Skill vs. Tasks: Task Approach

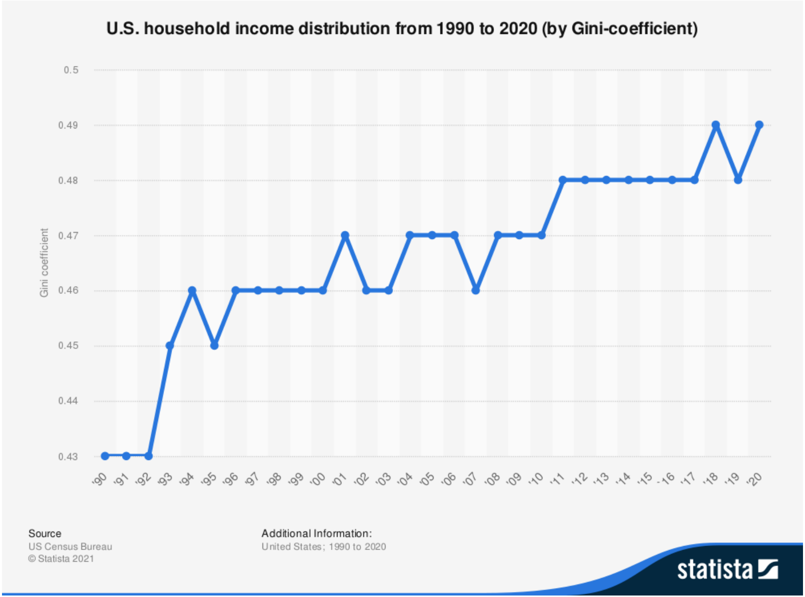
Lecture

Econ 350, Winter 2023

Road Map

- Motivation Facts
- Canonical Model (SBTC)
- Task Approach
  - a Task measure
  - b Data trend v.s. Models
  - c Job polarization
  - d Explain the employment and wage patterns:
    RBTC v.s. Complex-Task TC v.s. Automation and new tasks
- Multidimentional Skills
  - a Skill Demand Changes
  - b Skill Demand: Multiple Skill

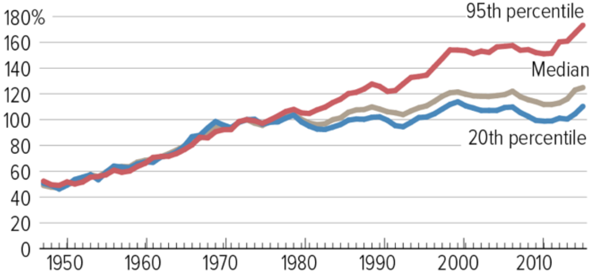
Motivation: Inequality is increasing



Motivation: Inequality is increasing

Income Gains Widely Shared in Early Postwar Decades — But Not Since Then

Real family income between 1947 and 2016, as a percentage of 1973 level



Note: In 2014 Census split its sample of survey respondents into two groups to test a set of redesigned income questions. In 2015 (reporting on 2014 income using the new questions), Census released two estimates of 2013 incomes, one based on the old questions and one on the new. The chart uses the estimate based on the old questions, based on CBPP's judgment that, due in part to sample size, it is likely more accurate for 2013.

Source: CBPP calculations based on U.S. Census Bureau Data

CENTER ON BUDGET AND POLICY PRIORITIES | CBPP.ORG

Motivation: Inequality is increasing

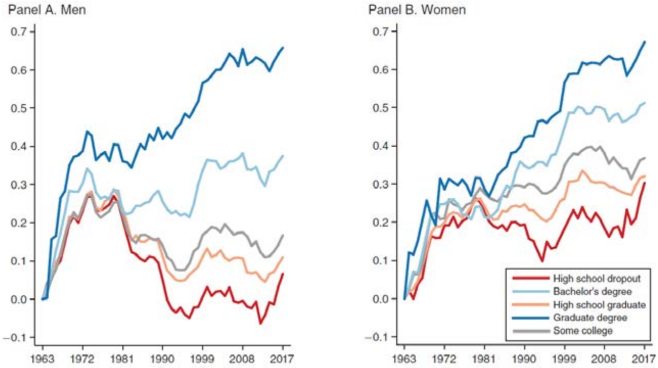
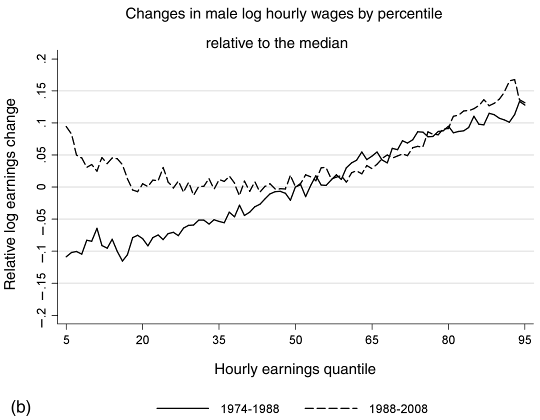


