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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    - Multi-dimensional skills, non-linear technology
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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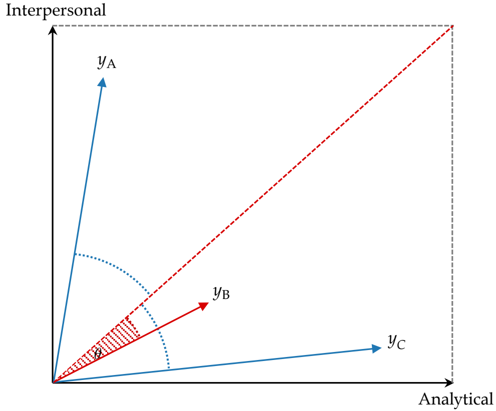
Evidence of Skill Mixing

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
  - Info on skill requirements and work environments (intensive margin)
  - Challenge: annually, avg. of 110 occupations updated
    - Broad and 4-year intervals using 4 versions; 274 7-digit occs consistently updated
- 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 and manual)
  - Additional skills: computer; leadership and design (other non-routine)
  - Lightcast: keywords based Braxton & Taska (2022)

First look of data: trend at 7-digit occupatoins

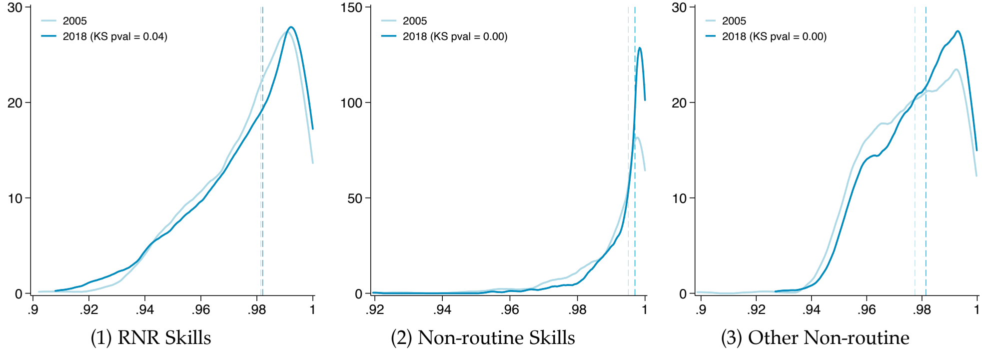


Figure: Density for Skill Mixing Indexes (Cosine Distances), 2005 vs. 2018

Weighted Density Non-parametric

Time Pattern

