Optimal Skill Mixing Under Technological Advancements

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Labor, Firms, and Macro

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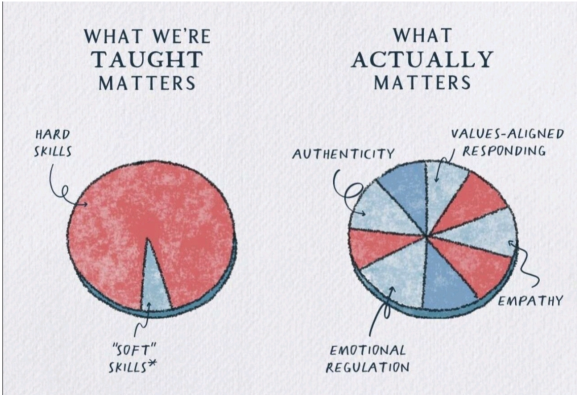
Motivation

- The *nature of work* has changed dramatically
  - Decline in "routine" tasks and related worker skills Acemoglu(1999), Autor, Levy and Murane (2003), Autor and Dorn (2013)
  - Rising importance of social skills Cortes, Jaimovich, and Siu (2021), Deming (2017)
- Remains unclear

  specific specialized skill $\Longleftrightarrow$ a broad range of skills (***"skill mixing"***)

- Different implications
  - Specialization in skill demand $\rightarrow$ experts in a single dimension
  - Skill mixing $\rightarrow$ multidisciplinary schooling and training

Motivation



Harvard Business Review

Hiring And Recruitment

Does Higher Education Still Prepare People for Jobs?

by Tomas Chamorro-Premuzic and Becky Frankiewicz

- European Commission: 45%-60% of all workers in Europe could be replaced by automation before 2030
- OECD: 27% of jobs at high risk from AI revolution

This Paper

1. Documents **new facts** about skill mixing
   - Rich data: incumbent jobs + new vacancies, employer vs. worker
   - New angle-based measure
2. A **directed search model** with occupation design
   - Multi-dimensional skills + non-linear technology
   - Before producing, firms first design the occupation, st a cost (Acemoglu, '99)
   - Endogenous human capital evolvement
3. **Quantify** the underlying drivers
   - Skill mixing changes and related employment, wage dynamics

Findings

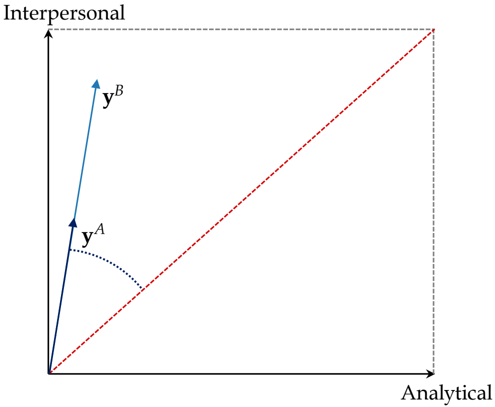
- Substantial $\uparrow$ in skill mixing 2005-2018, even within granular occ.
  - Mainly for non-routine [analytical, interpersonal, computer, leadership, design...]
  - Mainly for medium- to low-wage occupations
  - Source: within-occupation $>$ worker reallocation
    - Persists controlling gender, industry, occ, skill supply (edu, exp)
- Important distribution and wage implications
  - Explains major part of employment/wage polarization
  - Wage returns: 1.5 - 3 percent in skill mixed occupation/college major
- Main channel: $\uparrow$ skill complementarity, cost
  - Experts of analytical, computer / routine skills becomes $\uparrow/\downarrow$ efficienct
  - These drive skill mixing + employment & wage dynamics

Contributions to the Literature

- Labor market dynamics that focuses on skill mixing
  - Skill/task biased: Tinbergen (1975); Katz and Murphy (1992); ALM (2003); Acemoglu and Autor (2011); Autor and Dorn (2013); Deming (2017); Deming and Kahn (2018)
  - Within-occupation variation: Autor and Handel (2013); Atalay et al. (2020); Freeman, Ganguli, and Handel (2020); Cortes, Jaimovich, and Siu (2021)
- Directed search model w/. endogenous demand + multi-d non-linear
  - Menzio and Shi (2010,2011); Kaas and Kircher (2015); Schaal (2017); Baley, Figueiredo, and Ulbricht (2022); Braxton and Taska (2023)
- Matching focusing on firm skill demand trade-offs under GE forces
  - Roy (1951); 1-D: Shi (2001); Hagedorn, Law, and Manovskii (2017)
  - Multi-D: Yamaguchi (2012); Lindenlaub (2017); Lise and Vinay (2020); Ocampo (2022)
  - Bundling: Rosen (1983); Murphy (1986); Heckman and Sedlacek (1985), Choné and Kramarz (2021); Edmond and Mongey (2021)

Evidence of Skill Mixing

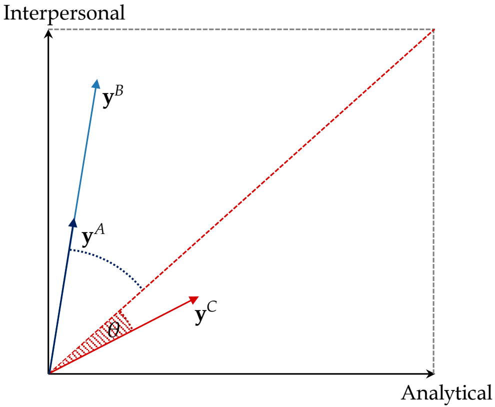
Angle Measure of Skill Mixing [2D]



Length	$\Leftrightarrow$	**Angle Similarity**
Skill intensity		Skill mixing

Occ.	Length	Angle (θ)	$Cosine(\theta)$
A $(\mathbf{y}_A)$	0.4	38.7	0.78
B $(\mathbf{y}_B)$	0.8	38.7	0.78

Angle Measure of Skill Mixing [2D]



Length	$\Leftrightarrow$	**Angle Similarity**
Skill intensity		Skill mixing

Occ.	Length	Angle (θ)	$Cosine(\theta)$
A $(\mathbf{y}_A)$	0.4	38.7	0.78
B $(\mathbf{y}_B)$	0.8	38.7	0.78
C $(\mathbf{y}_C)$	0.4	8.1	0.99

Angle Measure of Skill Mixing [Multi-D]

Definition (Degree of Skill Mixing of an occupation)

The skill mixing index for an occupation $\mathbf{y} = \{y_1, ..., y_k, \ldots, y_K\} \in S \subset \mathbb{R}^{K+}$ is the cosine similarity between its skill vector and the norm $\hat{\mathbf{v}}$.

$$Mix(\mathbf{y}) = \frac{\mathbf{y}\hat{\mathbf{v}}}{||\mathbf{y}|| \cdot ||\hat{\mathbf{v}}||}, \ where\ \hat{\mathbf{v}} = [1, 1, ..., 1]' \subseteq \mathbb{R}^{K+}$$

Angle Measure of Skill Mixing [Multi-D]

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- Interpretation
  - Essentially, $Cosine(\theta)$ in multi-d, $\hat{\mathbf{v}}$ is norm
  - In my analysis, $\mathbf{y} = \{y_{\text{analytical}}, y_{\text{interpersonal}}, y_{\text{computer}}, y_{\text{routine}}, \cdots\}$
  - Accommod. multi-d, focuses on angle similarity, normalized in [0,1]
  - Alternative: Inverse Herfindahl, Absolute Distance details

Data on Skill Demand

- **Occupational Information Network** (O*NET) 2005-2018
  - Detailed 270 descriptors into 9 modules for 970 7-digit occupations
  - Source: surveys of job analysts + incumbent workers example
  - Info on skill requirements and work environments (intensive margin) content
  - Challenge: annually, avg. of 110 occupations updated
    - Broad and 4-year intervals using 4 versions; 274 7-digit occs const. updated details
- **Lightcast** (formerly "Burning Glass") 2007-2017
  - Analyzes millions of online job postings into codified skills
  - Info on whether a skill is required for a vacancy (extensive margin)

Skill Measures

- O*NET - Acemoglu and Autor (2011) & More
  - Non-routine: analytical, interpersonal, computer; routine ["RNR"] details
  - More non-routine: leadership, design, these 5 ["broader non-routine"]
  - Normalize to [0,1] (alternative: standardize)
- Lightcast
  - Same skills, keywords based Deming & Kahn '18, Braxton & Taska '22 details
    - i.e., analytical: "research", "solving"; interpersonal: "teamwork", "collaboration"
  - At occ. level, share of ads that contain these key words (in [0,1])

