Optimal Skill Mixing Under Technological Advancements

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

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

This Paper

1. Documents **new facts** about skill mixing
   - 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)
   - Explains major part of employment/wage polarization
   - Wage returns: 1.5 - 3 percent in skill mixed occupation/major

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3. Quantitative analysis
   - Estimation: ↑ complementarity & cost of skills
   - Experts of analytical, computer / routine skills becomes ↑/↓ efficienct
   - These drive skill mixing & employment, wage dynamics

Contribution: LM dynamics on **skill mixing** + new theoretical perspective

Literature

- Long-term trend of skill demand
  - 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
  - Menzio and Shi (2010,2011); Kaas and Kircher (2015); Schaal (2017); Baley, Figueiredo, and Ulbricht (2022); Braxton and Taska (2023)
- Worker sort and matching
  - 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)

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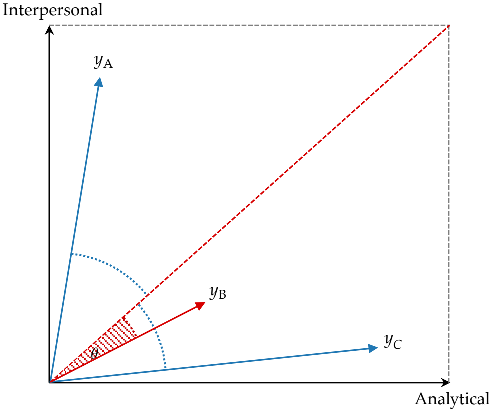
Evidence of Skill Mixing

Occupations in Multidimensional Space



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 $\hat{\mathbf{v}}$.

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

Data and Skill Measures

- 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 - Acemoglu and Autor (2011) & More
  - Non-routine: analytical, interpersonal; routine: cognitive + manual
  - Additional non-routine: computer, these 4 ["RNR"]
  - More non-routine: leadership, design, these 5 ["other non-routine"]
  - Lightcast: keywords based Braxton & Taska (2022) details