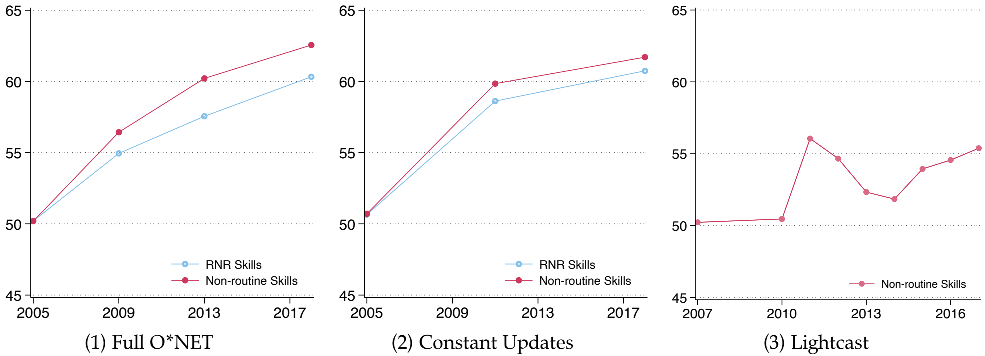


Figure: Trend of Skill Mixing in the US Economy, 2005-2018

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

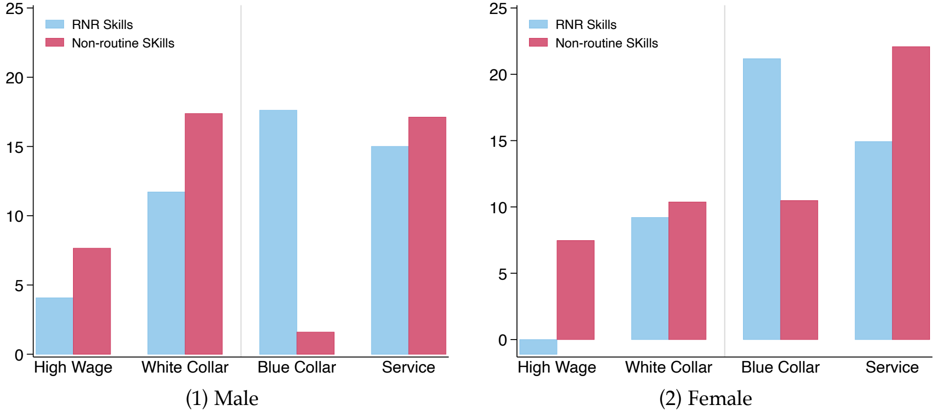


Figure: Skill Mixing Index Change by Occupation Groups and Gender, 2005-2018

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

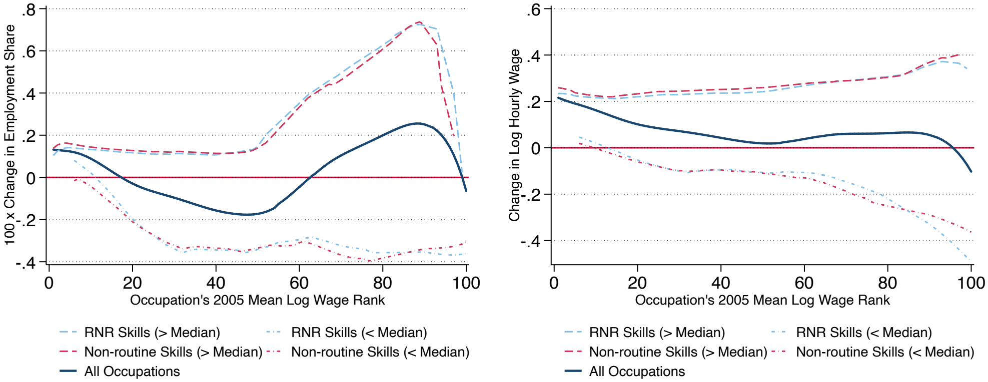


Figure: Smoothed Employment and Wage Changes by Skill Percentile, 2005-2018

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 $\mathbf{x} = \{x^1, ..., x^k, \dots, x^K\} \in S \subset \mathbb{R}^{K+}$
  - A mass of risk-neutral firms $\mathbf{y} = \{y^1, ..., y^k, \dots, y^K\} \in S \subset \mathbb{R}^{K+}$
  - 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

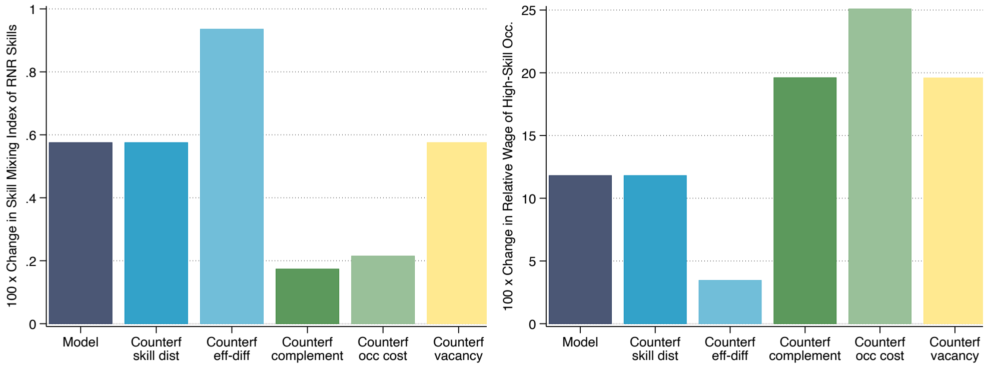
- Simulated Methods of Moments
  - NLSY 79 & 97 + O*NET, 2 periods: 2005–2006 and 2016–2019
  - Occ: high-skill (high-wage & white-collar), low-skill (blue-collar & service)
  - Worker: low-type (avg. of below median x_j), high-type ($\alpha_j x_j^{low}$)