O*NET Skill Measures and Composing Descriptors

Analytical

- Analyzing data/information
- Thinking creatively
- Interpreting information for others

Interpersonal

- Establishing and maintaining personal relationships
- Guiding, directing and motivating subordinates
- Coaching/developing others

Computer

- Interacting With Computers
- Programming
- Computers and Electronics

Routine

- Importance of repeating the same tasks
- Importance of being exact or accurate
- Structured work
- Pace determined by speed of equipment
- Controlling machines and processes
- Spend time making repetitive motions

Broader skill measures

Fact 1: Increase in Skill Mixing at 7-Digit Occupations

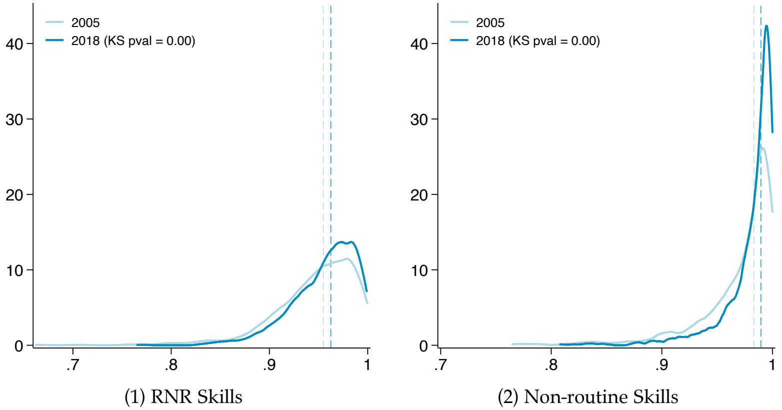


Figure: Density for Skill Mixing Indexes (Cosine Similarities), 2005 vs. 2018

Broader Non-routine | Weighted Density | Non-parametric

Fact 2: Growth in Skill Mixing

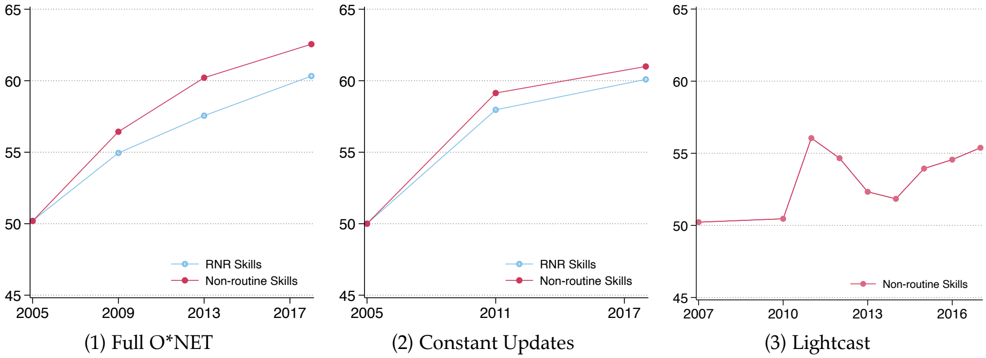
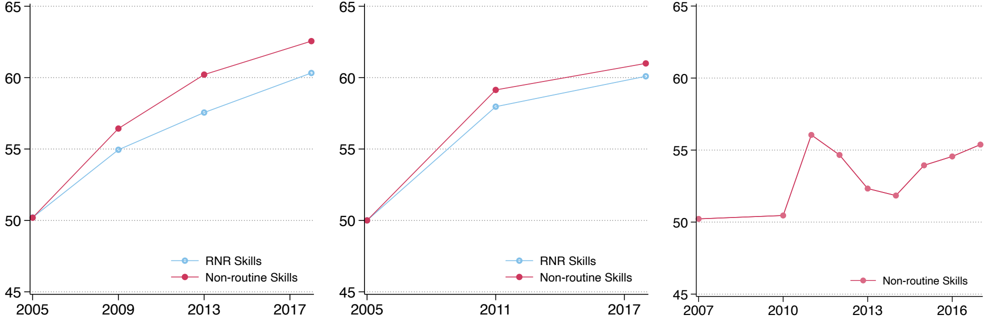


Figure: Trend of Skill Mixing in the US Economy, 2005-2018

Updating issue | Robust - measure | Robust - index | Skill pairs | Composition of updates

Fact 2: Growth in Skill Mixing



(1) Full O*NET (2) Constant Updates (3) Lightcast

Figure: Trend of Skill Mixing in the US Economy, 2005-2018

total	within	across
10.12	9.46	0.66
12.37	9.72	2.65

total	within	across
10.09	10.74	-0.65
11.00	9.69	1.31

total	within	across
5.16	4.37	0.78

Shift-share decomposition

Fact 3: Skill Mixing Increases Regardless of Workforce

	RNR Skills	Non-routine Skills
Full O*NET	0.70^{***}	0.71^{***}
	[0.10]	[0.09]
Constant Updates	0.75^{***}	0.65^{***}
	[0.11]	[0.11]
Lightcast		0.33^{**}
		[0.15]
Sex $\times$ industry $\times$ occ. FE	X	X
Exp. and edu. controls	X	X

Table: Within Occupation Changes in Skill Mixing Indexes

$$Mix(\mathbf{y})_{ijt}^{\text{percentile}} = Year_t + \xi X_{ijt} + \delta_j + \epsilon_{ijt} \text{ where } j = \text{sex} \times \text{industry} \times \text{occ.}$$

Fact 4: Medium- to Low-Wage Occupations More Mixed

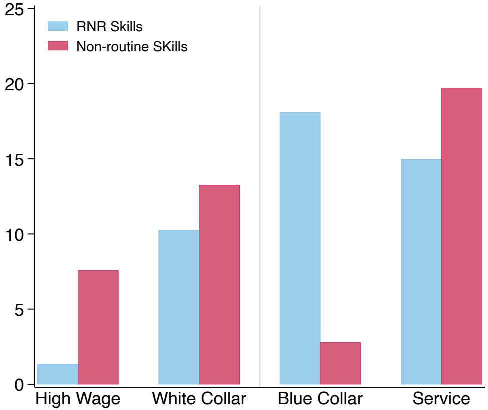


Figure: Skill Mixing Index Change by Occupation Groups, 2005-2018

By industry Skill pairs

Fact 5: Skill Mixing Accounts for Polarization

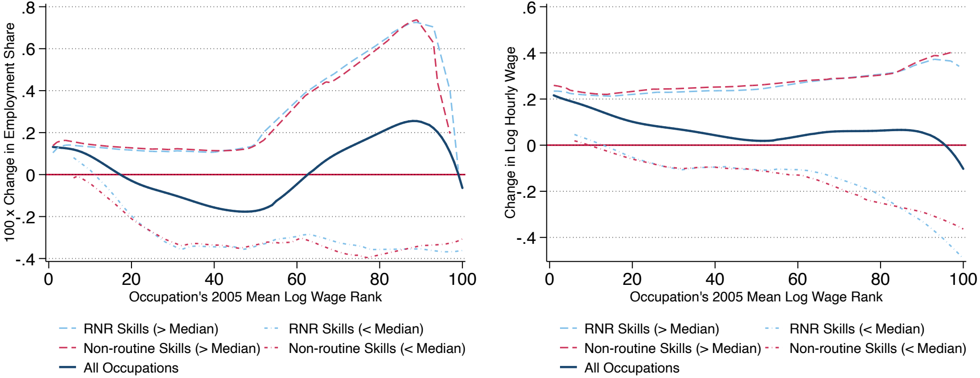


Figure: Smoothed Employment and Wage Changes by Skill Percentile, 2005-2018

Returns to Skill Mixing

- National Longitudinal Survey of Youth (NLSY) 2005-2019
  - Detailed employment and educational histories + pre-market abilities
    - Analytical: AFQT; Interpersonal: social (Deming, '17); Computer: occ/major's computer skill
  - Both 79 & 97 cohorts (median age: 37), outcome: real log hourly wage
    - Robust to restricting age < 50 or use hourly wage levels
  - College major's skill mixing: emp-weighted avg. of O*NET measures

Correspond skill measures   Top majors

Returns to Skill Mixing

Dependent: ln (hourly wage)	(1)	(2)	(3)
Mix (non-routine skills): Occ	0.017***	0.015***	0.014***
	[0.005]	[0.005]	[0.005]
Mix (non-routine skills): Worker		0.065***	
		[0.017]	
Ethnicity Gender, Age/Year, Region, Edu FE	X	X	X
Occupation FE	X	X	X
Worker FE			X
Observations	88,391	79,343	88,391
R-squared	0.416	0.430	0.756

