Occupational Skill Mixing Under Technological Advancements

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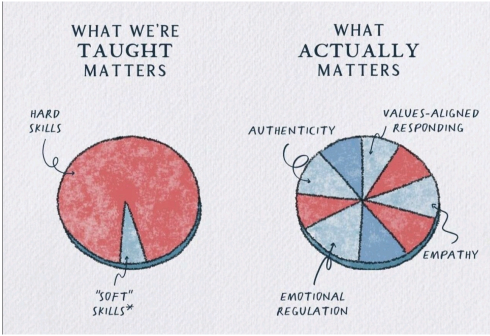
Motivation

- 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

  narrow 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



BUSINESS INSIDER

FINANCE

What does Goldman Sachs want in a coder? For them to have studied philosophy

Bianca Chan Apr 18, 2024, 6:26 PM GMT-4

This Paper

1. Documents **new facts** about skill mixing
   - Online job posting + O*NET
   - Network analysis, angle-based measure
2. **Breakthrough GPT** as a key driver of skill mixing
   - Identify breakthrough + GPT using patent citation (width + high impact)
   - NLP of patent abstracts to map technologies to occ.
   - Dynamic DID of breakthrough GPTs on skill mixing, wages
3. Structural lens: a **multi-d directed search model**
   - Production function interpretation of identified skill mixing
   - Quantification: skill mixing changes aggregate employment, wages

Findings

- Substantial skill mixing 2005-2024
  - Across-board, but mainly from high- to low-skill occupations
  - IT & business/data dominate, public/serv/facility for low-skill
  - Consistency: O*NET, non-routine & routine skills
- Breakthrough GPT ↑ skill mixing, wages, employment
  - ↑ Skill mixing by 5% on impact and persists, mainly in low-skill
  - ↑ Wages and employment by 2 % & 5 % in 5-8 years
  - Consistency: index measure, non-routine & routine skills
- Main channel: skill complementarity, costs
  - Account for 2/3 and 1/3 of growth in skill mixing
  - And 79% and 30% of Δ aggregate wage and emp. distributions

Contributions to the Literature

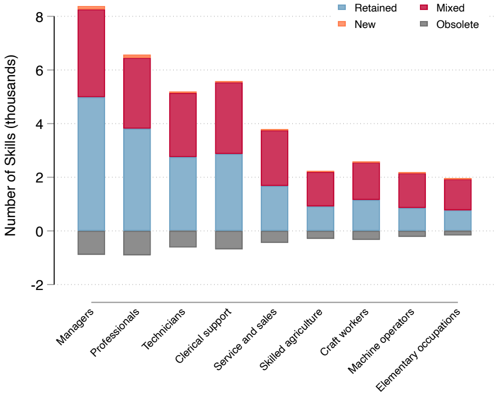
- Labor market dynamics that focuses on skill mixing
  - Skill/task biased: Tinbergen (1975); Katz and Murphy (1992); ALM (2003); Acemoglu and Autor (2011); Autor and Dorn (2013); Deming (2017); Deming and Kahn (2018)
  - Within-occupation variation: Autor and Handel (2013); Atalay et al. (2020); Freeman, Ganguli, and Handel (2020); Cortes, Jaimovich, and Siu (2021)
- Directed search model w/. multi-d + endogenous firm & worker
  - 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)

Data and Evidence of Skill Mixing

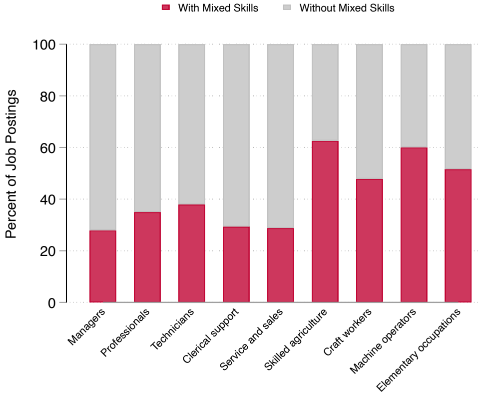
Data & Skill Measures

- **Lightcast Job Postings** (formerly ”Burning Glass”) 2010–2024
  - Near-universe of online job postings
  - Raw text parsed into a 33K+ skills taxonomy, updated continuously
  - Info on whether a skill is required for a vacancy (extensive margin)
  - [Consolidate] ∼2,000 similar skills via cosine similarity based on *embeddings*
    - Threshold chosen so the *adjusted similarity* exceeds a conservative anchor based on the lowest score in O*NET Abilities/Knowledge/Skills/Work Activities
- **Occupational Information Network** (O*NET) 2005-2022
  - Detailed descriptors for 970 7-digit occupations example content
  - Survey of incumbent workers, info on skill importance (intensive margin)
    - In 2022, O*NET starts to use Lightcast to track “Hot”, “In-Demand” technology skills
  - Non-routine: analytical, interpersonal, computer; routine [”RNR”] details

Decompose Skills and Postings



(a) Composition of Skills

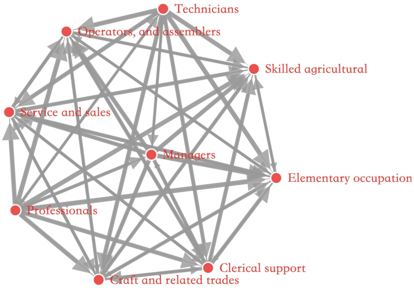


(b) Composition of Job Postings

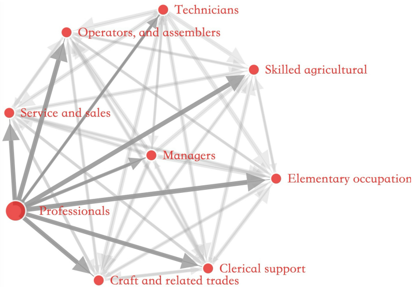
Figure: Composition of Skills in US Job Postings, 2010 to 2024

At 3-digit soc | Weighted by job posting

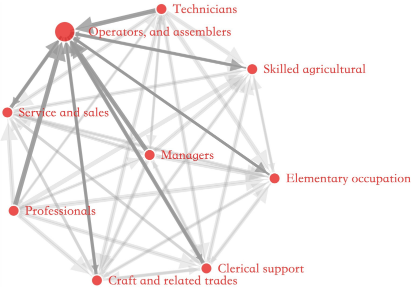
Direction: Network of Occupational Skill Mixing