First look of data: trend at 7-digit occupatoins

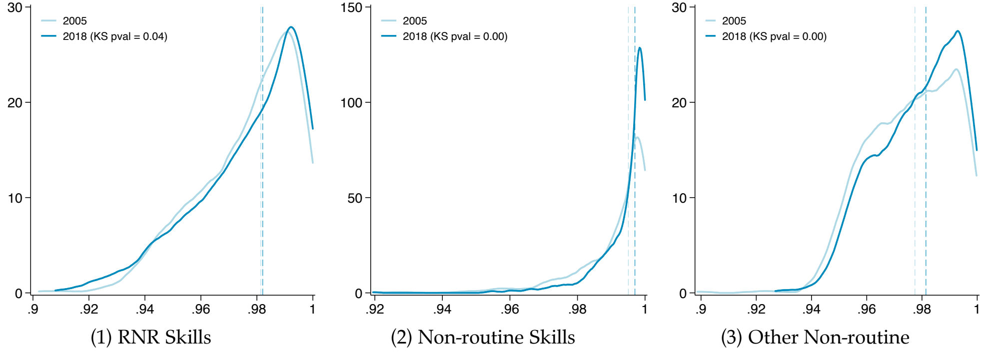


Figure: Density for Skill Mixing Indexes (Cosine Distances), 2005 vs. 2018

Weighted Density | Non-parametric

Time Pattern

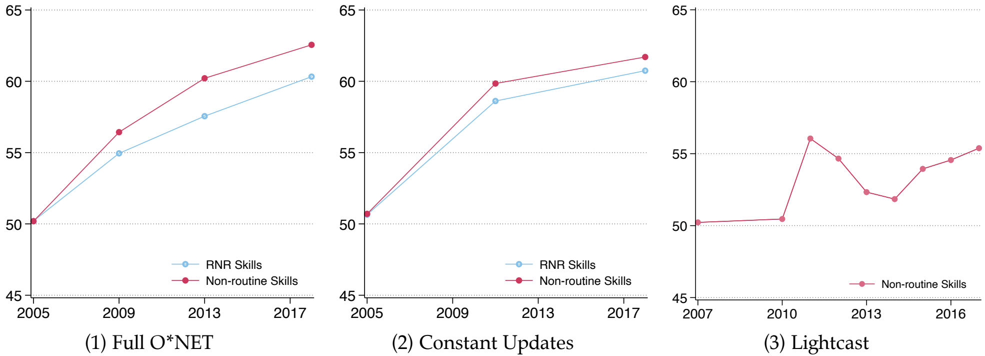


Figure: Trend of Skill Mixing in the US Economy, 2005-2018

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

Decomposition: Intensive vs. Extensive

	Skill Groups	6-digit Occupations			4-digit Occupations		
		total	within	across	total	within	across
Full O*NET	RNR Skills	6.78	4.93	1.85	12.23	9.26	2.97
	Non-routine Skills	9.21	5.62	3.59	14.07	9.53	4.54
Constant Updates	RNR Skills	5.59	6.73	-1.14	9.70	10.57	-0.87
	Non-routine Skills	4.05	5.33	-1.29	10.58	9.50	1.09
Lightcast	Non-routine Skills				4.66	4.37	0.28

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: Skill Supply within Occupation

	RNR Skills	Non-routine Skills
Full O*NET	0.70*** [0.10]	0.71*** [0.09]
Constant Updates	0.75*** [0.11]	0.65*** [0.11]
Lightcast		0.33** [0.15]
Sex × Industry × Occ. FE	X	X
Exp. and edu. controls	X	X

Table: Within Occupation Changes in Skill Mixing Indexes

*Notes: This table reports the results of regressing values of RNR skills and Non-routine skills on a time trend variable (year values) for the full ONET, Constant Updates, and Lightcast datasets combined with the ACS. The regressions include controls for sex-industry-occupation fixed effects, as well as 5-category (no high-school, high-school graduate, some college, college graduate, post-college) education fixed effects, polynomials of years of work experience up to power 4, and the interaction of experience polynomials and education as well as gender fixed effects. Robust standard errors are reported in brackets. *** p¡0.01, ** p¡0.05, and * p¡0.1.*

Occupation Heterogeneity

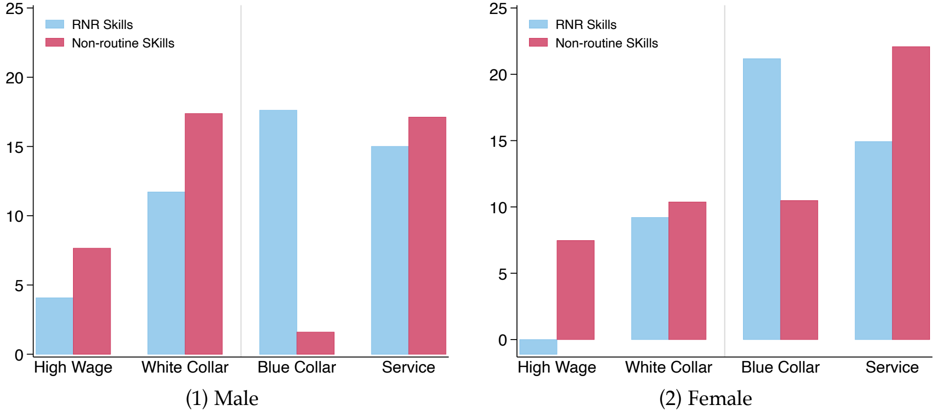


Figure: Skill Mixing Index Change by Occupation Groups and Gender, 2005-2018

Notes: The categorization into four groups is based on Acemoglu and Autor (2011). "High Wage" includes Managers, Professionals, and Technicians; "White Collar" comprises Office/Administrative and Sales roles; "Blue Collar" includes Production, as well as Operators/Laborers; and "Service" consists of Protective Services, Food/Cleaning Service, and Personal Care occupations.