Table: Return to Skill Mixing: Occupations and Workers

Full table with emp | Returns to college major | Robust - measures and index

A Directed Search Model with Occupation Design

Environment

- Multi-dimensional Skill Set-up
  - Discrete time, 1-1 matching, $K \geq 2$ skills
  - A unit of heterogeneous workers $\mathbf{x} = \{x_1, ..., x_k, \ldots, x_K\} \in S \subset \mathbb{R}^{K+}$
  - A mass of risk-neutral firms $\mathbf{y} = \{y_1, ..., y_k, \ldots, y_K\} \in S \subset \mathbb{R}^{K+}$
  - CES - Matching production Lindenlaub (2017); Lise & Postel-Vinay (2020)

$$f(\mathbf{x}, \mathbf{y}) = \left[\sum_{k=1}^{K} (x_k \alpha_k y_k)^{\sigma} \right]^{\frac{1}{\sigma}}$$

- Endogeneous Occupation Design
  - Both vacant & incumbent firms optimally choose $\mathbf{y}$ before producing
  - Pay $C(\mathbf{y}) = \tau [\sum_{k=1}^{K} (y_k)^{\rho}]$ rep. cost of operating an occ for given $\mathbf{y}$

Model in Action

Beginning of period

- δ share of workers separate

Occupation Design

- Firms (incumbent & vacant) choose $\mathbf{y}$

→

Labor Market Opens

(Search and Matching)

- Firms post in $(\mathbf{x}, \mathbf{y}, \omega)$
- Workers search for jobs

→

Production

- Firms produce $f(\mathbf{x}, \mathbf{y})$, pay $C(\mathbf{y})$
- Workers get benefits

→

Skill Evolvement

- Worker skill j change according to $\pi(x_j'|x_j, y_j)$ controlled by γ_j

- Continuum submarkets by $(\mathbf{x}, \mathbf{y})$, surplus share ω, tightness $\theta(\mathbf{x}, \mathbf{y}, \omega)$
- Endogenous skill investment & (multi-d) job ladder

$$\pi(x_j'|x_j, y_j) = \frac{x_j' - x_j}{y_j - x_j}\mathbf{1}(x_j < y_j) \times \gamma_j^{up} + \frac{x_j' - x_j}{y_j - x_j}\mathbf{1}(y_j < x_j) \times \gamma_j^{down}$$

$\gamma_j^{up/down}$ is the share of skill j that worker can catch in a period

Model Equilibrium

- Worker's Problem

$$U(\mathbf{x}) = b + \beta E\left\{\max_{\mathbf{y}',\omega'} \underbrace{p(\theta(\mathbf{x}',\mathbf{y}',\omega'))W(\mathbf{x}',\mathbf{y}',\omega')}_{\text{get employed}} + \underbrace{[(1 - p(\theta(\mathbf{x}',\mathbf{y}',\omega'))]U(\mathbf{x}')}_{\text{stay unemployed}}\right\}$$

$$W(\mathbf{x},\mathbf{y},\omega) = \underbrace{\omega(f(\mathbf{x},\mathbf{y}) - C(\mathbf{y}))}_{\text{get surplus}} + \beta(1-\delta)E\left\{\max_{\tilde{\mathbf{y}}',\tilde{\omega}'} \underbrace{p(\theta(\mathbf{x}',\tilde{\mathbf{y}}',\tilde{\omega}'))W(\mathbf{x}',\tilde{\mathbf{y}}',\tilde{\omega}')}_{\text{change employer}}\right.$$
$$\left. + \underbrace{[(1 - p(\theta(\mathbf{x}',\tilde{\mathbf{y}}',\tilde{\omega}'))]W(\mathbf{x}',\mathbf{y}',\omega)}_{\text{stay with current employer}}\right\} + \delta U(\mathbf{x}')$$

Model Equilibrium

- Worker's Problem

$$U(\mathbf{x}) = b + \beta E\Big\{\max_{\mathbf{y}',\omega'} p(\theta(\mathbf{x}',\mathbf{y}',\omega'))W(\mathbf{x}',\mathbf{y}',\omega') + [(1 - p(\theta(\mathbf{x}',\mathbf{y}',\omega'))]U(\mathbf{x}')\Big\}$$

$$W(\mathbf{x},\mathbf{y},\omega) = \omega(f(\mathbf{x},\mathbf{y}) - C(\mathbf{y})) + \beta(1-\delta)E\Big\{\max_{\tilde{\mathbf{y}}',\tilde{\omega}'} p(\theta(\mathbf{x}',\tilde{\mathbf{y}}',\tilde{\omega}'))W(\mathbf{x}',\tilde{\mathbf{y}}',\tilde{\omega}') + [(1 - p(\theta(\mathbf{x}',\tilde{\mathbf{y}}',\tilde{\omega}'))]W(\mathbf{x}',\mathbf{y}',\omega)\Big\} + \delta U(\mathbf{x}')$$

- Firm's Problem

$$J(\mathbf{x},\mathbf{y},\omega) = \max_{\mathbf{y}} \underbrace{(1-\omega)(f(\mathbf{x},\mathbf{y}) - C(\mathbf{y}))}_{\text{design occupation}} + \beta(1-\delta)E\Big\{\underbrace{(1 - p(\theta(\mathbf{x}',\tilde{\mathbf{y}}',\tilde{\omega}'))J(\mathbf{x}',\mathbf{y}',\omega)}_{\text{retain the worker}}\Big\}$$

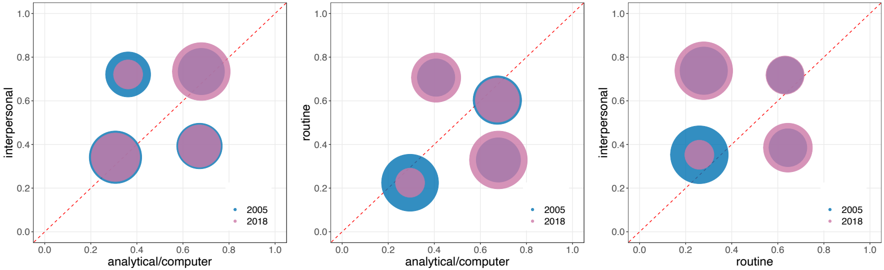
By free-entry: $c = \beta E\Big\{q(\theta(\mathbf{x},\mathbf{y},\omega))J(\mathbf{x},\mathbf{y},\omega)\Big\}$

- Equilibrium Properties
  - Block-recursive Menzio & Shi (2010,2011) due to directed search + submarkets
  - Δ skill mixing, wage, employment: complementarity, cost, skill supply

What Are the Drivers of Skill Mixing and How Do They Affect Labor Market Dynamics?

Measurement and Calibration

- Measurement (NLSY, 2005–2006 and 2016–2019)
  - Occ: high-wage (professional & white-collar), low-wage (blue-collar & service)
  - Worker: low-type (avg. of below mean x_j^{low}), high-type
- Skill Supply Variation
  - Skill change at rate $\gamma_j \times$ skill gap Lise & Postel-Vinay (2020) Skill supply
  - *Across period*: according to occ or college major in NLSY more
  - *Within period*: according to occ via Markov process



Calibrated Parameters

Param.	Description	Value		Source/Target
	A. Search			
β	Discount Rate	0.96		Interest rate of 4%
δ	Job separation rate	0.10		Shimer (2005)
ω	Worker share of surplus	0.60		Labor share of GDP
b	Unemploy. benefit % of output	0.42		Braxton et. al (2020)
η	Elasticity of matching	0.50		Mercan & Schoefer (2020)
μ	Matching efficiency	0.65		Mercan & Schoefer (2020)
	B. Annual skill adjustment	(Up)	(Down)	
γ_a	Analytical/computer skill	0.36	0.10	Lise & Postel-Vinay (2020)
γ_p	Interpersonal skill	0.05	0.00	Lise & Postel-Vinay (2020)
γ_r	Routine skill	1.00	0.36	Lise & Postel-Vinay (2020)

