-49	Natural Resources, Construction, and Maintenance Occupations	0.056
3	31-39	Service Occupations	0.134
4	41-43	Sales and Office Occupations	0.236
5	11-29	Management, Business, Science, and Arts Occupations	1

Table: Distance matrix between 1-digit 2002 SOC occupations

	11-29	31-39	41-43	45-49	51-53
11-29	0	10.18	8.25	12.43	12.90
31-39	10.18	0	2.84	3.12	3.26
41-43	8.25	2.84	0	5.84	5.96
45-49	12.43	3.12	5.84	0	0.75
51-53	12.90	3.26	5.96	0.75	0

Visibility: $\lambda_{j\tilde{j}} = \frac{\lambda}{[1+d(j,\tilde{j})]^\xi}$, where

$$d(j,\tilde{j}) = \sqrt{(\mathbf{v}^j - \mathbf{v}^{\tilde{j}})' \Sigma^{-1} (\mathbf{v}^j - \mathbf{v}^{\tilde{j}})}$$