FIGURE 1: Cumulative growth of real wages by gender and education (from Autor, 2019)

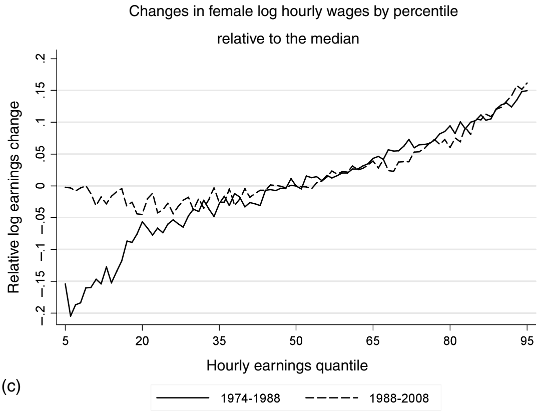
Motivation: "Wage Polarization"



- During 1988-2008, Federal minimum wage increases from 3.35 to 5.85
- It is not ranked by skill percentile

Acemoglu and Autor (2011)

Motivation: "Wage Polarization"



- Log hourly wages are calculated for all workers,excluding the self-employed and those employed in military occupations.
- The log wage change at median is normalized to zero in each time interval

Acemoglu and Autor (2011)

Canonical Model

The production function for the aggregate economy as following:

$$Y = ((A_L L)^{\frac{\sigma-1}{\sigma}} + (A_H H)^{\frac{\sigma-1}{\sigma}})^{\frac{\sigma-1}{\sigma}}$$

Therefore, the wage for high and low skill workers can be expressed as:

- $w_L = \frac{\partial Y}{\partial L} = A_L^{\frac{\sigma-1}{\sigma}}[A_L^{\frac{\sigma-1}{\sigma}} + A_H^{\frac{\sigma-1}{\sigma}}(H/L)^{\frac{\sigma-1}{\sigma}}]^{\frac{1}{\sigma-1}}$
- $w_H = \frac{\partial Y}{\partial H} = A_H^{\frac{\sigma-1}{\sigma}}[A_L^{\frac{\sigma-1}{\sigma}}(H/L)^{-\frac{\sigma-1}{\sigma}} + A_H^{\frac{\sigma-1}{\sigma}}]^{\frac{1}{\sigma-1}}$

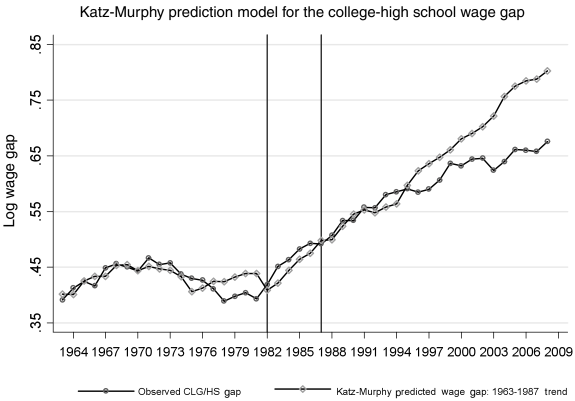
The changes in the demand for skills can be expressed as:

$$d\ln(\frac{w_H}{w_L}) = -\frac{1}{\sigma}d\ln(\frac{H}{L}) + \frac{\sigma-1}{\sigma}d\ln(\frac{A_H}{A_L})$$

where w_H/w_L is the skill premium, H/L is the relative supply of skills, σ is the elasticity of substitution between skilled and unskilled workers, A_H and A_L are factor-augmenting technologies for skill and unskill workers, respectively.