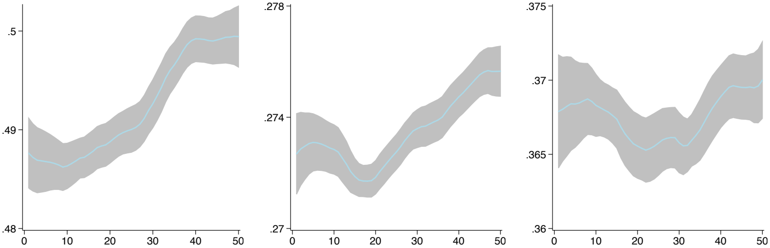
Estimated Parameters

	C. Skill efficiency	(2005)	(2018)	
α_a	Analytical/computer skill	0.63	0.95	Lindenlaub (2017)
α_p	Interpersonal skill	0.05	0.08	Lise & Postel-Vinay (2020)
α_r	Routine skill	0.14	0.06	Lindenlaub (2017)
	D. Internally estimated	(2005)	(2018)	Moments Identification
σ	Inverse elasticity (low)	0.64	0.41	Within-occ covar abilities & wage
σ	Inverse elasticity (high)	0.60	0.36	Within-occ covar abilities & wage
τ	Scaler of cost	0.74	0.53	Employ. distribution & relative wage
ρ	Convexity of cost	3.63	4.90	Degree of skill mixing
c	Vacancy posting cost % output	0.56	0.82	Unemployment rate

- Estimation strategy - SMM Numerical algorithm
  1. Given $\Theta = \{\sigma, \rho, \tau, c\}$, solve SS firm and worker policy
  2. Simulate 10,000 workers for $T(T > 100)$ periods, obtain dist of LM outcomes
  3. Minimizes the distance between the model vs. data moments

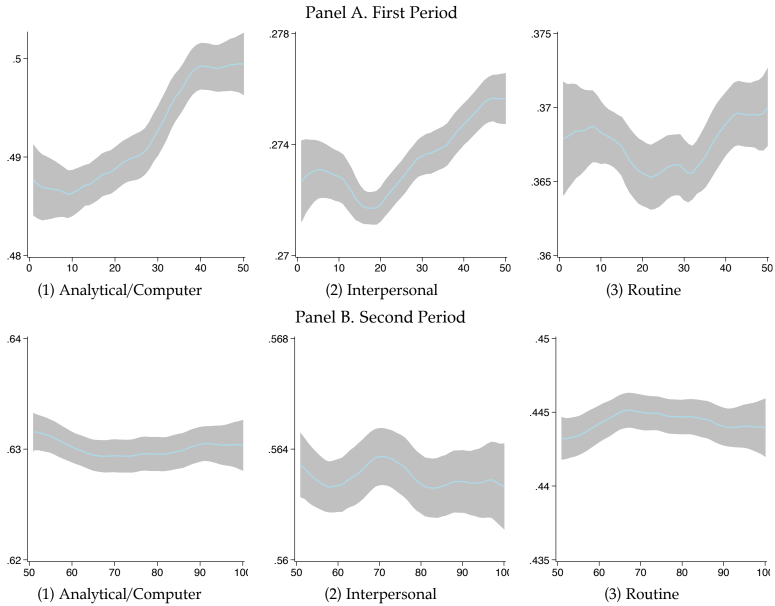
Worker Job Ladder

Panel A. First Period



(1) Analytical/Computer (2) Interpersonal (3) Routine

Worker Job Ladder

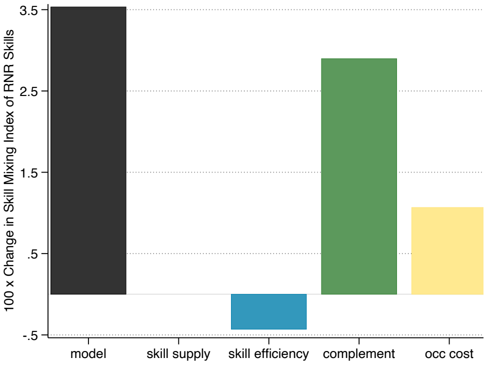


(Collapse of job ladder)

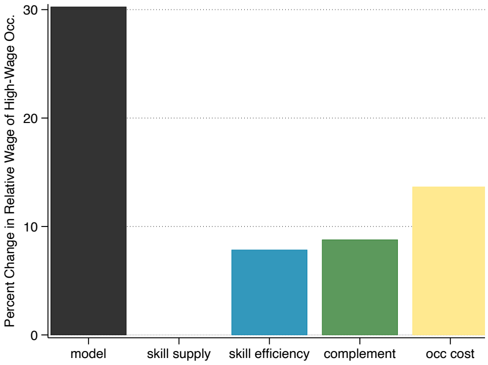
Counterfactuals

- Shut down channels sequentially from the ”2018 economy”
  1. Skill efficiencies α_k
  2. Inverse elasticity σ
  3. Scaler of cost τ
  4. Convexity of cost ρ
  5. Vacancy posting cost c
- Non-linear interaction → remove forces in different orders and average across orders
- Contribution of a ”channel”: difference between the actual and channel-free economy

Forces at Play: Skill Mixing, Wages



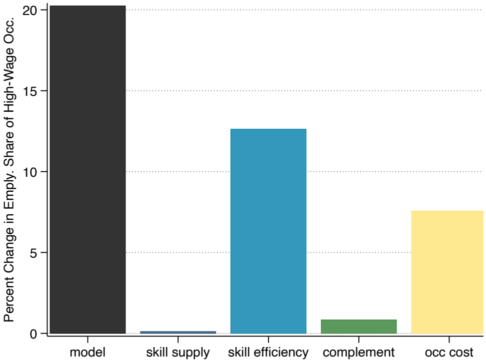
(1) Skill Mixing



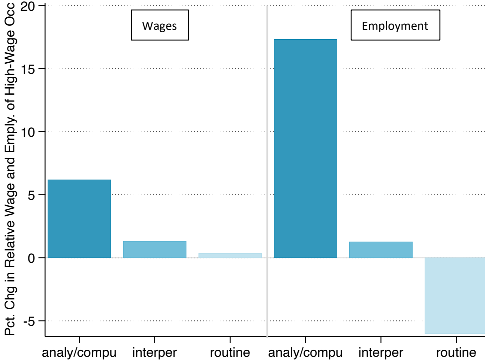
(2) Relative Wages of High-Wage Occupation

- Complementarity & cost explain 2/3 and 1/3 of the increase in skill mixing
- They account for 74% of the ↑ wage premium of high-wage occupation

Forces at Play: Employment, Different Skills



(3) Employment Shares of High-Wage Occupation



(4) Role of Individual Skills for Wages and Employment

- Skill efficiency most important for ↑ employment of high-wage occupation (62%)
- Analytical/Computer skill biggest role

More on Education | Additional counterfactual

Conclusion

- Skills are *inevitably* embedded in workers → demand of skill mixtures
- **New facts** about skill mixing, important for distributions & workers
- **New framework** of multi-d search & occ. design, complementarity matters

Educators and policymakers ought to provide more "mixed" skills to workers to take advantage of the complementarity side of technological change.

Lastly

Lastly

HAPPY NEW YEAR of 2024!

Intro
Evidence
Returns
Model
Quantitative
Conclusion

Appendix

Worker Survey back

13. Negotiation **Bringing others together and trying to reconcile differences.**

A. How <u>important</u> is NEGOTIATION to the performance of *your current job*?

Not Important*	Somewhat Important	Important	Very Important	Extremely Important
1	2	3	4	5

* If you marked Not Important, skip LEVEL below and go on to the next skill.

B. What <u>level</u> of NEGOTIATION is needed to perform *your current job*?

1	2	3	4	5	6	7
	Present justification to a manager for altering a work schedule		Contract with a wholesaler to sell items at a given cost		Work as an ambassador in negotiating a new treaty	Highest Level

O*NET Modules and Principle Content back

Survey	Main content
Education/ training	Required education, related work experience, training
Knowledge	Various specific functional and academic areas (e.g., physics, marketing, design, clerical, food production, construction)
Skills	Reading, writing, math, science, critical thinking, learning, resource management, communication, social relations, technology
Abilities	Writing, math, general cognitive abilities, perceptual, sensory-motor, dexterity, physical coordination, speed, strength
Work activities	Various activities (e.g., information processing, making decisions, thinking creatively, inspecting equipment, scheduling work)
Work context	Working conditions (e.g., public speaking, teamwork, conflict resolution, working outdoors, physical strains, exposure to heat, noise, and chemicals, job autonomy)
Work style	Personal characteristics (e.g., leadership, persistence, cooperation, adaptability)