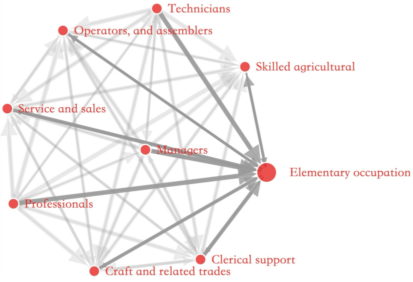
(a) All Occupations



(b) Professionals

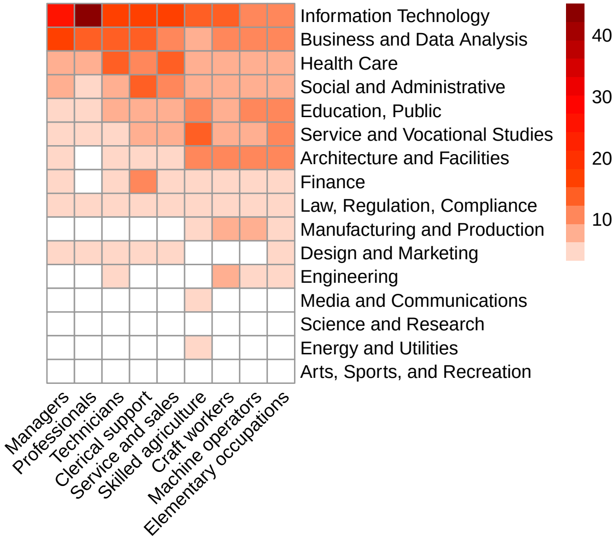


(c) Operators and Assemblers



(d) Elementary Occupations

Categories

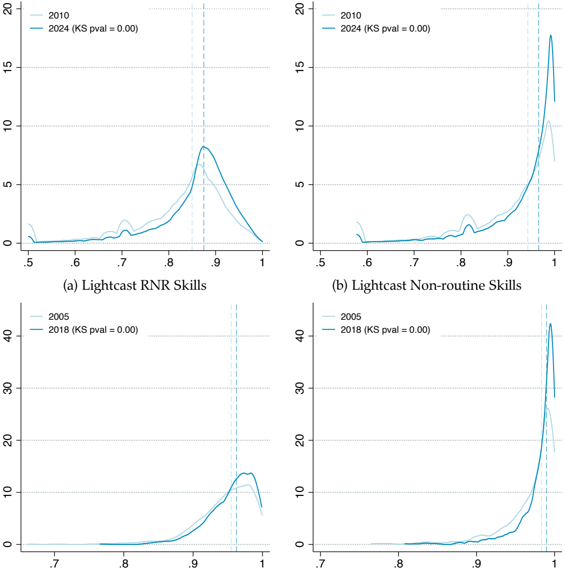


Analytical	0.004
	[0.008]
Interpersonal	−0.003
	[0.007]
Computer	0.034^{***}
	[0.008]
Routine	-0.038^{**}
	[0.017]

Correlation with RNR Skills

Consistency: Mixing Index and O*NET Trends

Broad non-routine | Weighted



(a) Lightcast RNR Skills

(b) Lightcast Non-routine Skills

(c) O*NET RNR Skills

(d) O*NET Non-routine Skills

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

The Role of Breakthrough GPT

Breakthrough GPT: Definition and Mapping

Idea. Technologies that are widely adopted and highly innovative.

- Data: USPTO PatentsView
- Definition
  - Breakthrough GPT: $\mathbb{1}\{\text{HighGen} = 1 \wedge \text{BK} = 1\}$
  - Breakthrough based on forward / backwark similarity Kelly et al. '21; Autor et al. '24
  - Generality: for patent i, 5-year forward-citation (Hall–Jaffe–Trajtenberg)

$$\text{Gen}_i \;=\; 1 - \textstyle\sum_j s_{ij}^2, \quad s_{ij} = \frac{\text{cites CPC-2d } j}{\text{all forward cites}}.$$

  - $\text{HighGen}_i = 1$ if Gen_i top 25%; $BK_i = 1$ if breakthrough score top 10%
- Map to Occupations (tech-centric)
  - Patents $\rightarrow$ Technologies: embedding of both patent abstract & O*NET Technology; compute cosine similarity, keep top matches
  - Technologies $\rightarrow$ Occupations: O*NET Technology to occ. crosswalk

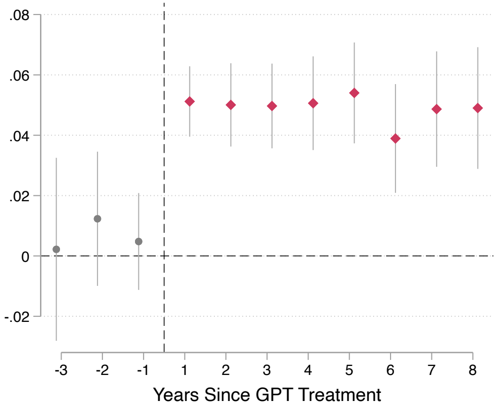
Empirical Strategy: Dynamic DID with Staggered Adoption

Specification:

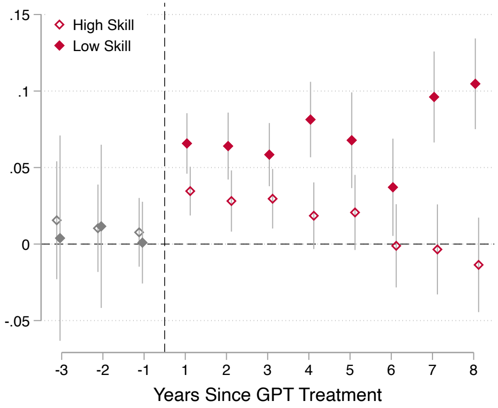
$$Y_{cot} = \sum_{k=-3}^{10} \beta_k \cdot \mathbb{1}\{t - T^*_{co} = k\} + \gamma X_{ct} + \delta_{co} + \delta_{ct} + \delta_{ot} + \epsilon_{cot}$$