Canonical Model

- In Katz and Murphy's seminal paper σ is estimated to be around 1.4
- With combining with steady growth path for A_H/A_L, this model accounts for the time series of the college premium in the US fairly successfully

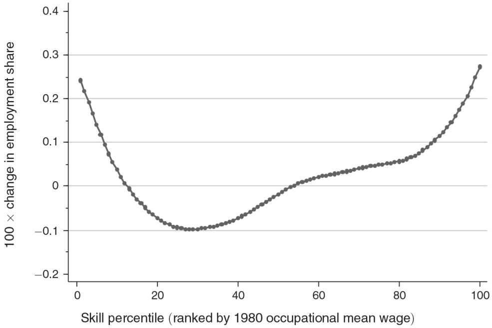


Automation and New Tasks

- The canonical model cannot help understand the occupational trends in the labor market: the disappearance of middle-skill occupations (production and clerical jobs)

Job Polarization

Figure: Smoothed Changes in Employment 1980-2005



Autor and Dorn (2013) AER

Task Approach

The need of Task Approach

- We want to examine demand vs. supply side effects on labor market outcomes (e.g. employment rate and wages)
- There are two aspects of production:
  - which factors are used as inputs (e.g., capital, different types of skills)
  - what services these factors provide (e.g. task). Task is occupation.
  - Therefore, the problem comes to whether we should write production function in terms of tasks or skills. If tasks=f(skills), it is just an issue of representation.
- The canonical production function does not distinct these two aspects.
- Task approach is helpful to analyze the composition change of employment and the analysis of "polarization" in the earning distributions

Definition

- A task: a unit of work activity (i.e., a bundle of skills) that produces output
- A skill: a worker's stock of capability for performing different tasks (e.g., Heckman and Sedlacek (1985))

Comparative advantage in production:

- the factor (may a bundle of skills) with the lowest economic cost of performing a task is assigned that task
- the economic cost reflects both technological capability and its opportunity cost

Task Measurement

Task Measurement

There are three approaches to measure task in current literature.

- Using occupations as proxies for job tasks
- DOT (O*NET) type
- IAB/BIBB labor force data

Using occupations as proxies for job tasks

- Usually there are hundreds of distinct occupations. To make this problem manageable, it is necessary to reduce the dimensions.
- Aggregate many detailed occupations into a few broad categories, e.g., professional, technical, managerial, clerical, production, service, etc
- Limitation: It ignores the similarities in task content cross occupational boundaries. For example, truck drivers and food service workers serve intensively non-routine manual tasks

Task Measurement: DOT

Dictionary of Occupational Titles (DOT)

- First published in 1938, and last updated in 1991. It contains 44 objective and subjective content scales.

For example: Job Title: Faculty member, college or university (education)

- GOE: 11.02.01 STRENGTH: L GED: R6 M5 L5 SVP:8 DLU:81
- GOE means Guide for Occupational Exploration (GOE) with twelve interest areas. In the example, 11.02 means Learning-Influencing (Educational and Library)
- Strength is a physical demanding measure with five levels: Sedentary, Light, Medium, Heavy, and Very Heavy
- Date of Last Update (DLU)

Task Measurement: DOT

- General Educational Development (GED): including three divisions: Reasoning Development, Mathematical Development, and Language Development (Level 1-6), which is not GED test.
- Usually researchers calculate the mean of GED at three digit level occupations or give the percentile across occupations

Scale of General Education Development (GED)

LEVEL	REASONING DEVELOPMENT	MATHEMATICAL DEVELOPMENT	LANGUAGE DEVELOPMENT
6	Apply principles of logical or scientific thinking to a wide range of intellectual and practical problems. Deal with nonverbal symbolism (formulas, scientific equations, graphs, musical notes, etc.) in its most difficult phases. Deal with a variety of abstract and concrete variables. Apprehend the most abstruse classes of concepts.	Advanced calculus: Work with limits, continuity, real number systems, mean value theorems, and implicit function theorems. Modern Algebra: Apply fundamental concepts of theories of groups, rings, and fields. Work with differential equations, linear algebra, infinite series, advanced operations methods, and functions of real and complex variables. Statistics: Work with mathematical statistics, mathematical probability and applications, experimental design, statistical inference, and econometrics.	Same as Level 5.
5	Apply principles of logical or scientific thinking to define problems, collect data, establish facts, and draw valid conclusions. Interpret an extensive variety of technical instructions in mathematical or diagrammatic form. Deal with several abstract and concrete variables.	Algebra: Work with exponents and logarithms, linear equations, quadratic equations, mathematical induction and binomial theorem, and permutations. Calculus: Apply concepts of analytic geometry, differentiations, and integration of algebraic functions with applications. Statistics: Apply mathematical operations to frequency distributions, reliability and validity of tests, normal curve, analysis of variance, correlation techniques, chi-square application and sampling theory, and factor analysis.	Reading: Read literature, book and play reviews, scientific and technical journals, abstracts, financial reports, and legal documents. Writing: Write novels, plays, editorials, journals, speeches, manuals, critiques, poetry, and songs. Speaking: Coversant in the theory, principles, and methods of effective and persuasive speaking, voice and diction, phonetics, and discussion and debate.