O*NET Versions and Corresponding Years back

	Released Year	Division	Work Context	Work Activities	Knowledge	Skills	Abilities	Considered Year
O*NET 13.0	2008	Post 2005	73.79%	73.79%	73.79%	73.79%	73.79%	2005
		Before 2005	26.21%	26.21%	26.21%	26.21%	26.21%	
O*NET 18.0	2013	Post 2009	57.15%	57.21%	57.21%	99.89%	57.21%	2009
		Before 2009	42.85%	42.79%	42.79%	0.11%	42.79%	
O*NET 22.0	2017	Post 2013	57.84%	57.67%	57.67%	57.67%	57.67%	2013
		Before 2013	42.16%	42.33%	42.33%	42.33%	42.33%	
O*NET 25.0	2022	Post 2018	54.52%	54.52%	54.52%	54.52%	54.52%	2018
		Before 2018	45.48%	45.48%	45.48%	45.48%	45.48%	

*Notes: The table summarizes different versions of the O*NET (Occupational Information Network) database, along with their released year, year division for the 5 modules (work context, work activities, knowledge, skills, abilities), and the considered year for each version. The "Post" and "Before" rows indicate whether the data in each version was collected post or before a particular year. The "Considered Year" column represents the year considered to be corresponding to each release of O*NET based on the year division of data.*

O*NET Skills back

Non-routine Analytical

- Analyzing data/information
- Thinking creatively
- Interpreting information for others

Non-routine Interpersonal

- Establishing and maintaining personal relationships
- Guiding, directing and motivating subordinates
- Coaching/developing others

Computer

- Interacting With Computers
- Programming
- Computers and Electronics

Design

- Design
- Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment

Routine

- Importance of repeating the same tasks
- Importance of being exact or accurate
- Structured v. Unstructured work (reverse)
- Pace determined by speed of equipment
- Controlling machines and processes
- Spend time making repetitive motions

Leadership

- Making Decisions and Solving Problems
- Developing Objectives and Strategies
- Organizing, Planning, and Prioritizing Work
- Coordinating the Work and Activities of Others
- Developing and Building Teams
- Guiding, Directing, and Motivating Subordinates
- Provide Consultation and Advice to Others

Broad O*NET Skills back

Analytical	Mechanical	Interpersonal
• Deductive Reasoning	• Multilimb Coordination	• Assisting and Caring for Others
• Inductive Reasoning	• Speed of Limb Movement	• Selling or Influencing Others
• Mathematical Reasoning	• Mechanical	• Resolving Conflicts and Negotiating
• Number Facility	• Performing General Physical Activities	• Coaching and Developing Others
• Mathematics	• Handling and Moving Objects	• Staffing Organizational Units
• Economics and Accounting	• Controlling Machines and Processes	• Service Orientation
• Reading Comprehension	• Operate Vehicles, Mechanized Devices or Equipmnt	• Administration and Management
• Writing	• Repairing and Maintaining Mechanical Equipment	• Customer and Personal Service
• Speaking	• Repairing and Maintaining Electronic Equipment	
• Oral Comprehension	• Installation	
• Written Comprehension	• Equipment Maintenance	
• Oral Expression	• Repairing	
• Written Expression	• Production and Processing	

Lightcast Key Words back

Analytical	Interpersonal	Computer
• "research"	• "communication"	• “computer”
• "analy"	• "teamwork"	• Any skill flagged as software related
• "decision"	• "collaboration"	
• "solving"	• "negotiation"	
• "math"	• "presentation"	
• "statistic"		
• "thinking"		

Skill Mixing at 7-digit Occupations back

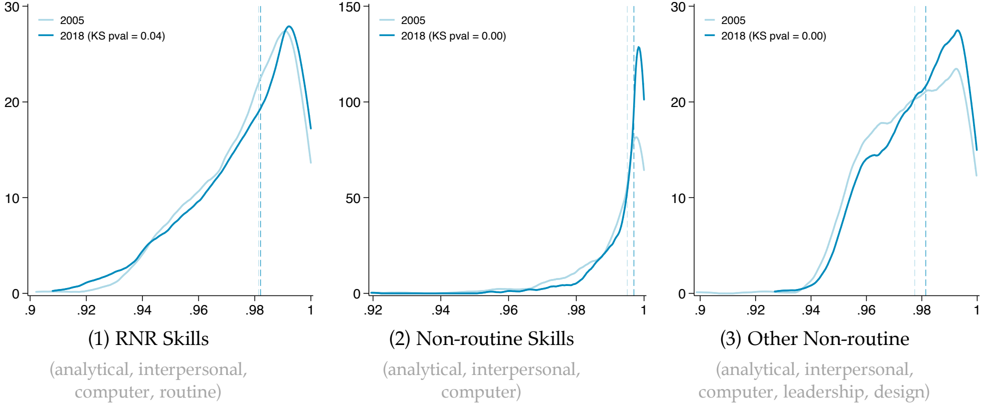


Figure: Density for Skill Mixing Indexes (Cosine Distances), 2005 vs. 2018

Skill Mixing at 7-digit Occupatoins back

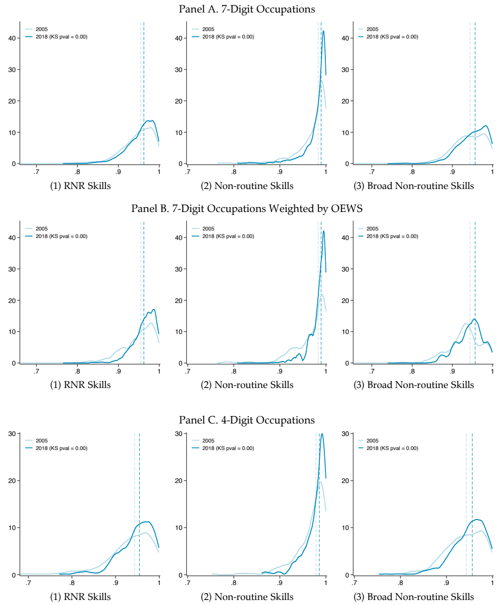


Figure: Density for Skill Mixing Indexes (Weighted Cosine Distances), 2005 vs. 2018

Alternative Depiction of Skill Mixing

back

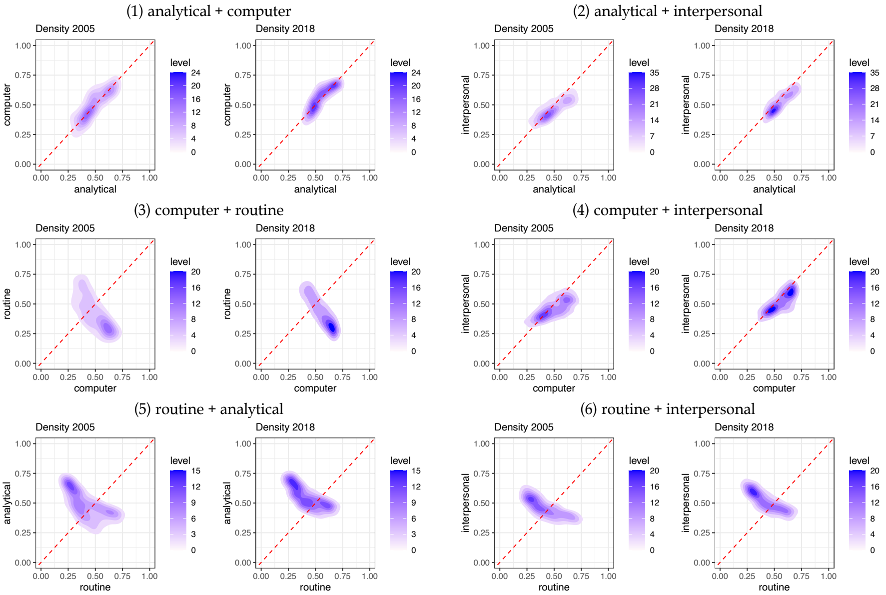


Figure: Non-parametric Depiction of Skill Intensities, 2005 vs. 2018

Time Pattern back

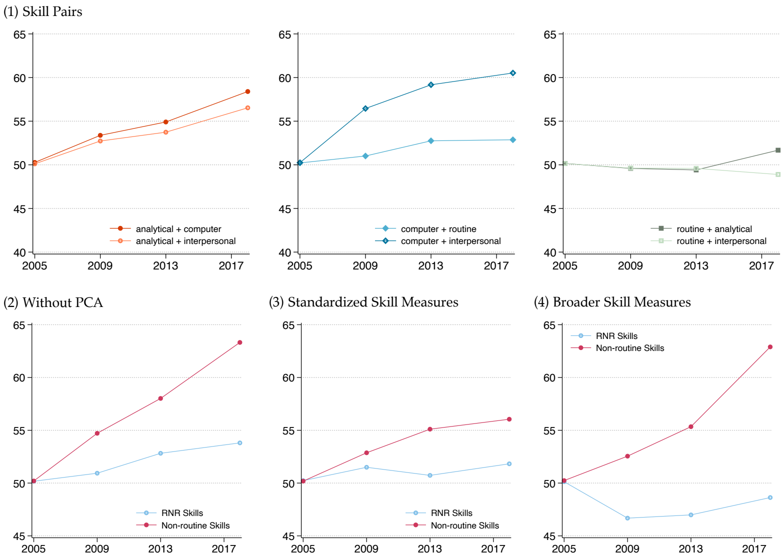


Figure: Trend of Skill Mixing with Alternative Skill Measures

Alternative Skill Mixing Indexes back

- Inverse Herfindahl–Hirschman Index (HHI)

$$\left[\left(\frac{y_a^j}{y_a^j + y_s^j}\right)^2 + \left(\frac{y_s^j}{y_a^j + y_s^j}\right)^2\right]^{-1}$$