- Setup
  - Unit: (c, o, t) where c is commuting zone, o is occupation, year t
  - Treatment: $T^*_{co} = \min\{t : \texttt{BKGPT\_patent}_{cot} = 1\}$.
  - Outcome: $Y_{cot} \in \{\ln(\text{mixed skills}), \ln(\text{wage}), \ln(\text{employed}), \text{mixing index}\}$
    - Covariates X_{ut}: demographic shares, education levels, low-wage shares, sectoral employment shares, unemployment, and RNR skill levels.
- Estimator: de Chaisemartin & D'Haultfoeuille (2023, 2024)
  - Immune to forbidden regression / negative weights in staggered adoption
  - Allows non-absorbing treatment, unbiased under effect heterogeneity

Event Study: Skills Mixed



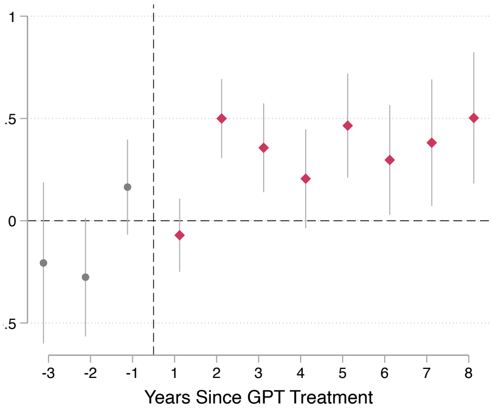
(a) Log Number of Mixed Skills



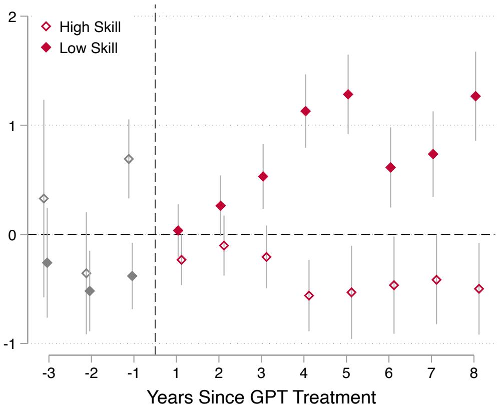
(b) Log Number of Mixed Skills by Occupations

- BKGPT ↑ number of skills mixed by 5 %, the effect persists
- Mainly driven by low-skill occupations, high-skill's mixing fade in the medium term

Consistency: Mixing Index



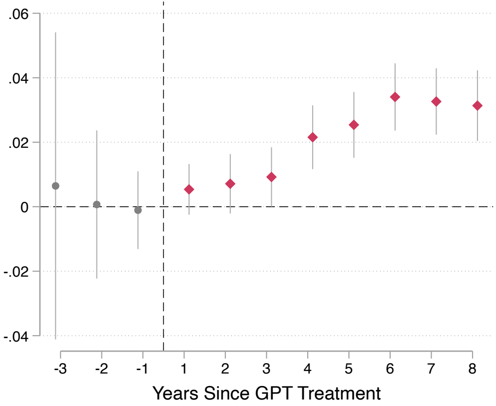
(c) 100 × Skill Mixing Index



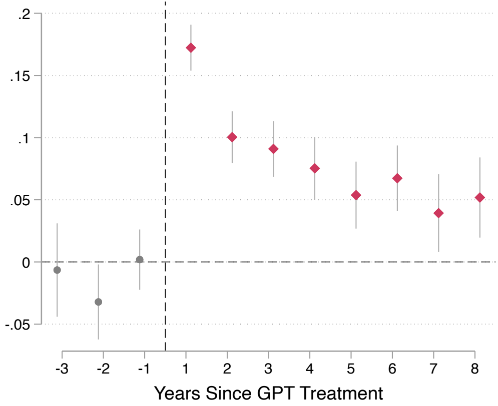
(c) 100 × Skill Mixing Index by Occupations

- BKGPT ↑ mixing index ($\times 100$) by .5, mainly driven by low-skill occupations
- Accumulatively: 3.4 on average for low-skill $\rightarrow$ moment for model

Event Study: Wages and Employmnet



(a) Log Hourly Wage



(b) Log Employement

- BKGPT ↑ wage by 2 % in 5-8 years
- Immediate jump of employment, settles down to 5 %

Structural Understanding & Aggregate Effects

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)

$$f(\mathbf{x}, \mathbf{y}; \boldsymbol{\alpha}, \sigma) = \left[\sum_{k=1}^{K} (x_k \alpha_k y_k)^{\sigma}\right]^{\frac{1}{\sigma}}, \quad \alpha_k > 0, \quad \sigma \in (-\infty, 0)$$

- Endogeneous Occupation Design
  - Both vacant & incumbent firms optimally choose $\mathbf{y}$ before producing
  - Pay $C(\mathbf{y}) = [\sum_{k=1}^{K} (y_k)^{\rho}]$ any cost that $\uparrow$ in $\mathbf{y}$ paid before wage

Skill Mixing in the Model & Identification

- From firm choice

$$\ln y_k = \underbrace{\frac{1}{\rho - \sigma} \ln \Lambda}_{\text{level term}} + \underbrace{\frac{\sigma}{\rho - \sigma}}_{c(\sigma,\rho)} \left(\ln \alpha_k + \ln x_k \right), \quad \frac{\partial c}{\partial \sigma} = \frac{\rho}{(\rho - \sigma)^2} > 0$$

- Skill mixing in the model

$$Mix(\mathbf{y}) = \frac{\sum_{k=1}^{K} (\alpha_k x_k)^c}{\sqrt{K}\sqrt{\sum_{k=1}^{K} (\alpha_k x_k)^{2c}}}$$

  - 1) A decrease in σ, or 2) increase in ρ, increases $Mix(\mathbf{y})$
  - 3) A decrease in $\mathrm{Var}(\alpha_k)$, or 4) decrease in $\mathrm{Var}(x_k)$, increases $Mix(\mathbf{y})$

- Identification
  - Conditional on worker skills x_k (data) and α_k (Lindenlaub, '17), left σ and ρ
  - To separate, x_k enters the output not cost, $\rightarrow$ Identify σ from within–occ wage responses to variation in x; ρ identified as well