By industry | Skill pairs

Distributional Implications

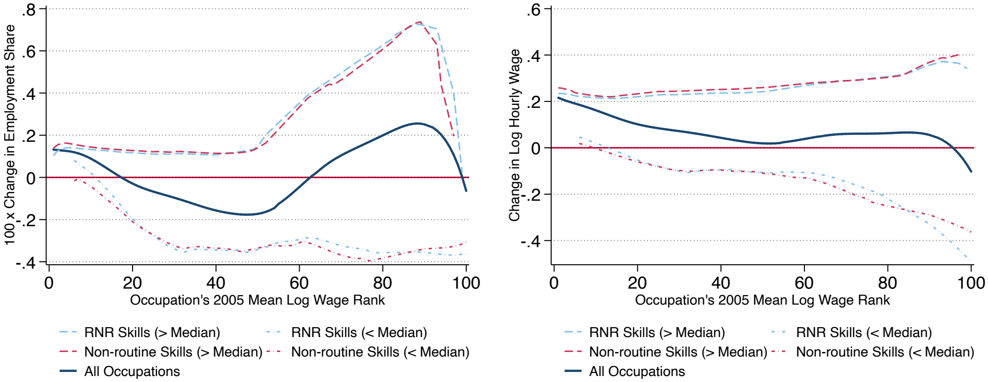


Figure: Smoothed Employment and Wage Changes by Skill Percentile, 2005-2018

Returns to Skill Mixing

Data and Measurement

- National Longitudinal Survey of Youth (NLSY) 2005-2019
  - Detailed employment and educational histories + pre-market abilities
  - Both 79 & 97 cohorts (median age: 37), outcome: real log hourly wage
  - Skill measures:
    - Analytical: AFQT; Interpersonal: social skill (Deming, 2017); Routine: ASVAB mechanical; Computer: occ/major's computer skill
- College Major's Skill Mixing
  - Uses NLSY college major, emp-weighted avg. of O*NET measures
  - Top majors:
    - Non-routine: Arch. & Environ. Design, Computer and Info Sciences, Communications
    - Routine & non-routine: Social Sciences, Agriculture and Natural Resources

Correspond skill measures | Non-parametric

Wage Returns

Dependent: ln(hourly wage)	(1)	(2)	(3)	(4)
Mix (analytical + computer + social)	0.017***	0.015***	0.014***	0.005
	[0.005]	[0.005]	[0.005]	[0.009]
Mix (afqt + computer + social)		0.065***		0.030**
		[0.017]		[0.013]
Ethnicity*Gender, Age/Year, Region, Edu FE	X	X	X	X
Occupation FE	X	X	X	X
Worker FE			X	X
Observations	88,391	79,343	88,391	31,029
R-squared	0.416	0.430	0.756	0.704

Table: Return to Skill Mixing: Occupations, Workers, and Collge Majors

Full table
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)

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

- 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 $\mathbf{y}$
- Labor Market
  - Continuum submarkets by $(\mathbf{x}, \mathbf{y})$ and surplus share ω, tightness $\theta(\mathbf{x}, \mathbf{y}, \omega)$
  - δ separatn, matching $M(s, v) = \mu s^{\eta} v^{1-\eta}$, markov evolvement $\pi(x_j' | x_j, y_j)$

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

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

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

Quantitative Analysis

Measurement and Calibration

- Simulated Methods of Moments
  - NLSY 79 & 97 + O*NET, 2 periods: 2005–2006 and 2016–2019
  - Occ: high-skill (high-wage & white-collar), low-skill (blue-collar & service)
  - Worker: low-type (avg. of below median x_j), high-type ($\alpha_j x_j^{low}$) Calibrate skill supply

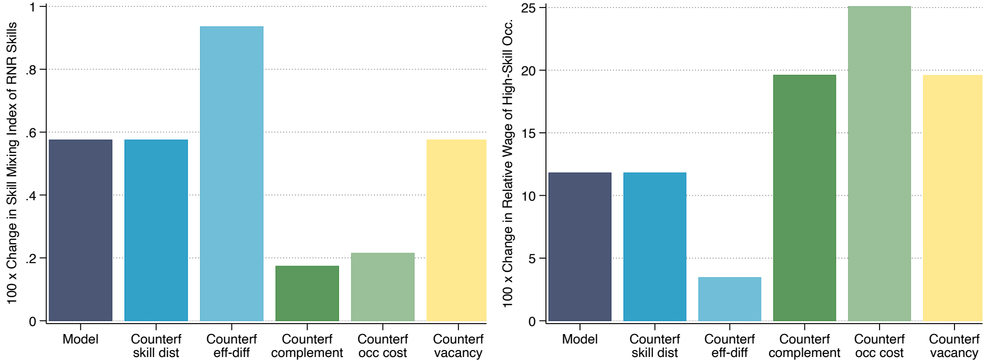
	First Period		Second Period	
	Data	Model	Data	Model
Worker moments				
Relative wage of high type				
Analytical/computer	1.30	1.29	0.95	1.02
Interpersonal	1.00	1.00	1.25	1.28
Routine	1.52	1.53	1.54	1.40
Unemployment rate	0.05	0.06	0.04	0.04
Occupation moments				
Relative wage of high skill	1.30	1.30	1.56	1.41
Employ. share (low skill)	0.43	0.42	0.37	0.32
Employ. share (high skill)	0.57	0.58	0.63	0.68
$100 \times$ Skill mixing (low skill)	97.54	96.83	98.96	99.10
$100 \times$ Skill mixing (high skill)	95.74	96.84	94.12	95.11