Task Measurement: DOT

- Specific Vocational Preparation (SVP): Job Analysts evaluate how long to prepare skills to perform the tasks

SCALE OF SPECIFIC VOCATIONAL PREPARATION

Level	Time[1]
1	Short demonstration only
2	Anything beyond short demonstration up to and including 1 month
3	Over 1 month up to and including 3 months
4	Over 3 months up to and including 6 months
5	Over 6 months up to and including 1 year
6	Over 1 year up to and including 2 years
7	Over 2 years up to and including 4 years
8	Over 4 years up to and including 10 years
9	Over 10 years

Task Measurement: DOT

There are 11 Aptitudes.

- G (General Learning Ability); V (Verbal); N (Numerical); S (Spatial); P (Form Perception); Q (Clerical Perception); K (Motor Coordination); F (Finger Dexterity); M (Manual Dexterity); E (Eye-Hand-Foot Coordination), and C (Color Discrimination)
- Rated on a 1-5 scale
  - 1 (Extremely High)= top 10% of work population
  - 2 (High)= highest 1/3, exclusive of top 10%
  - 3 (Medium)= middle 1/3
  - 4 (Lower)= lowest 1/3, exclusive of bottom 10%
  - 5 (Markedly Low)= lowest 10% of work population

Note: scaled by job analysts, supposed to be independent of jobs

Task Measurement: O*NET

Occupational Information Network (O*NET):

- It is the successor for DOT, which starts since 1998.
- It maps highly specific DOT job codes (over 12,000) to O*NET occupational units(1,102)
- Data for O*NET was collected mostly through self-report by incumbent workers.
- Advantage: O*NET contained around 400 separate rating scales
- Some Concern: One potential problem is that researcher would "freely" choose among the available rating scale.

Task Measurement: O*NET

Task Measurement: O*NET

Knowledge

All 6 displayed

- **Economics and Accounting** — Knowledge of economic and accounting principles and practices, the
reporting of financial data.
- **Mathematics** — Knowledge of arithmetic, algebra, geometry, calculus, statistics, and their application
- **English Language** — Knowledge of the structure and content of the English language including the m
and grammar.
- **Computers and Electronics** — Knowledge of circuit boards, processors, chips, electronic equipment
applications and programming.
- **Education and Training** — Knowledge of principles and methods for curriculum and training design, f
and the measurement of training effects.
- **Law and Government** — Knowledge of laws, legal codes, court procedures, precedents, government
democratic political process.

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Skills

5 of 17 displayed

- **Active Listening** — Giving full attention to what other people are saying, taking time to understand th
appropriate, and not interrupting at inappropriate times.
- **Instructing** — Teaching others how to do something.
- **Reading Comprehension** — Understanding written sentences and paragraphs in work related docum
- **Speaking** — Talking to others to convey information effectively.

Task Measurement: O*NET

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Skills Save Table (XLS/CSV)

10 of 35 displayed (17 important)

Importance	Skill
75	**Active Listening** — Giving full attention to what other people are saying, taking time to understand the points being made, asking questions as appropriate, and not interrupting at inappropriate times.
75	**Instructing** — Teaching others how to do something.
75	**Reading Comprehension** — Understanding written sentences and paragraphs in work related documents.
75	**Speaking** — Talking to others to convey information effectively.
72	**Critical Thinking** — Using logic and reasoning to identify the strengths and weaknesses of alternative solutions, conclusions or approaches to problems.
72	**Writing** — Communicating effectively in writing as appropriate for the needs of the audience.
69	**Learning Strategies** — Selecting and using training/instructional methods and procedures appropriate for the situation when lear teaching new things.
63	**Active Learning** — Understanding the implications of new information for both current and future problem-solving and decision-m
60	**Complex Problem Solving** — Identifying complex problems and reviewing related information to develop and evaluate options a implement solutions.
56	**Mathematics** — Using mathematics to solve problems.

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Abilities Save Table (XLS/CSV)

10 of 52 displayed (18 important)

Importance	Ability
81	**Oral Expression** — The ability to communicate information and ideas in speaking so others will understand.
78	**Oral Comprehension** — The ability to listen to and understand information and ideas presented through spoken words and sente
78	**Written Comprehension** — The ability to read and understand information and ideas presented in writing.
75	**Speech Clarity** — The ability to speak clearly so others can understand you.
75	**Written Expression** — The ability to communicate information and ideas in writing so others will understand.