- Normalized Absolute Distance

$$-\frac{|y_a^j - y_s^j|}{y_a^j + y_s^j}$$

Time Pattern back

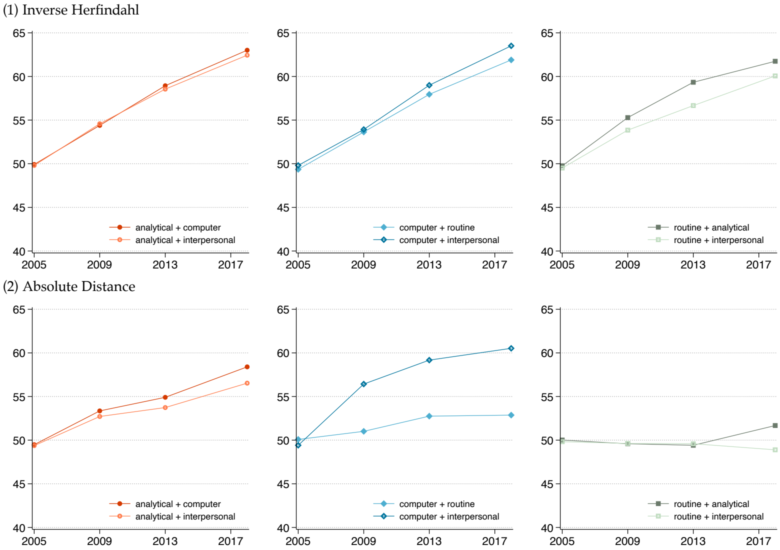
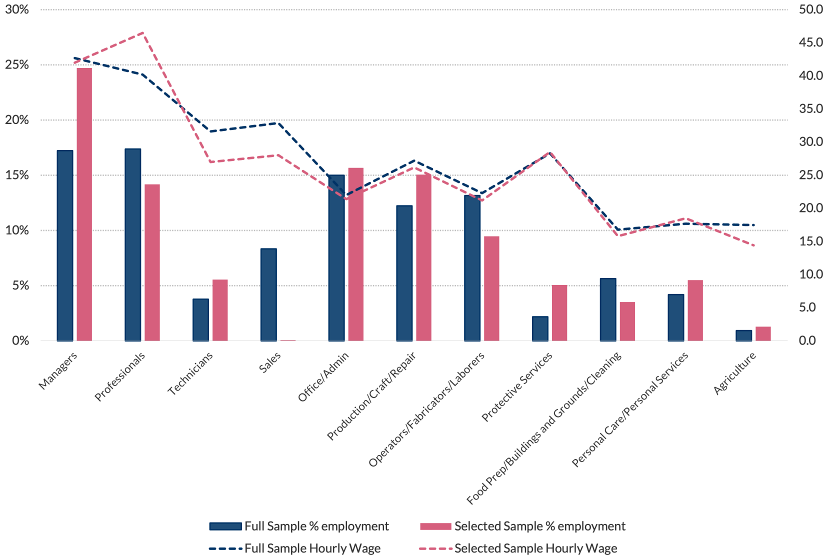


Figure: Trend of Skill Mixing with Alternative Indexes

Full and Updated O*NET back



Decomposition: Intensive vs. Extensive back

	Skill Groups	7-digit Occupations			4-digit Occupations		
		total	within	across	total	within	across
Full O*NET	RNR Skills	6.78	4.93	1.85	10.12	9.46	0.66
	Non-routine Skills	9.21	5.62	3.59	12.37	9.72	2.65
Constant Updates	RNR Skills	5.59	6.73	-1.14	10.09	10.74	-0.65
	Non-routine Skills	4.05	5.33	-1.29	11.00	9.69	1.31
Lightcast	Non-routine Skills				5.16	4.37	0.78

Table: Shift-Share Decomposition of Skill Mixing Index Changes

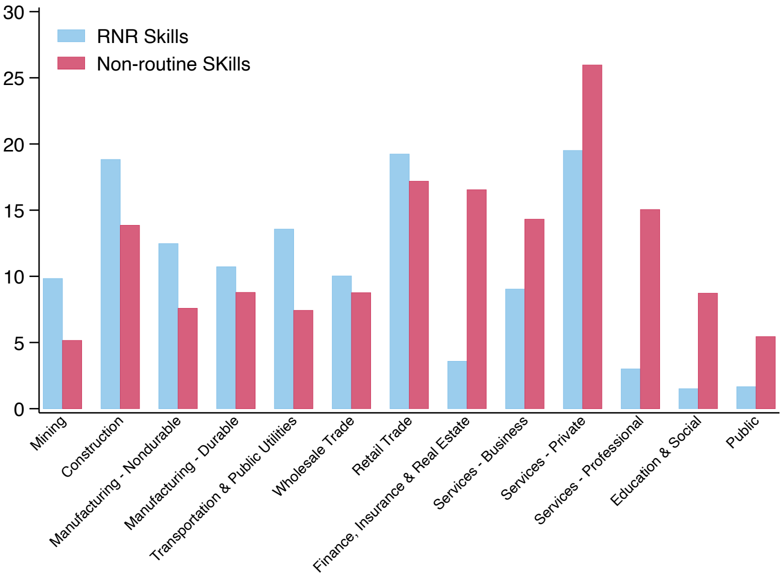
Notes: This table shows a shift-share decomposition of changes in the average level of different mixing indexes between 2005-2018 in percentile units. Specifically, for a change in the percentile of a mixing index over two periods t and τ, its change $\Delta T_\tau = T_\tau - T_t$ which can be decomposed to $\Delta T = \sum_j \left(\Delta E_{j\tau}\alpha_j\right) + \sum_j \left(E_j \Delta\alpha_{j\tau}\right) = \Delta T^a + \Delta T^w$ where $E_{j\tau}$ is employment weight in occupation j in year τ, and $\alpha_{j\tau}$ is the level of mixing index h in occupation j in year τ, $E_j = \frac{1}{2}(E_{jt} + E_{j\tau})$ and $\alpha_j = \frac{1}{2}(\alpha_{jt} + \alpha_{j\tau})$. ΔT^a and ΔT^w then represent across-occupation and within-occupation change.

Decomposition: Intensive vs. Extensive back

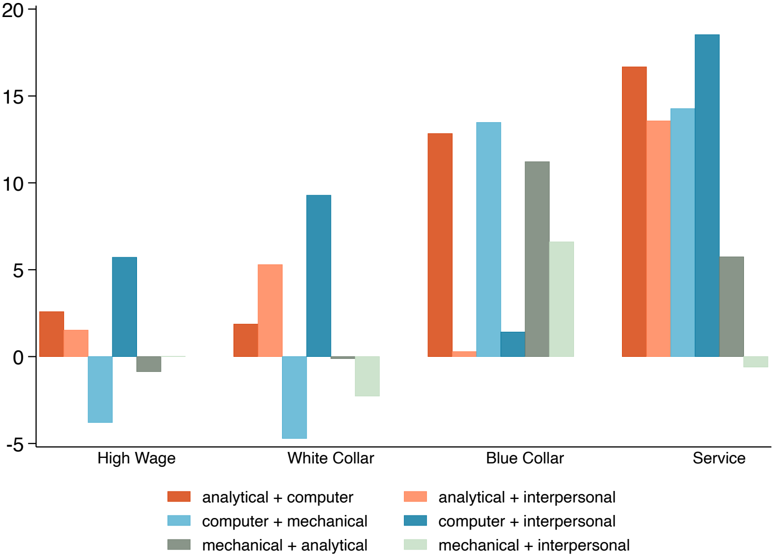
	Skill Groups	6-digit Occupations			4-digit Occupations		
		total	within	across	total	within	across
Full O*NET	analytical + computer	10.52	6.40	4.12	10.49	6.60	3.89
	analytical + interpersonal	5.36	2.90	2.46	8.17	4.08	4.09
	computer + routine	4.38	2.41	1.97	5.16	2.94	2.22
	computer + interpersonal	7.23	3.60	3.63	11.81	7.51	4.30
	routine + analytical	4.00	2.29	1.71	4.23	3.16	1.07
	routine + interpersonal	1.93	0.12	1.81	2.35	1.08	1.26
Constant Updates	analytical + computer	5.59	6.03	-0.44	6.42	5.89	0.53
	analytical + interpersonal	3.53	4.58	-1.05	4.00	3.00	1.00
	computer + routine	2.88	3.69	-0.81	0.52	1.93	-1.42
	computer + interpersonal	0.78	1.86	-1.09	6.86	5.93	0.93
	routine + analytical	2.04	2.13	-0.09	1.48	3.60	-2.12
	routine + interpersonal	0.81	0.82	-0.01	-0.33	1.47	-1.80
Lightcast	analytical + computer				12.64	11.74	0.90
	analytical + interpersonal				2.51	2.20	0.31
	computer + interpersonal				-4.18	-3.79	-0.39