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

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

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

[skip] Model Equilibrium

- Worker's Problem

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

$$W(\mathbf{x},\mathbf{y},\omega) = \underbrace{\omega(f(\mathbf{x},\mathbf{y}) - C(\mathbf{y}))}_{\text{get surplus}} + \beta(1-\delta)E\Big\{\max_{\tilde{\mathbf{y}}',\tilde{\omega}'} \underbrace{p(\theta(\mathbf{x}',\tilde{\mathbf{y}}',\tilde{\omega}'))W(\mathbf{x}',\tilde{\mathbf{y}}',\tilde{\omega}')}_{\text{change employer}}$$

$$+ \underbrace{[(1-p(\theta(\mathbf{x}',\tilde{\mathbf{y}}',\tilde{\omega}'))]W(\mathbf{x}',\mathbf{y}',\omega)}_{\text{stay with current employer}}\Big\} + \delta U(\mathbf{x}')$$

- Firm's Problem

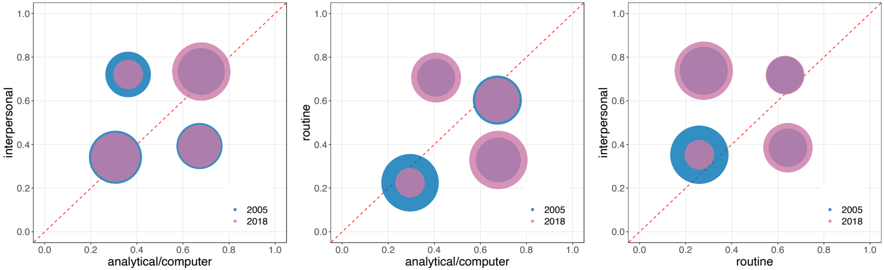
$$J(\mathbf{x},\mathbf{y},\omega) = \max_{\mathbf{y}} \underbrace{(1-\omega)(f(\mathbf{x},\mathbf{y}) - C(\mathbf{y}))}_{\text{design occupation}} + \beta(1-\delta)E\Big\{\underbrace{(1-p(\theta(\mathbf{x}',\tilde{\mathbf{y}}',\tilde{\omega}'))J(\mathbf{x}',\mathbf{y}',\omega)}_{\text{retain the worker}}\Big\}$$

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 to model parameters

Measurement and Calibration

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



Intro
Evidence
Driver
Model
Conclusion

Externally Calibrated

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

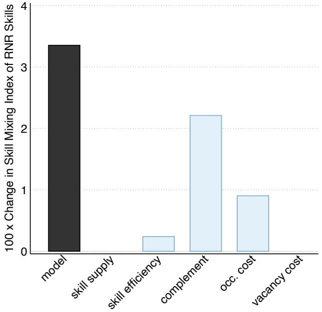
	C. Skill efficiency	(2005)	(2018)	
α_a	Analytical/computer skill	0.63	0.95	Lindenlaub (2017)
α_p	Interpersonal skill	0.05	0.08	Lise & Postel-Vinay (2020)
α_r	Routine skill	0.14	0.06	Lindenlaub (2017)
	D. Internally estimated	(2005)	(2018)	Moments Identification
σ	Inverse elasticity (low)	0.62	0.30	$Cov(a_i, w_i \mid \text{occ}_{low}), Mix(\mathbf{y})_{low}$
σ	Inverse elasticity (high)	0.61	0.29	$Cov(a_i, w_i \mid \text{occ}_{high}), Mix(\mathbf{y})_{high}$
ρ	Convexity of cost	3.92	4.99	$Mix(\mathbf{y})$
c	Vacancy posting cost % output	0.93	0.90	Unemployment rate

- Estimation strategy - SMM Numerical algorithm
    1. Given $\Theta = \{\sigma, \rho, c\}$, 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

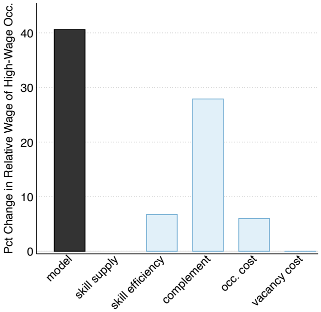
Counterfactuals

- Shut down channels sequentially from the "2018 economy"
    1. Skill efficiencies α_k
    2. Initial skill distribution $G(\mathbf{x})$
    3. Inverse elasticity σ
    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

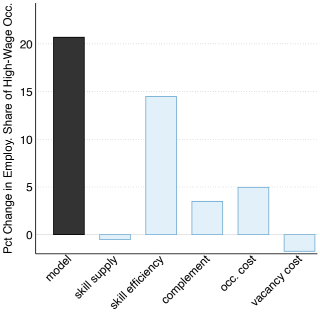
Forces at Play: Skill Mixing, Wages, Employment



(1) Skill mixing



(2) Wages



(3) Employment

- Complementarity & cost explain 2/3 and 1/3 of the increase in skill mixing
- They account for 79% of the ↑ wage premium of high-wage occ
- They are less important than skill efficiency for ↑ employment of high-wage occ (70%)

Conclusion

- Skills are *inevitably* embedded in workers → demand of skill mixtures
- **New facts** about skill mixing (high- to low-skill, IT & business/data)
- **Breakthrough GPT** as a key driver (wage and employment gains)
- **New framework** of multi-d search & occ. design, complementarity matters

Important to consider demand of ”skill mixtures” and provide right “mixed” sets of skills to workers to face the challenge brought by technological change.

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*?