Task Measurement: O*NET

Team Assemblers

Skills Save Table (XLS/CSV)

10 of 35 displayed (7 important)

Importance	Skill
53	**Coordination** — Adjusting actions in relation to others' actions.
53	**Monitoring** — Monitoring/Assessing performance of yourself, other individuals, or organizations to make improvements or take co action.
53	**Quality Control Analysis** — Conducting tests and inspections of products, services, or processes to evaluate quality or performar
50	**Active Listening** — Giving full attention to what other people are saying, taking time to understand the points being made, asking questions as appropriate, and not interrupting at inappropriate times.
50	**Critical Thinking** — Using logic and reasoning to identify the strengths and weaknesses of alternative solutions, conclusions or approaches to problems.
50	**Speaking** — Talking to others to convey information effectively.
50	**Time Management** — Managing one's own time and the time of others.
47	**Management of Personnel Resources** — Motivating, developing, and directing people as they work, identifying the best people f job.
47	**Operation Monitoring** — Watching gauges, dials, or other indicators to make sure a machine is working properly.
47	**Reading Comprehension** — Understanding written sentences and paragraphs in work related documents.

Task Measurement: O*NET

- Since there are 400 measures, current most researchers just choose some related measures to evaluate occupation skills.
- In terms of how to measure occupation skills, they either use the principle component method to uncover the skills or just calculate average scores for each occupation
- Then, we give an example of constructing occupation skills by Deming (2017)

Construct Task Measures: Deming (2017)

Routine Task

- how automated is the job
- how important is repeating the same activities to perform this job

Nonroutine Analytical Task

- the extent to which an occupation requires mathematical reasoning
- whether the occupation requires using mathematics to solve problems
- whether the occupation requires knowledge of mathematics

Social Skill Task

- coordination, negotiation, persuasion, and social perceptiveness

Construct Task Measures: Deming (2017)

Deming uses the first version of O*NET (1998), which is slightly different from what we show previously. In that version all task skills are measured on an ordinal "level":

- ranges from 1 (low) to 7 (high).
- 1 ("minimally important") to 5 ("extremely important")

Calculating the measures

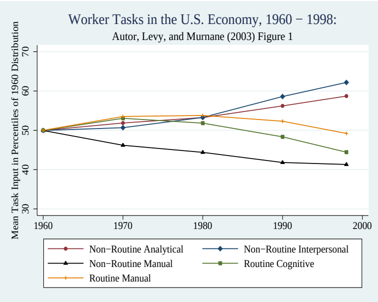
- He rescales all variables between 0 and 10, and then calculates average scores by each occupation
- Then he transfers all O*NET variables into percentiles of average scores, weighted by the 1980 labor supply distribution

Task Measurement: IAB/BIBB Labor force data

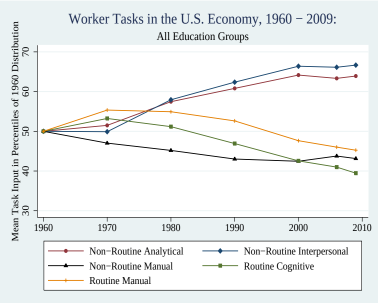
- Employment Surveys on Qualification and Working Conditions
- Collected in 1979,1985/86, 1991/92, 1998/99, 2005/06
- Detailed self-reported data on workers' primary activities at their jobs
- Collect job task information directly

Findings from Literature

Worker Tasks in the U.S. Economy



(a) ALM (2003)



(b) Autor and Price (2013)

Figure: Worker Tasks in the U.S. Economy 1960-2009

The Trend of DOT Task Mean

Table 1. Trends in Task Input in the U.S. Economy, 1960 - 2009
Updated Values 1960 - 2009, and Comparison with ALM 2003 for 1960-1998

	1960	1970	1980	1990	2000/1998 Update/ALM	2006	2009
A. Non-Routine Analytical							
Update	50.0	51.5	57.5	60.8	64.2	63.3	63.9
ALM	50.0	51.9	53.2	56.2	58.7		
G. Non-Routine Interpersonal							
Update	50.0	49.9	57.9	62.4	66.4	66.1	66.7
ALM	50.0	50.7	53.3	58.6	62.2		
C. Routine Cognitive							
Update	50.0	53.2	51.2	46.9	42.6	41.0	39.5
ALM	50.0	53.1	51.8	48.3	44.4		
D. Routine Manual							
Update	50.0	55.3	54.9	52.6	47.6	46.0	45.2
ALM	50.0	53.5	53.8	52.3	49.2		
E. Non-Routine Manual							
Update	50.0	47.0	45.2	43.0	42.5	43.8	43.1
ALM	50.0	46.2	44.4	41.8	41.3		