Calibrated Parameters

Parameter	Description	Value	
	A. Externally Calibrated		
β	Discount Rate	0.99	
δ	Job separation rate	0.1	
ω	Worker share of surplus	0.6	
b	Unemployment benefit	0.25	
η	Elasticity of the matching function	0.5	
μ	Matching efficiency	0.65	
	B. Internally Estimated	Period 1	Period 2
σ	Elasticity parameter of skills in production	0.5	0.3
τ	Scaler of occupation operation cost	1.4	1.9
ϕ	Rate of increasing marginal cost	1.2	1.7
α_a	Efficiency differential of analytical/computer skill	1.2	1.6
α_p	Efficiency differential of interpersonal skill	1.0	1.5
α_r	Efficiency differential of routine skill	1.2	1.1
c	Vacancy posting cost as a share of output	0.1	0.4

Identification Numerical algorithm

Counterfactual Analysis



Notes: Panel 1 plots the model generated changes in skill mixing in low-skill occupations and Panel 2 changes in relative wage of high-skill occupation. Different model channels are shut down individually by eliminating the changes in calibrated values.

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 directed search & occ. design, complementarity matters

In a world with inevitable technological advancements and an increasing trend of skill mixing, educators and policymakers ought to provide more "mixed" skills to workers to take advantage of the complementarity side of technological change.

Thank you!

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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	Considered Year	Percent Updated
O*NET 13.0	2008	Post 2005	73.79%	73.79%	73.79%	2005	–
		Before 2005	26.21%	26.21%	26.21%		
O*NET 18.0	2013	Post 2009	57.15%	57.21%	57.21%	2009	59.8
		Before 2009	42.85%	42.79%	42.79%		
O*NET 22.0	2017	Post 2013	57.84%	57.67%	57.67%	2013	45.8
		Before 2013	42.16%	42.33%	42.33%		
O*NET 25.0	2022	Post 2018	54.52%	54.52%	54.52%	2018	64.2
		Before 2018	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.*

Lightcast Key Words back

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

First Look: Skill Mixing at 7-digit Occupatoins back

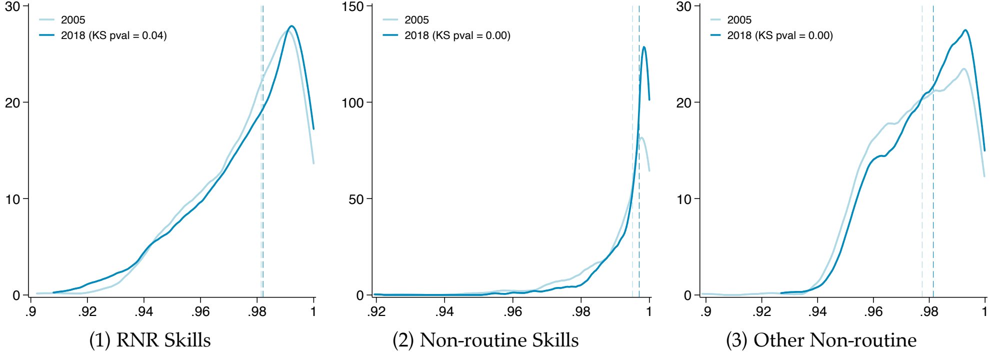


Figure: Density for Skill Mixing Indexes (Weighted Cosine Distances), 2005 vs. 2018