	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	
1	2	3	4	5	6	7
						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.*

Top Occupations in Mixing Non-routine Skills back

Top Occupations	Year	Analytical	Computer	Inter-personal	Routine	Mixing Index	Percentile
Sales counter clerks	2005	0.13	0.32	0.30		0.946	7
(Sales)	2018	0.50	0.52	0.39		0.993	99
Recreation facility attendants	2005	0.24	0.18	0.39		0.947	7
(Personal Care and Services)	2018	0.38	0.40	0.35		0.998	99
Data entry keyers	2005	0.56	0.77	0.27		0.935	3
(Office/Admin)	2018	0.55	0.66	0.43		0.985	90
Packers, fillers, and wrappers	2005	0.58	0.44	0.16		0.915	1
(Operators/Fabricators/Laborers)	2018	0.52	0.40	0.42		0.994	99

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

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

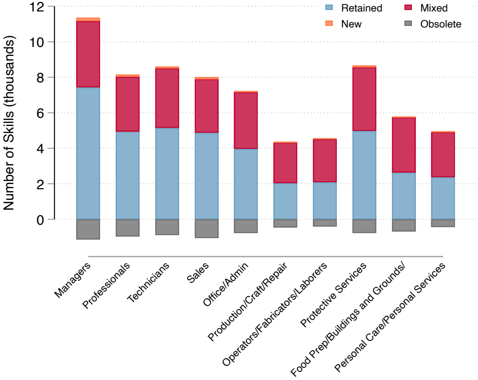
Broad O*NET Skills back

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	

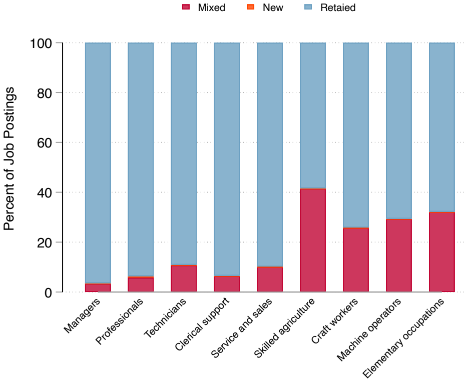
Lightcast Key Words back

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

Decompose Skills and Postings back



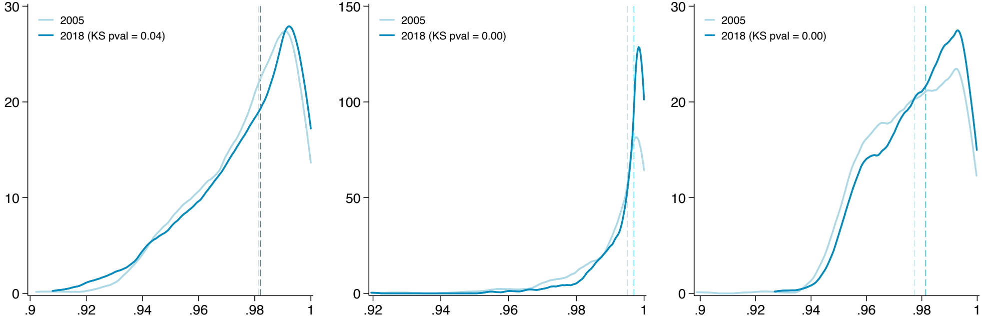
(a) Composition of Skills at 3 Digit SOC



(b) Composition of Posted Skills

Figure: Composition of Skills in US Job Postings, 2010 to 2024

Skill Mixing at 7-digit Occupations back



(1) RNR Skills
(analytical, interpersonal, computer, routine)

(2) Non-routine Skills
(analytical, interpersonal, computer)

(3) Other Non-routine
(analytical, interpersonal, computer, leadership, design)

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

Skill Mixing at 7-digit Occupatoins back

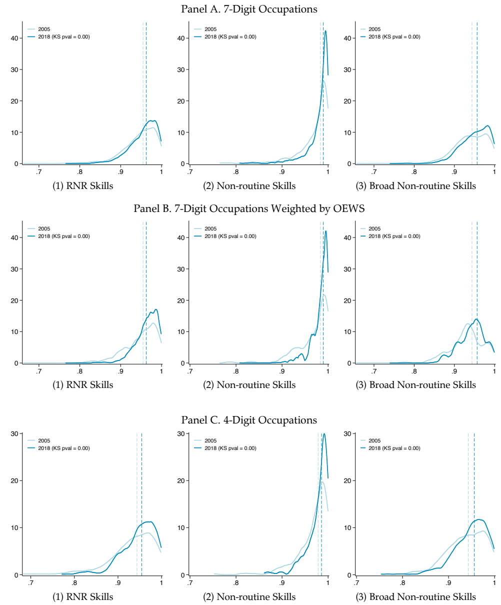


Figure: Density for Skill Mixing Indexes (Weighted Cosine Distances), 2005 vs. 2018

Leaving One Skill Out from Non-routine back

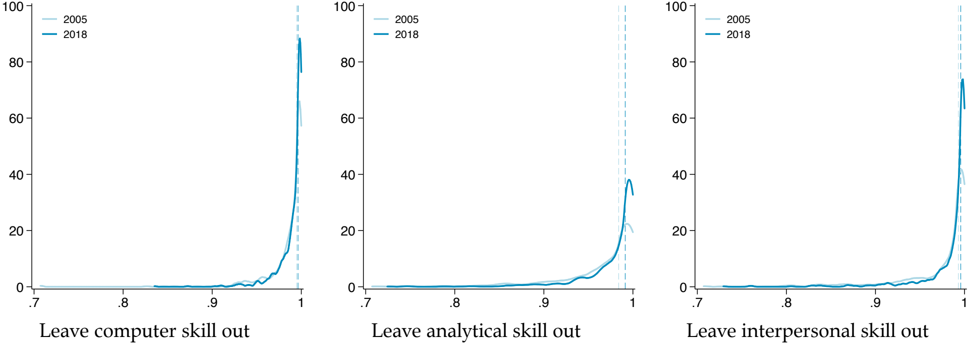


Figure: Density for Skill Mixing Indexes (Weighted Cosine Distances), 2005 vs. 2018

Decomposition of Skill Mixing at 7-Digit back

Table: R-Squared Values for Non-Routine Skills' Mixing Index by Polynomial Order

	Analytical	Computer	Interpersonal
3rd Order Polynomial			
All occupations	0.15	0.48	0.21
High-wage	0.03	0.45	0.55
White-collar	0.21	0.20	0.52
Blue-collar	0.05	0.56	0.15
Service	0.30	0.62	0.20
5th Order Polynomial			
All occupations	0.18	0.50	0.22
High-wage	0.04	0.46	0.55
White-collar	0.22	0.21	0.53
Blue-collar	0.07	0.57	0.16
Service	0.38	0.73	0.26

$$\text{Mix}(\mathbf{y})_{jt} = \beta_1 y_{jt}^1 + \beta_2 y_{jt}^2 + \ldots + \beta_N y_{jt}^N$$