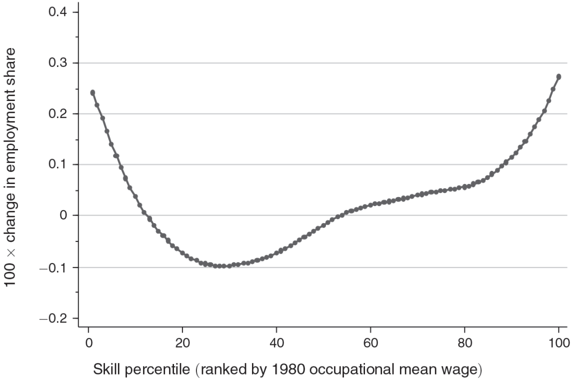
Notes: In the column marked "1998/2000," ALM use 1998 values, and the Update reports 2000 values.

- Subsequent points depict the employment weighted mean of each assigned percentile over each decade

Note: Autor and Price claim that the numbers are different since they use census population data in later version. The occupation codes are slightly different.

Employment

Figure: Smoothed Changes in Employment 1980-2005

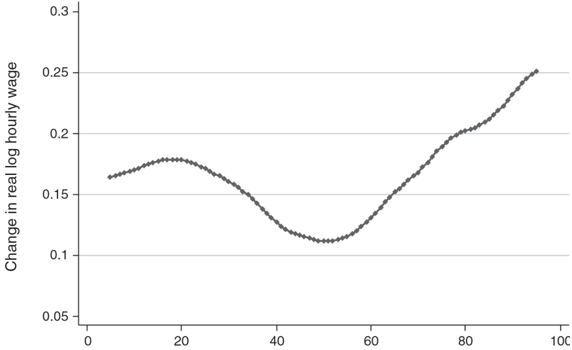


- Including both male and female

Autor and Dorn (2013) AER

Wage

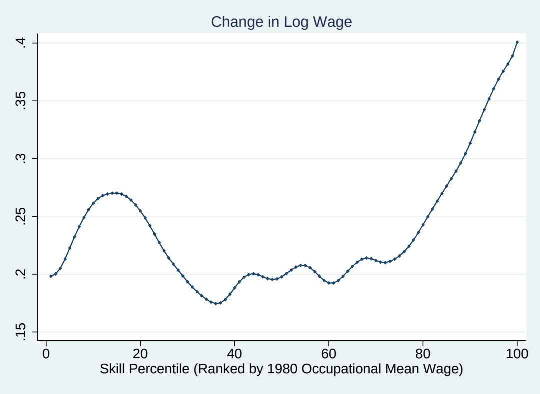
Figure: Smoothed Changes in Employment 1980-2005



- Including both male and female

Autor and Dorn (2013) AER

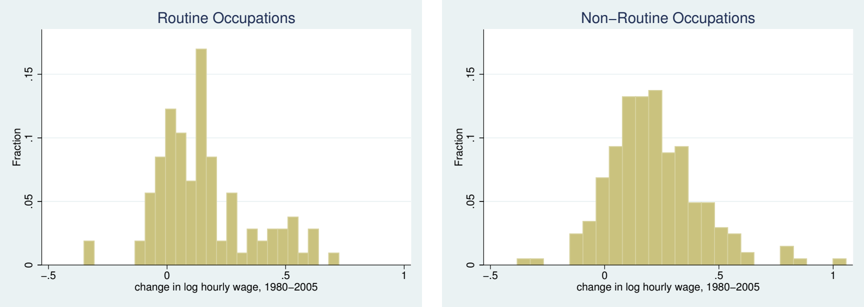
Wage



Note: Authors mention that they use similar definition as that in Autor and Dorn (2013).
Colin, Hoffmann, and Kambourov (2017)

Wage

Figure 1: Distribution of Hourly Wage Growth for Routine and Non-Routine Occupations



Notes: Data taken from the 1980 5% Sample of the US Census and the 2005 American Community Survey (ACS). Hourly wages constructed from total wage and salary data (adjusted using PCE deflator), number of weeks worked per year, and usual number of hours worked per year. Data is defined on the 3-digit occupation level. Routine occupations defined as in Autor and Dorn (2013), all other occupations defined as non-routine.