Alternative Depiction of Skill Mixing back

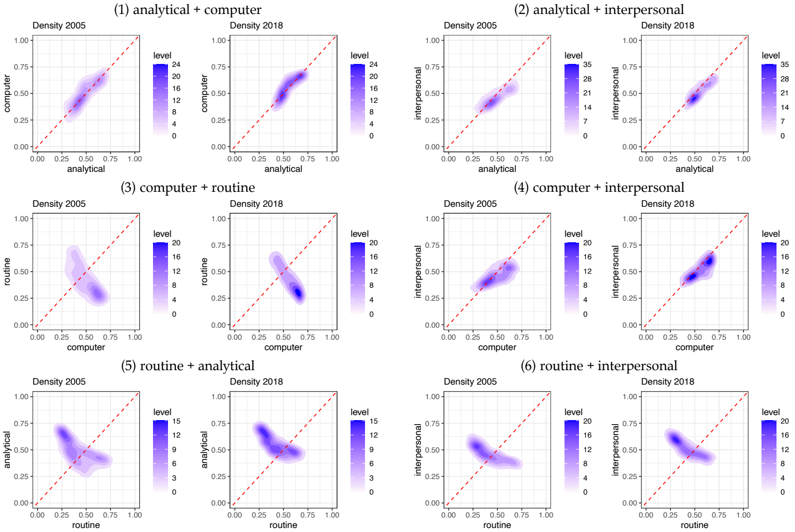


Figure: Non-parametric Depiction of Skill Intensities, 2005 vs. 2018

Time Pattern back

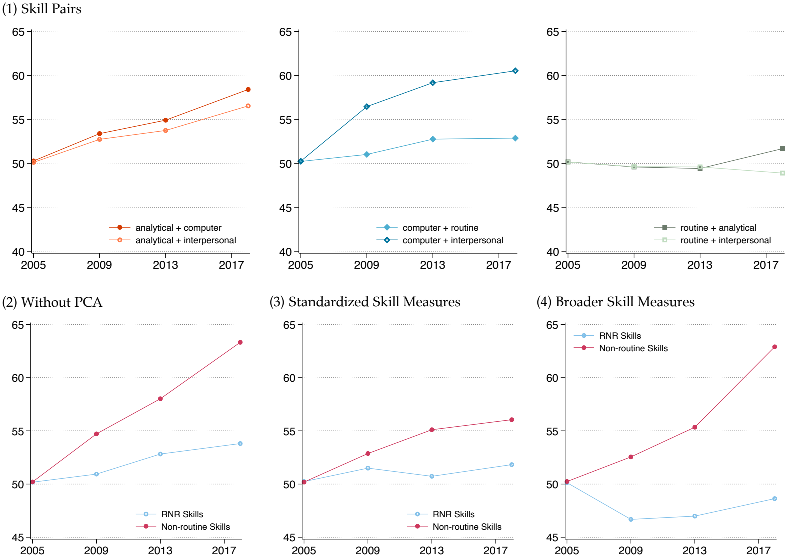


Figure: Trend of Skill Mixing with Alternative Skill Measures

Time Pattern back

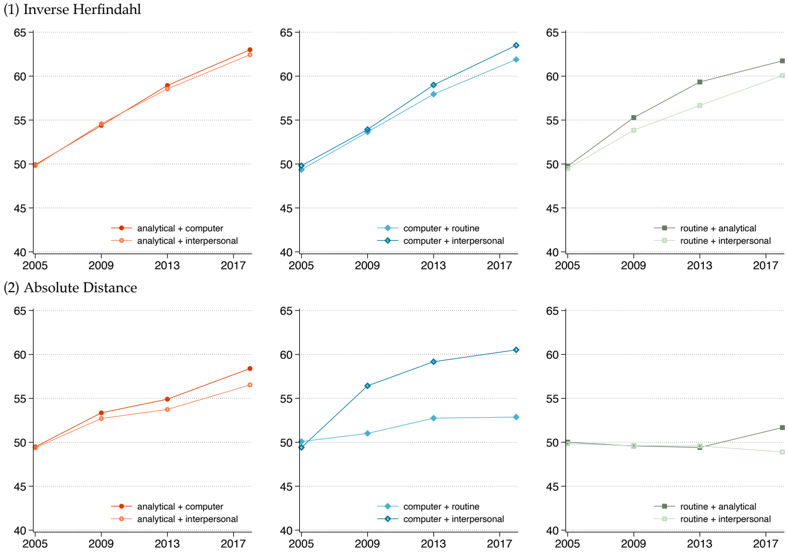
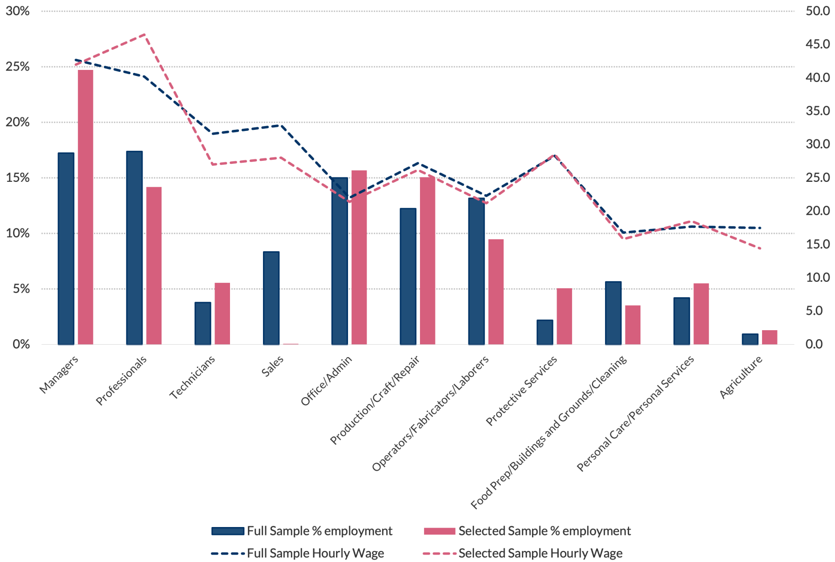