Fact 2: Growth in Skill Mixing

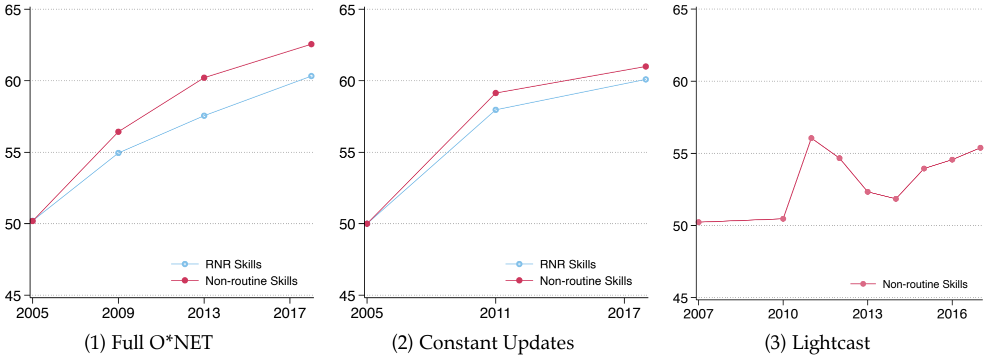
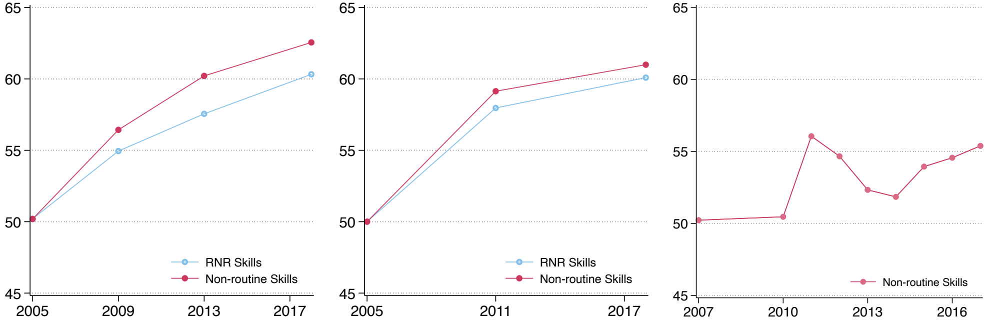


Figure: Trend of Skill Mixing in the US Economy, 2005-2018

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

Fact 2: Growth in Skill Mixing

Appendix



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

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

$$\Delta Y = \sum_j \left(E_j \Delta y_{j\tau}\right) + \sum_j \left(\Delta E_{j\tau} y_j\right) = \Delta Y^{within} + \Delta Y^{across}$$

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

7-digit results

Fact 3: Skill Mixing Increases Regardless of Workforce

Table: Annual Changes in Skill Mixing Indexes (in Percentiles)

	RNR Skills (1)	Non-routine Skills (2)
*A. Full O*NET, 2005-2018*		
Year indicator	0.70^{***}	0.71^{***}
	[0.07]	[0.06]
Observations	237,885	237,885
R-squared	0.83	0.83
*B. O*NET Constant Updates, 2005-2018*		
Year indicator	0.75^{***}	0.65^{***}
	[0.11]	[0.11]
Observations	107,956	107,956
R-squared	0.81	0.82
C. Lightcast, 2007-2017		
Year indicator		0.33^{**}
		[0.15]
Observations		532,636
R-squared		0.87
Experience and edu controls	X	X
Gender $\times$ edu $\times$ ind $\times$ occ FE	X	X