Table: Decomposition of Mixing Indexes' Changes by Skill Pairs

Mixing Index Change by Industries, 2005-2018 back



Mixing Index Change by Skill Pairs, 2005-2018 back



Figure

Skill Measures in NLSY

back NLSY back quant

O*NET Measure	NLSY Measure	γ_{school}^{learn}	γ_j^{up}	γ_j^{down}
analytical	AFQT score	0.33	0.36	0.10
interpersonal	Deming (2017) social skill	0.33	0.05	0.00003
routine	ASVAB	0.33	1	0.36
computer	OCC/Major's 2005 Value	0.33	0.36	0.10

Table: Skill Measures in NLSY and Annual Skill Learning and Depreciation Rate

*Notes: This table illustrates for each O*NET skill measure, its corresponding skill measure using NLSY79&97 data, and the learning and depreciation rate for these different skills. The AFQT is the same as the one used by Altonji, Bharadwaj, and Lange (2012) followed by Deming (2017), which controls for age-at-test, test format, and other idiosyncrasies. Deming (2017)'s social skill measure consists of sociability in childhood and sociability in adulthood in NLSY79, and two questions from the Big 5 inventory gauging the extraversion in NLSY97. The average of workers' ASVAB mechanical orientation and electronics test scores are used for mechanical skill. Since ASVAB scores are not available for the NLSY97 survey, they are imputed based on predictive regression using the NLSY79 survey. Workers' occupations' or college majors' O*NET computer skill scores in the year 2000 are used as their endowed computer skill. The skill accumulation/depreciation rate is directly from Lise and Postel-Vinay (2020)'s estimates based on monthly data converted to annual values. Skill learning/depreciating while attending college is specified to be 33% per year.*

Illustration of Labor Market

Salesperson ($\boldsymbol{x}^s$)

- Unemployed
- Occupation B ($\boldsymbol{y}^A$)
  - Surplus share ω_1: $p(\theta(\boldsymbol{x}^s, \boldsymbol{y}^A, \omega_1))$
  - Surplus share ω_2: $p(\theta(\boldsymbol{x}^s, \boldsymbol{y}^A, \omega_2))$
  - ...
- Occupation B ($\boldsymbol{y}^B$)
  - Surplus share ω_1: $p(\theta(\boldsymbol{x}^s, \boldsymbol{y}^B, \omega_1))$
  - Surplus share ω_2: $p(\theta(\boldsymbol{x}^s, \boldsymbol{y}^B, \omega_2))$
  - ...
- Occupation ...

Computer Scientist ($\boldsymbol{x}^c$)

- Unemployed
- Occupation A ($\boldsymbol{y}^A$)
  - Surplus share ω_1: $p(\theta(\boldsymbol{x}^c, \boldsymbol{y}^A, \omega_1))$
  - Surplus share ω_2: $p(\theta(\boldsymbol{x}^c, \boldsymbol{y}^A, \omega_2))$
  - ...
- Occupation B ($\boldsymbol{y}^B$)
  - Surplus share ω_1: $p(\theta(\boldsymbol{x}^c, \boldsymbol{y}^B, \omega_1))$
  - Surplus share ω_2: $p(\theta(\boldsymbol{x}^c, \boldsymbol{y}^B, \omega_2))$
  - ...
- Occupation ...

$\pi(x_j' | x_j, y_j)$

Calibration of Skill Supply

back

- Skill supply calibration: between data periods and within model period
- **Across-period Skill Supply Variation**:
  - Skills adjusted based on occupation or college major requirements.
  - Skill accumulation at rate $\gamma_j \times$ skill gap.
  - Annual rates adjusted by number of working weeks (47).
- **Markov Skill Supply Adjustment**:
  - Skill evolution follows Markov process $\pi(x_j'|x_j, y_j)$.
  - Upward adjustment probability:

$$\frac{x_j^{up} - x_j}{y_j - x_j}\mathbf{1}(x_j^{up} < y_j) \times \frac{\gamma_j^{up}}{4}$$

  - Downward adjustment probability:

$$\frac{x_j^{down} - x_j}{y_j - x_j}\mathbf{1}(y_j < x_j^{down}) \times \frac{\gamma_j^{down}}{4}$$

Targeted Moments back

	First Period		Second Period	
	Data	Model	Data	Model
Worker moments				
Relative wage of high type				
Analytical/computer	1.46	1.62	1.60	1.78
Interpersonal	1.05	1.09	1.20	1.25
Routine	1.12	1.23	0.92	1.21
Wage return of skill mixing (untargeted)	0.07	0.04	0.07	0.04
Unemployment Rate	0.05	0.03	0.04	0.04
Occupation moments				
Relative wage of high skill	1.30	1.07	1.56	1.38
Corr. wage & abilities (low wage)	0.23	0.23	0.49	0.49
Corr. wage & abilities (high wage)	0.35	0.32	0.60	0.71
Employ. share (low wage)	0.43	0.31	0.37	0.09
Employ. share (high wage)	0.57	0.69	0.63	0.91
$100 \times$ Skill mixing (low wage)	97.54	95.11	98.96	98.82
$100\times$ Skill mixing (high wage)	95.74	96.03	94.12	94.60

Table: Moments and Model Match

Identification of Parameters back

- Estimate σ using relative wage within occupation:

$$\Delta w(\mathbf{x}, \mathbf{y}) = \omega \left[\sum_{k=1}^{K} (x^k y^k)^\sigma \right]^{\frac{1}{\sigma}} - A$$

- Adjust wage for occupation fixed effects and other factors; use MLE for σ.
- Cost parameters ρ and τ identified via firms' optimization of skill demand and employment distribution across occupations.
- Vacancy posting cost c and relative skill level of high-skill worker α_k determined by unemployment levels and relative wages, respectively.

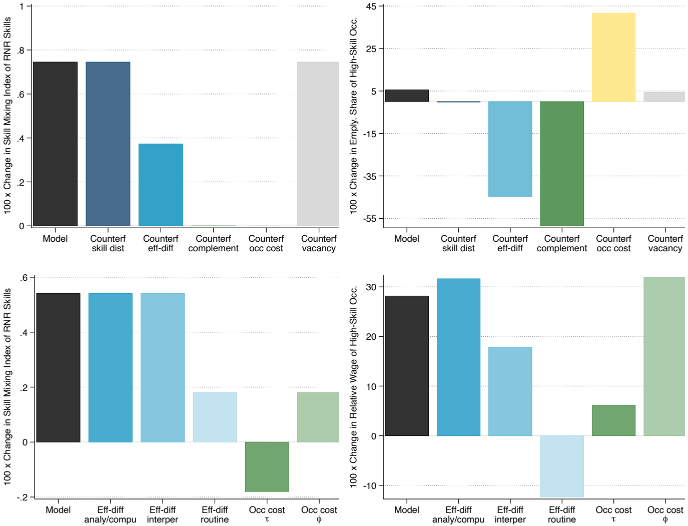
Algorithm back

- Given $\Theta = \{\sigma, \rho, \tau, c, \alpha_k\}$, each iteration of SMM first solves the steady state firm and worker policy function
  1. Fix the number of periods T
  2. Starting from the terminal period T, solve the firm problem
  3. Use the free entry condition to obtain the market tightness $\theta_T(\mathbf{x}, \mathbf{y}, \omega)$
  4. With the market tightness, solve the worker dynamic programming problem
  5. Repeated stepping back from $t = T - 1, ..., 1$
  6. Check if the difference in worker value $U_{t+1} - U_t$, $W_{t+1} - W_t$ and the firm value $J_{t+1} - J_t$ is less than a predetermined tolerance level. If yes stop, if not increase T and go back to first step
- Next, simulate 10,000 workers for $T(T > 200)$ periods, burning the first 40
- Obtain dist of LM outcomes across different occ. and worker types
- SMM minimizes the distance between the model vs. data moments