Figure: Trend of Skill Mixing with Alternative Indexes

Full and Updated O*NET back

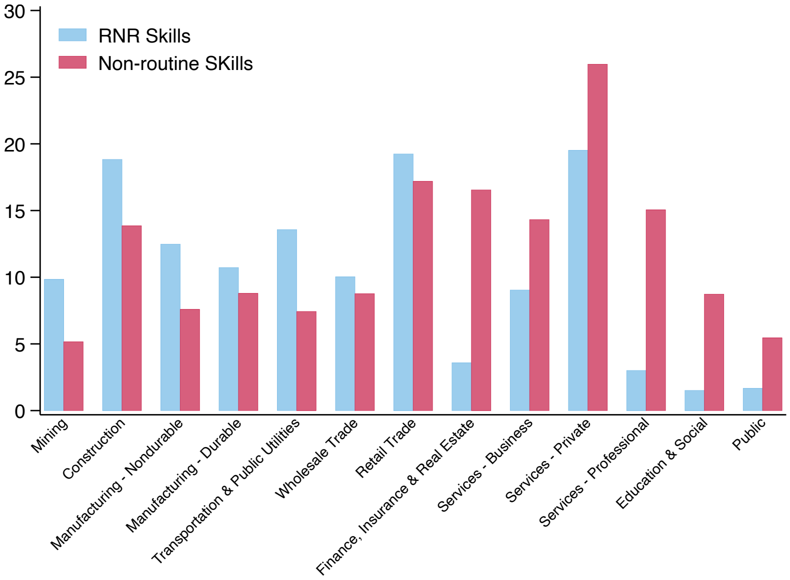


Decomposition: Intensive vs. Extensive back

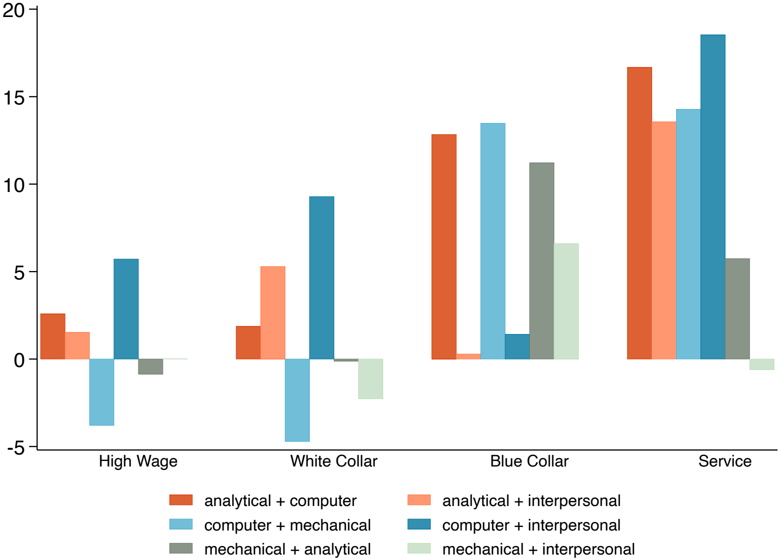
	Skill Groups	6-digit Occupations			4-digit Occupations		
		total	within	across	total	within	across
Full O*NET	analytical + computer	10.52	6.40	4.12	10.49	6.60	3.89
	analytical + interpersonal	5.36	2.90	2.46	8.17	4.08	4.09
	computer + routine	4.38	2.41	1.97	5.16	2.94	2.22
	computer + interpersonal	7.23	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.*

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.