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

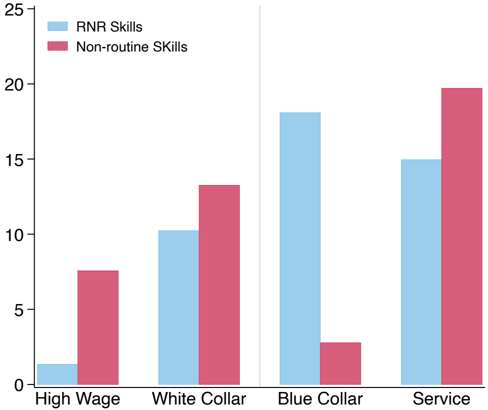


Figure: Skill Mixing Index Change by Occupation Groups, 2005-2018

By gender & edu
By industry
Skill pairs
Polarization

Alternative Depiction of Skill Mixing back

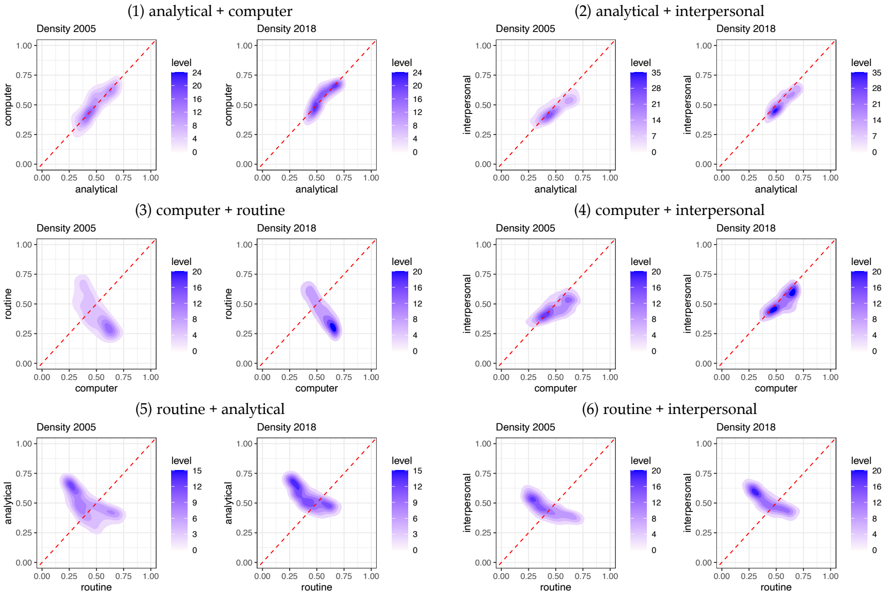


Figure: Non-parametric Depiction of Skill Intensities, 2005 vs. 2018

Time Pattern back

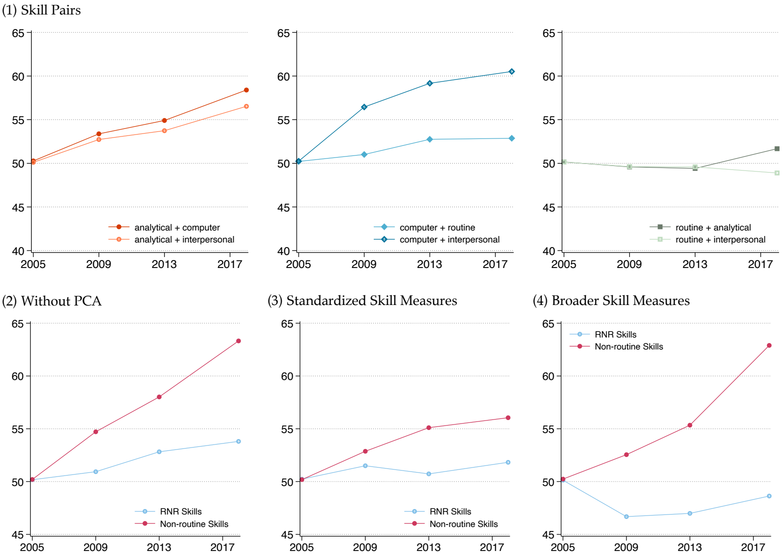


Figure: Trend of Skill Mixing with Alternative Skill Measures

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

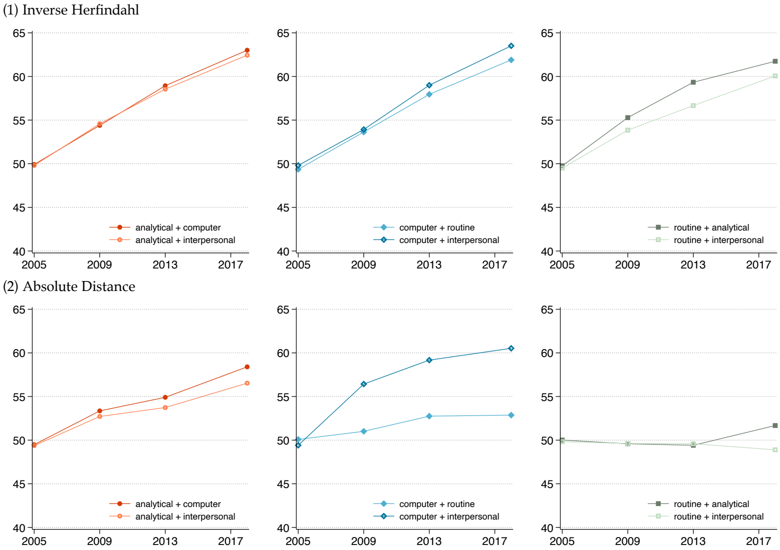
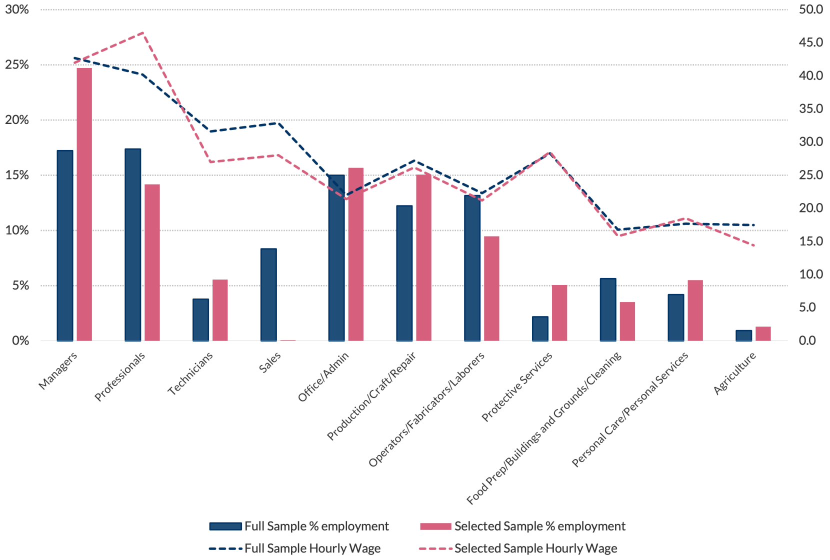


Figure: Trend of Skill Mixing with Alternative Indexes

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

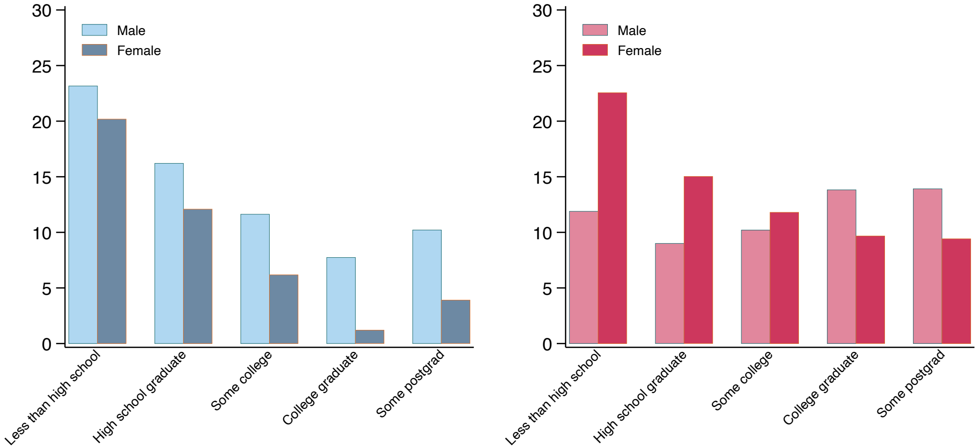
Notes: This table shows a shift-share decomposition of changes in the average level of different mixing indexes between 2005-2018 in percentile units. Specifically, for a change in the percentile of a mixing index over two periods t and τ, its change $\Delta T_\tau = T_\tau - T_t$ which can be decomposed 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