Role of Skill Supply back

Decomposition	Analytical/ Computer	Interpersonal	Routine
Full model	15.45	15.16	-3.72
Skill supply	-2.60	-0.52	-3.13
Skill efficiency	26.59	1.60	-11.82
Complementarity	-23.86	11.01	12.33
Occ. cost	10.82	0.80	-7.42

Additional Counterfactual Analysis back



Notes: These figures plot the model generated changes in skill mixing in high-skill occupations (panel 1) and changes in employment share of high-skill occupation (panel 2). Panel (3) and (4) depict the model generated changes in skill mixing in low-skill occupation and the relative wage of high-skill occupations by shutting down the skill efficiency differential for analytical/computer, interpersonal, and routine skills individually; also by shutting down τ and ϕ individually.

Caliberated Parameters back

Parameter	Description	Value	
	A. Externally calibrated -- search		
β	Discount Rate	0.96	
δ	Job separation rate	0.10	
ω	Worker share of surplus	0.60	
b	Unemployment benefit as a share of output	0.42	
η	Elasticity of the matching function	0.50	
μ	Matching efficiency	0.65	
	B. Externally calibrated – skill adjustment	(Upward)	(Downward)
γ_a	Annual adjustment speed of analytical/computer skill	0.36	0.10
γ_p	Annual adjustment speed of interpersonal skill	0.05	0.00
γ_r	Annual adjustment speed of routine skill	1.00	0.36
	C. Externally calibrated – skill efficiency	(Period 1)	(Period 2)
α_a	Skill efficiency of analytical/computer skill	0.63	0.95
α_p	Skill efficiency of interpersonal skill	0.05	0.08
α_r	Skill efficiency of routine skill	0.14	0.06
	D. Internally estimated	(Period 1)	(Period 2)
σ^{low}	Elasticity parameter of skills in production (low-wage)	0.64	0.41
σ^{high}	Elasticity parameter of skills in production (high-wage)	0.60	0.36
τ	Scaler of occupation operation cost	0.74	0.53
ϕ	Convexity of occupation operation cost	3.63	4.90
c	Vacancy posting cost as a share of output	0.56	0.82

Top College Majors in Skill Mixing back

Hybrid Index – Level	Hybrid Index – Change
analytical + computer + interpersonal	
Physical Sciences	Architecture and Environmental Design
Engineering	Computer and Information Sciences
Letters	Communications
analytical + computer	
Physical Sciences	Interdisciplinary Studies
Engineering	Area Studies
Letters	Computer and Information Sciences
analytical + interpersonal	
Public Affairs and Services	Architecture and Environmental Design
Business and Management	Computer and Information Sciences
Social Sciences	Communications
computer + interpersonal	
Social Sciences	Architecture and Environmental Design
None, General Studies	Computer and Information Sciences
Public Affairs and Services	Engineering
routine + computer	
Transportation	Social Sciences
Fine and Applied Arts	Agriculture and Natural Resources
Engineering	Foreign Languages
routine + analytical	
Transportation	Agriculture and Natural Resources
Health Professions	Social Sciences
Computer and Information Sciences	Foreign Languages
routine + interpersonal	
Transportation	Agriculture and Natural Resources
Health Professions	Architecture and Environmental Design
Military Sciences	Social Sciences

Return to Skill Mixing Full Table with Individual Skills back

Dependent: ln(hourly wage)	(1)	(2)	(3)	(4)	(5)
Occupation Skills					
Analytical	-0.023**	-0.023**	-0.015*	-0.026*	
	[0.009]	[0.010]	[0.008]	[0.014]	
Computer	-0.008	-0.014	-0.009	-0.019	
	[0.010]	[0.011]	[0.009]	[0.016]	
Interpersonal	-0.009	-0.014	-0.013*	-0.002	
	[0.009]	[0.009]	[0.008]	[0.012]	
Mechanical	0.021**	0.029***	0.019**	0.034*	
	[0.010]	[0.011]	[0.009]	[0.018]	
Mix (non-routine skills)	0.017***	0.015***	0.014***	0.005	
	[0.005]	[0.005]	[0.005]	[0.009]	
Mix (routine + computer)	-0.035***	-0.045***	-0.037***	-0.045***	
	[0.008]	[0.008]	[0.007]	[0.013]	
Mix (routine + analytical)	-0.041***	-0.045***	-0.039***	-0.007	
	[0.007]	[0.008]	[0.007]	[0.013]	
Mix (routine + interpersonal)	0.029***	0.035***	0.025***	0.014	
	[0.009]	[0.009]	[0.008]	[0.015]	
Worker Skills					
Afqt (analytical)		0.074***		-0.048*	-0.009**
		[0.011]		[0.028]	[0.004]
Computer		0.045***		0.031	0.056***
		[0.006]		[0.025]	[0.002]
Social (interpersonal)		0.016***		0.032	-0.001
		[0.005]		[0.030]	[0.002]
ASVAB (routine)		-0.015		0.015	-0.002
		[0.015]		[0.024]	[0.005]
Mix (non-routine skills)		0.065***		0.030**	0.135***
		[0.017]		[0.013]	[0.009]
Mix (ASVAB mechanical + computer)		0.029*		-0.004	0.038***
		[0.017]		[0.018]	[0.010]
Mix (ASVAB mechanical + afqt)		0.006		-0.013	0.000
		[0.008]		[0.026]	[0.004]
Mix (ASVAB mechanical + social)		-0.039***		0.011	-0.030***
		[0.008]		[0.017]	[0.004]
Ethnicity*Gender, Age, Region, Edu FE	X	X	X	X	X
Occupation FE	X	X	X	X	
Worker FE			X	X	
Observations	88,391	79,343	88,391	31,029	94,062
R-squared	0.416	0.430	0.756	0.704	0.136

Return to Skill Mixing Including Major back

Dependent: ln(hourly wage)	(1)	(2)	(3)
Mix (Non-routine Skills): Occupation	0.017***	0.015***	0.014***
	[0.005]	[0.005]	[0.005]
Mix (Non-routine Skills): Worker		0.065***	
		[0.017]	
Ethnicity*Gender, Age/Year, Region, Edu FE	X	X	X
Occupation FE	X	X	X
Worker FE			X
Observations	88,391	79,343	88,391
R-squared	0.416	0.430	0.756

Robustness Checks of Return to Skill Mixing back

Dependent: ln(hourly wage)	(1)	(2)	(3)	(4)
Analytical	-0.014*	-0.008	-0.009	-0.013
	[0.008]	[0.033]	[0.008]	[0.008]
Computer	-0.002	0.069**	0.002	-0.038***
	[0.009]	[0.027]	[0.009]	[0.010]
Interpersonal	-0.019**	-0.118***	-0.018**	-0.014*
	[0.008]	[0.030]	[0.008]	[0.008]
Routine	0.026***	0.091***	0.005	0.010
	[0.009]	[0.017]	[0.008]	[0.008]
Mix (analytical + computer)	0.007	-0.040	0.008*	0.020***
	[0.005]	[0.036]	[0.005]	[0.007]
Mix (analytical + interpersonal)	0.010**	0.156***	0.006	0.025***
	[0.004]	[0.042]	[0.004]	[0.005]
Mix (computer + routine)	-0.028***	-0.045***	-0.021**	-0.087***
	[0.007]	[0.015]	[0.008]	[0.013]
Mix (computer + interpersonal)	-0.011**	-0.019	-0.013***	-0.021***
	[0.005]	[0.033]	[0.005]	[0.008]
Mix (routine + analytical)	-0.033***	-0.080***	-0.041***	-0.041**
	[0.007]	[0.015]	[0.008]	[0.018]
Mix (routine + interpersonal)	0.010	0.033**	0.033***	0.026**
	[0.007]	[0.016]	[0.006]	[0.012]
Ethnicity × Gender, Age, Region, Edu FE	X	X	X	X
Occupation FE	X	X	X	X
Worker FE	X	X	X	X
Observations	87,655	87,655	87,655	87,655
R-squared	0.757	0.757	0.757	0.758