	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

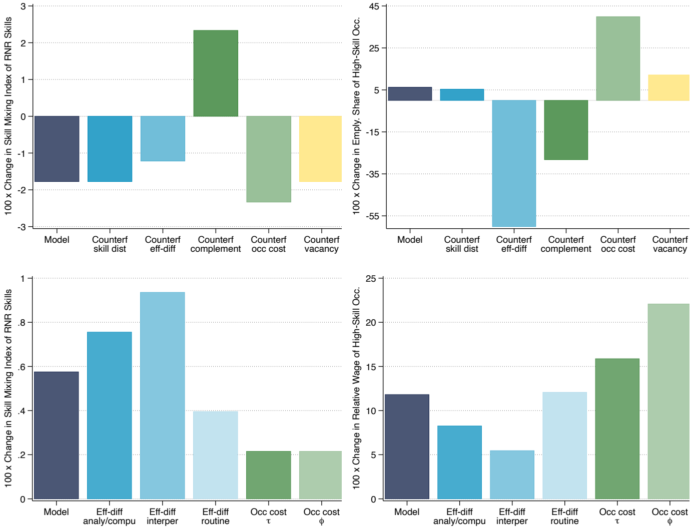
Counterfactual Analysis



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

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.*

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

First Look: Skill Mixing at 7-digit Occupatoins back

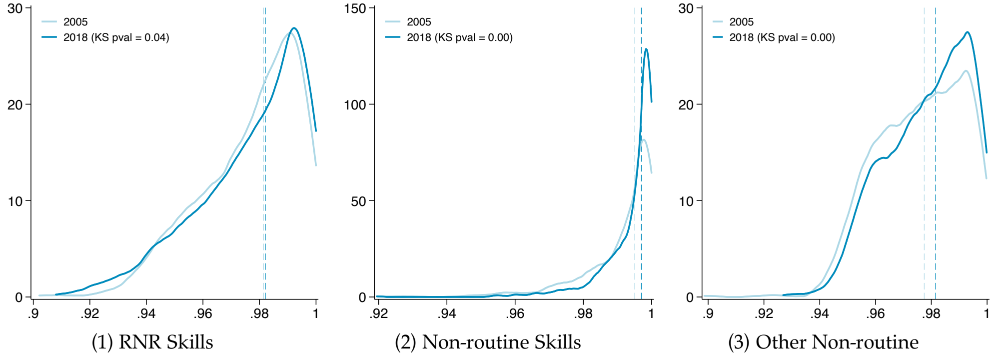


Figure: Density for Skill Mixing Indexes (Weighted Cosine Distances), 2005 vs. 2018