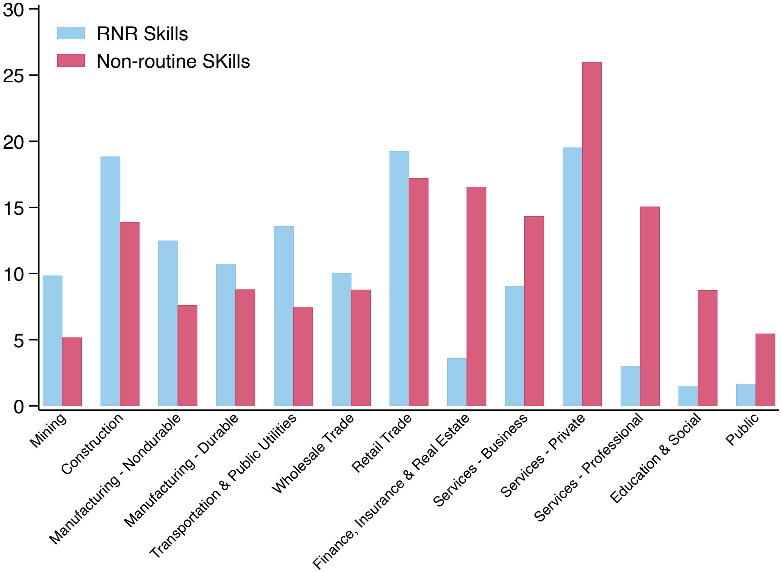
	Skill Groups	6-digit Occupations			4-digit Occupations		
		total	within	across	total	within	across
Full O*NET	analytical + computer	10.52	6.40	4.12	10.49	6.60	3.89
	analytical + interpersonal	5.36	2.90	2.46	8.17	4.08	4.09
	computer + routine	4.38	2.41	1.97	5.16	2.94	2.22
	computer + interpersonal	7.23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

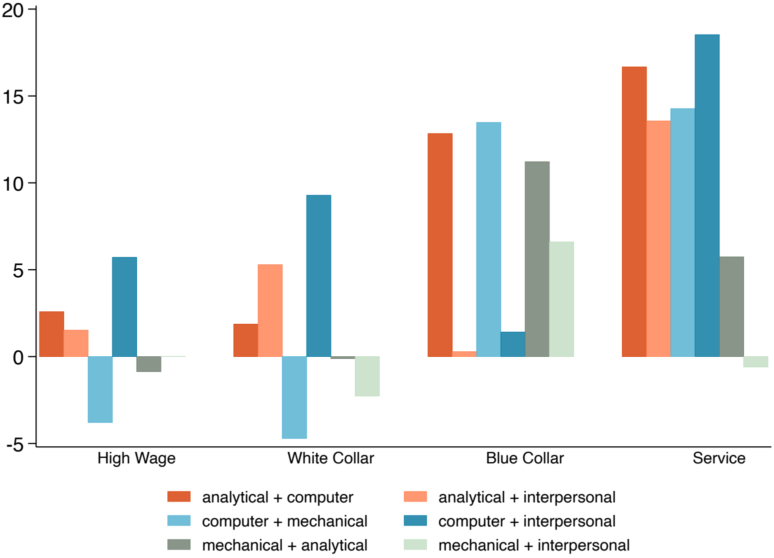
Mixing Index Change by Gender and Education, 2005-2018



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.*

Fact 5: Skill Mixing Accounts for Polarization back

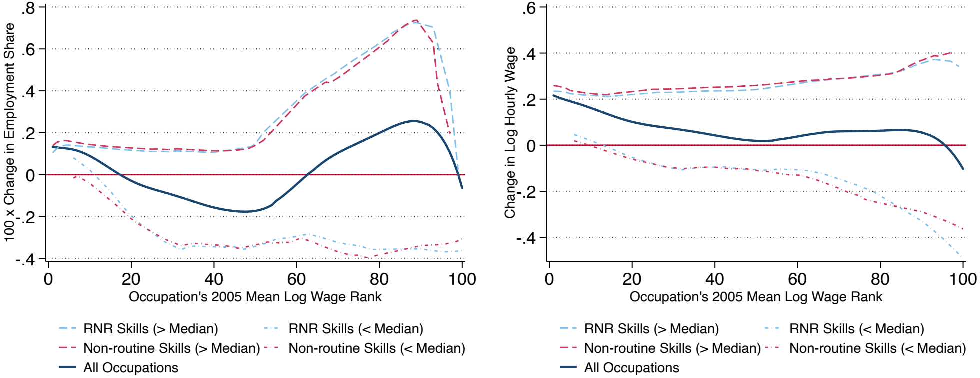


Figure: Smoothed Employment and Wage Changes by Skill Percentile, 2005-2018

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 within occupation variation:

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

- Within-occ covariance between $\mathbf{x}$ and $w(\mathbf{x}, \mathbf{y})$ identifies σ
- Cost parameter ρ identified via firms' optimization of skill demand
- Cost parameter τ identified via employment distribution and relative wages
- Vacancy cost c determined by unemployment conditional on b

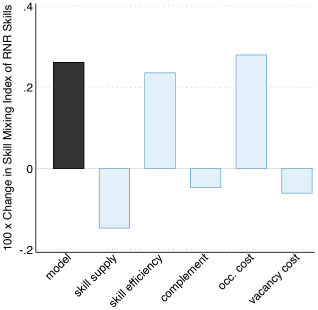
Algorithm back

- 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

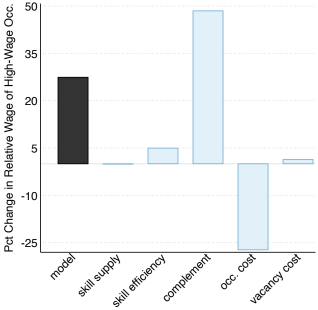
Role of Skill Supply back

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

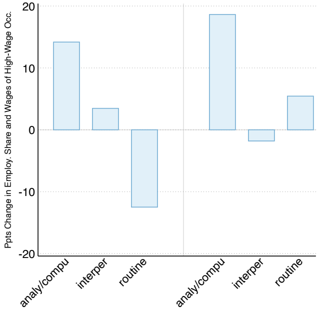
Additional Counterfactual Analysis back



(1) Skill mixing



(2) Wages – unweighted



(3) Wages (left) and employment (right) by individual skills

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