- Both routine and non-routine occupations feature a significant share of low- and high wage growth occupations

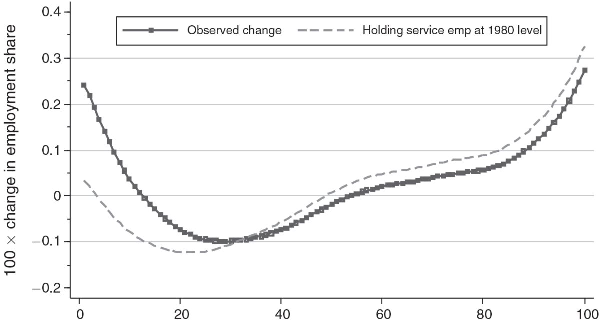
Colin, Hoffmann, and Kambourov (2017) RED

Explanations

How to explain the change of employment and wages?

Now we provide competing stories Autor and Dorn (2013), Colin, Hoffmann, and Kambourov (2017) and Acemoglu and Restrepo (2018, 2019, 2020)

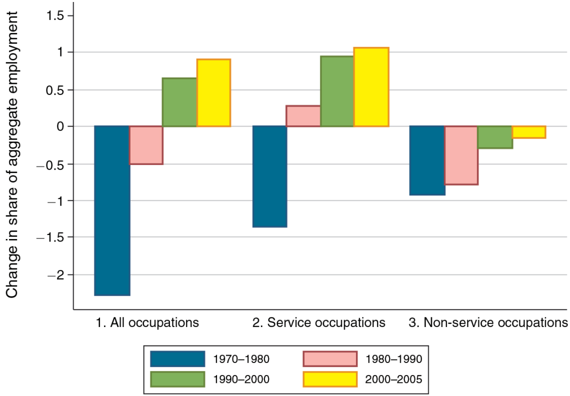
Figure: Observed and Counterfactural Changes in Employment 1980-2005



Autor and Dorn (2013) AER

RBTC-Autor and Dorn (2013)

Figure: Change in Aggregate Employment Share 1970-2005



- Here all occupations mean that the occupations that comprised the lowest skill quintile of employment in 1980.

Autor and Dorn (2013) AER

RBTC-Autor and Dorn (2013)

- Autor's sequence of papers propose the answer is that routine-biased technological change (RBTC) can explain middle-skill occupations have been under pressure of automatization.

Since in their model, workers supply either routine,abstract or manual tasks. Therefore they construct

$$\text{Routine Task Intensity}_o = \ln(\text{Routine}_o) - \ln(\text{Manual}_o) - \ln(\text{Abstract}_o)$$

Then, they calculate routine employment share (RSH_{jt}) for each commuting zones:

$$RSH_{jt} = \Big(\sum_{k=1}^{K} L_{jkt} \times 1[RTI_k > RTI^{66}]\Big)\Big(\sum_{k=1}^{K} L_{jkt}\Big)^{-1}$$

where L_{jkt} is the employment in occupation k in commuting zone j at time t

RBTC-Autor and Dorn (2013)

Figure: Computer Adoption and Task within Commuting Zones 1980-2005

	(1)	(2)	(3)
Panel A. Δ Adjusted PCs per employee, 1980–2000			
	1980–1990	1990–2000	1980–2000
Share of routine occs$_{-1}$	0.695***	0.490***	0.619***
	(0.061)	(0.076)	(0.044)
R^2	0.577	0.332	0.385
Panel B. Δ Share routine occupations, 1980–2005			
	All workers	College	Noncollege
Share of routine occs$_{-1}$	−0.254***	−0.153***	−0.295***
	(0.023)	(0.024)	(0.018)
R^2	0.433	0.206	0.429

- Panel A: share of routine employment is highly predictive of computer adoption.
- Panel B: commuting zones with higher routine task saw declines in routine intensive occupations
- Commuting zones: groups of counties with strong commuting ties (fraction of commuters across counties)

Autor and Dorn (2013) AER

RBTC-Autor and Dorn (2013)