Alternative Depiction of Skill Mixing back

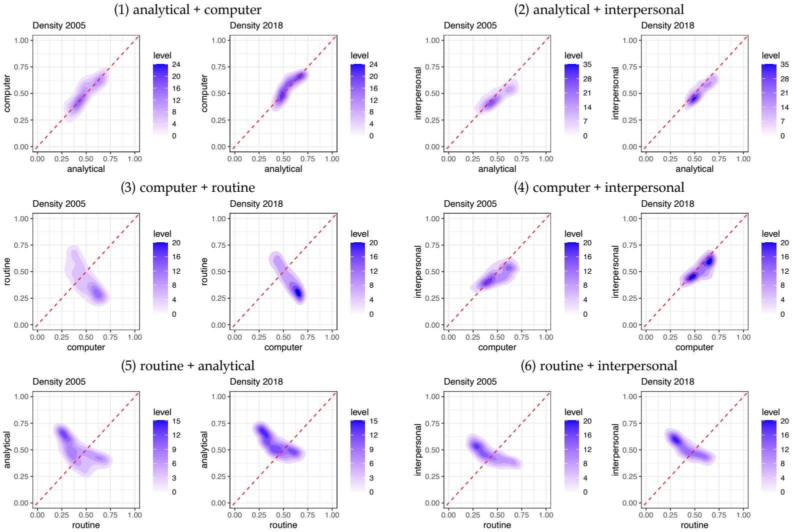


Figure: Non-parametric Depiction of Skill Intensities, 2005 vs. 2018

Time Pattern back

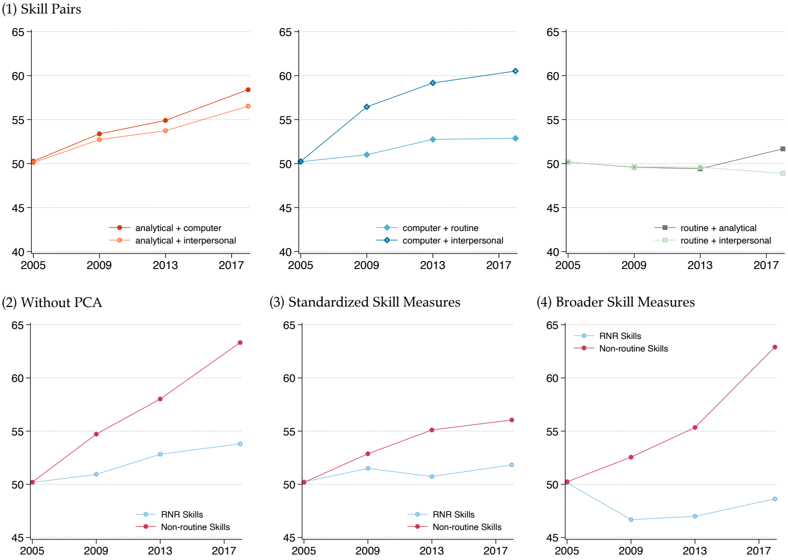


Figure: Trend of Skill Mixing with Alternative Skill Measures

Time Pattern back

(1) Inverse Herfindahl

(2) Absolute Distance

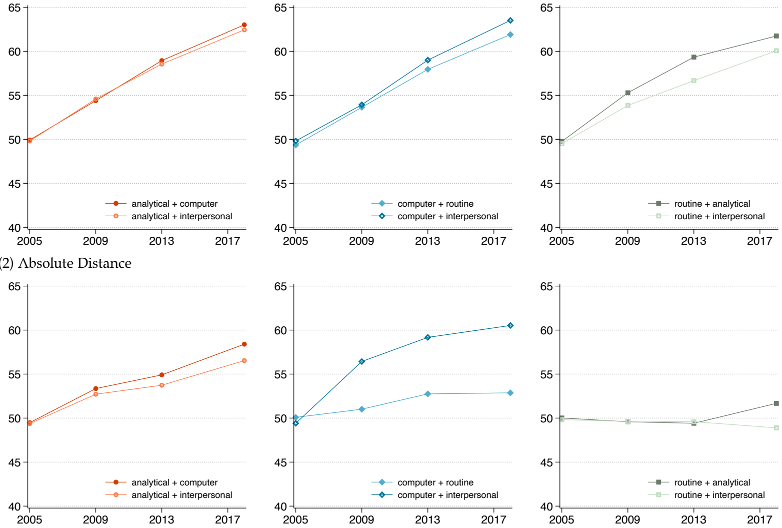
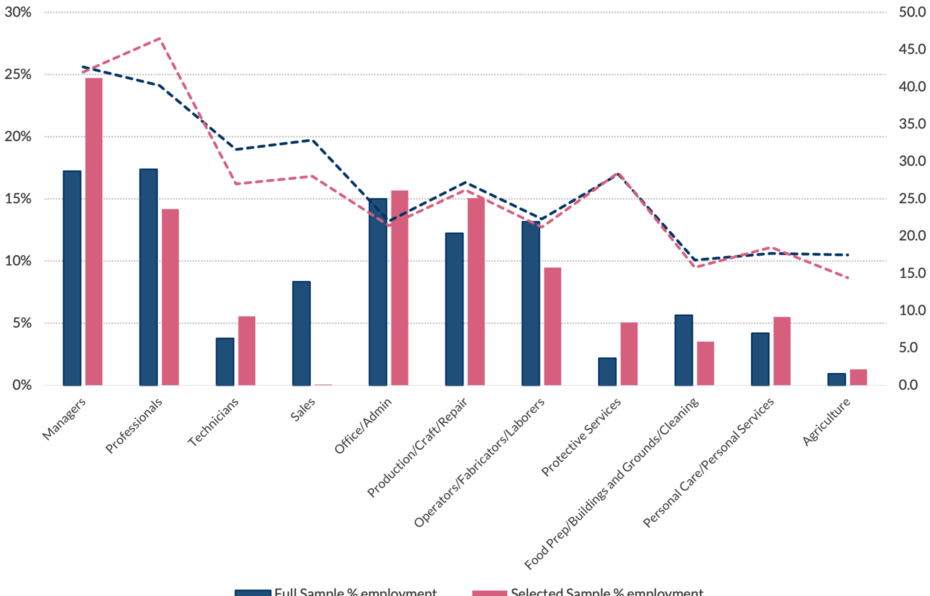