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:

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

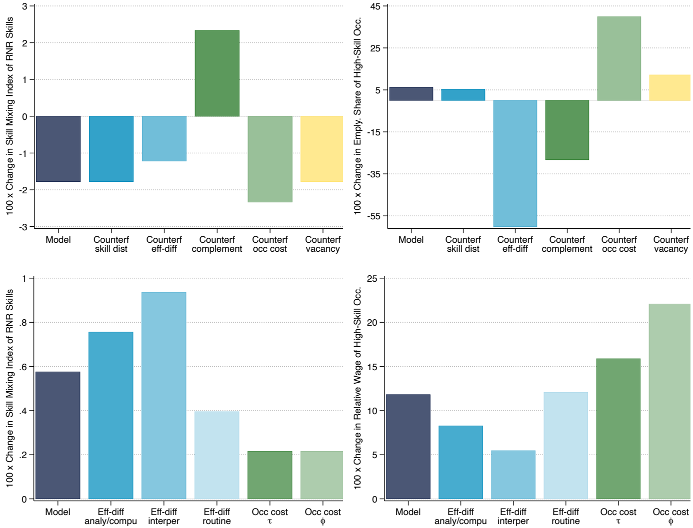
  - Downward adjustment probability:

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

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-implied moments data moments

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.*

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)
Occupation Skills				
Analytical	-0.019**	-0.019**	-0.012	-0.033***
	[0.009]	[0.009]	[0.008]	[0.011]
Computer	-0.002	-0.008	-0.003	-0.017
	[0.010]	[0.011]	[0.009]	[0.013]
Interpersonal	-0.019**	-0.022**	-0.021***	-0.027**
	[0.009]	[0.009]	[0.008]	[0.011]
Routine	0.027***	0.035***	0.025***	0.047***
	[0.010]	[0.011]	[0.009]	[0.015]
Mix (analytical + computer)	0.007	0.011**	0.013***	0.012
	[0.005]	[0.005]	[0.005]	[0.008]
Mix (analytical + interpersonal)	0.016***	0.016***	0.015***	0.028***
	[0.005]	[0.005]	[0.004]	[0.007]
Mix (computer + routine)	-0.022**	-0.029***	-0.021***	-0.026**
	[0.009]	[0.009]	[0.008]	[0.012]
Mix (computer + interpersonal)	-0.008	-0.012**	-0.014***	-0.012
	[0.006]	[0.006]	[0.005]	[0.009]
Mix (routine + analytical)	-0.050***	-0.056***	-0.050***	-0.058***
	[0.008]	[0.009]	[0.008]	[0.012]
Mix (routine + interpersonal)	0.023***	0.029***	0.019**	0.023*
	[0.008]	[0.009]	[0.008]	[0.012]
Worker Skills				
Afqt (analytical)		0.065***		-0.038
		[0.012]		[0.023]
Computer		0.045***		0.017
		[0.006]		[0.023]
Social (interpersonal)		0.015***		-0.003
		[0.005]		[0.029]
ASVAB (routine)		-0.008		-0.012
		[0.016]		[0.022]
Mix (afqt + computer)		0.044*		0.017
		[0.023]		[0.013]
Mix (afqt + social)		0.028*		-0.075***
		[0.015]		[0.020]
Mix (computer + asvab mech)		0.013		-0.070***
		[0.025]		[0.026]
Mix (computer + social)		0.008		0.061***
		[0.013]		[0.019]
Mix (asvab mech + afqt)		0.001		0.096**
		[0.009]		[0.039]
Mix (asvab mech + social)		-0.040***		-0.045
		[0.011]		[0.042]
Ethnicity*Gender, Age/Year, Region, Edu FE	X	X	X	X
Occupation FE	X	X	X	X
Worker FE			X	X
Observations	87,655	78,719	87,655	50,580
R-squared	0.426	0.439	0.758	0.761

Robustness Checks of Return to Skill Mixing back

Dependent: ln(hourly wage)	(1)	(2)	(3)	(4)
Occupation Skills				
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