Figure: Trend of Skill Mixing with Alternative Indexes

Time Pattern back

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



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

Decomposition: Intensive vs. Extensive back

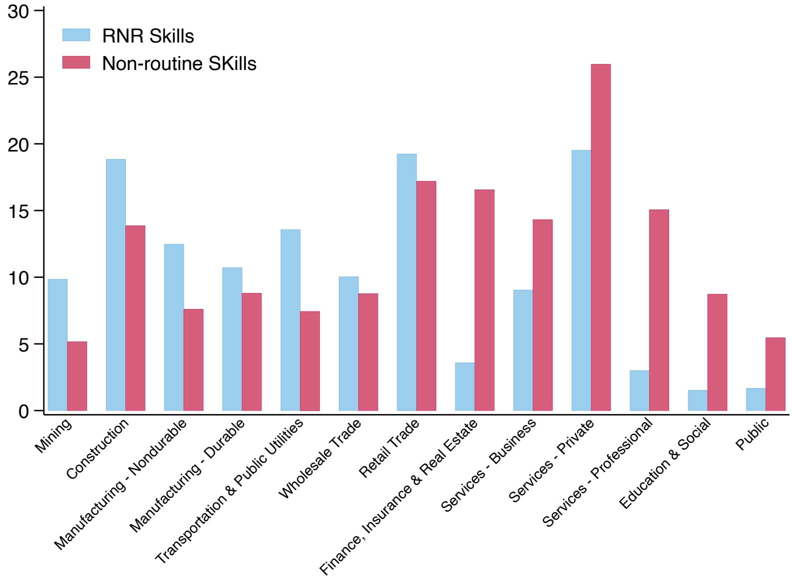


Figure: Mixing Index Change by Industry and Occupation Groups, 2005-2018

Decomposition: Intensive vs. Extensive back

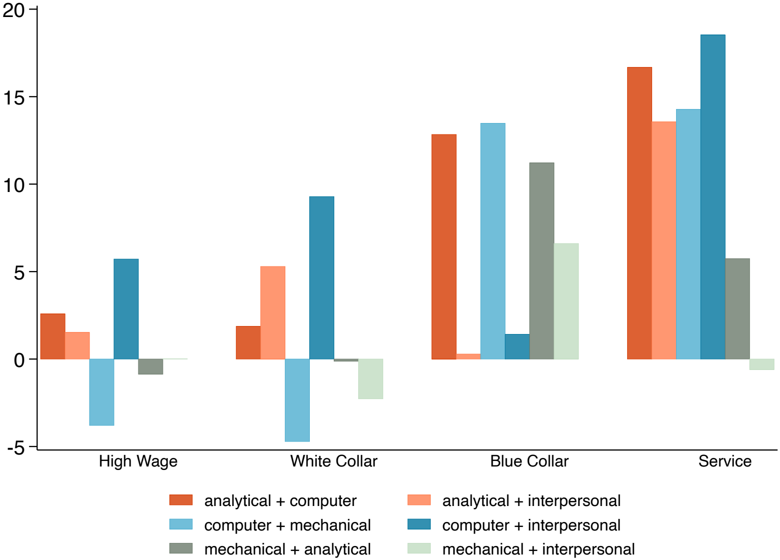


Figure: Mixing Index Change by Industry and Occupation Groups, 2005-2018

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.*

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

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 $\times$ 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