Figure: Routine Employment Share and Growth of Service Employment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. OLS estimates: covariates specified in lagged levels							
Share of routine occs$_{-1}$	0.105***	0.066*	0.066**	0.110***	0.110**	0.069*	0.111***
	(0.032)	(0.036)	(0.029)	(0.031)	(0.049)	(0.035)	(0.034)
College/noncollege pop$_{-1}$		0.012***					0.011**
		(0.004)					(0.005)
Immigr/noncollege pop$_{-1}$			0.042**				0.025**
			(0.017)				(0.011)
Manufact/empl$_{-1}$				−0.056***			−0.036***
				(0.015)			(0.011)
Unemployment rate$_{-1}$				−0.067			−0.313***
				(0.069)			(0.068)
Female empl/pop$_{-1}$					−0.044		−0.200***
					(0.039)		(0.037)
Age 65+/pop$_{-1}$					−0.114***		−0.061***
					(0.035)		(0.020)
Share workers with wage$_t$ < min wage$_{t+1}$						−0.134***	−0.197***
						(0.020)	(0.029)
R^2	0.179	0.189	0.196	0.195	0.191	0.196	0.233
Panel B. 2SLS estimates: covariates specified in lagged levels							
Share of routine occs$_{-1}$	0.192***	0.118***	0.148***	0.162***	0.218***	0.174***	0.149***
	(0.035)	(0.046)	(0.044)	(0.031)	(0.054)	(0.035)	(0.056)
R^2	0.169	0.186	0.189	0.192	0.182	0.182	0.264
Panel C. 2SLS estimates: covariates specified in ten year changes							
Share of routine occs$_{-1}$	0.192***	0.173***	0.152***	0.170***	0.180***	0.174***	0.112**
	(0.035)	(0.043)	(0.032)	(0.035)	(0.035)	(0.035)	(0.044)
R^2	0.169	0.174	0.188	0.232	0.186	0.182	0.265

Autor and Dorn (2013) AER

RBTC-Autor and Dorn (2013)

Figure: Routine Employment Share and Growth of Service Employment

			I. Occupations with low routine content			II. Occupations with high routine content		
			Service occs	Transport, construct, mechanics, mining, farm	Managers, prof, tech, finance, public safety	Administrative support, retail sales	Precision production, craft workers	Machine operators, assemblers
			(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Change in share of noncollege employment								
(i)	All	Share of routine occs$_{-1}$	0.192***	0.248***	0.028	−0.277***	−0.085***	−0.107**
			(0.035)	(0.037)	(0.029)	(0.038)	(0.017)	(0.044)
(ii)	Males	Share of routine occs$_{-1}$	0.210***	0.246***	−0.043	−0.055*	−0.145***	−0.213***
			(0.027)	(0.046)	(0.036)	(0.030)	(0.026)	(0.046)
(iii)	Females	Share of routine occs$_{-1}$	0.253***	0.002	0.117***	−0.431***	−0.028**	0.087
			(0.073)	(0.045)	(0.030)	(0.062)	(0.012)	(0.055)
Panel B. log hourly wages of noncollege workers								
(i)	All	Share of routine occs$_{80}$ × 2005	0.381***	0.023	0.433***	0.337***	−0.078	−0.388***
			(0.091)	(0.099)	(0.113)	(0.082)	(0.109)	(0.085)
(ii)	Males	Share of routine occs$_{80}$ × 2005	0.346***	0.015	0.287*	0.187*	−0.075	−0.374***
			(0.132)	(0.097)	(0.149)	(0.097)	(0.140)	(0.106)
(iii)	Females	Share of routine occs$_{80}$ × 2005	0.328***	0.310*	0.618***	0.468***	−0.223	−0.415***
			(0.095)	(0.183)	(0.116)	(0.092)	(0.139)	(0.105)

Autor and Dorn (2013) AER

Complex-Task Biased Technological Change vs. RBTC

Caines, Hoffmann, and Kambourov (2017)

- They compare their "Complex-Task Biased Technological Change" to "Routine Biased Technological Change"
- Use O*NET descriptors to measure a task complexity score
  - They choose 35 O*NET descriptors e.g., Abilities, Skills, Generalized Work Activities
  - Using factor model (principal components analysis), to generate a single measure of task complexity

$$C_o = \gamma X_o$$

$$\gamma = argmin \sum_o (X_o - C_o \gamma')$$

  - They use relative employment shares of each occupation as weights

Occupation List and Complexity Percentile

Occupation	Complexity Index, Weighted	Complexity Index, Raw
Vehicle washers and equipment cleaners	.0016101	0
Clothing pressing machine operators	.0019852	.0474957
Food preparation workers	.0022551	.058032
Janitors	.0249187	.0918971
Shoemakers, other prec. apparel and fabric workers	.0252782	.0925525
Housekeepers, maids, butlers, and cleaners	.02768	.1111131
Crossing guards	.027743	.1378214
Butchers and meat cutters	.032228	.1428061
Washing, cleaning, and pickling machine operators	.0323416	.1434333

Note: since they do not provide weights but provide the comparison of weighted index and raw index.
Caines, Hoffmann, and Kambourov (2017) RED

C-T BTC: Complexity index

Routinizable Occupations with High Complex Content

Occupation Title	Routine Index Percentile	Complexity Index Percentile
Financial Managers	82.832	96.107
Real Estate Sales Occupations	87.421	66.059
Accountants & Auditors	95.505	80.246
Insurance Underwriters	95.978	66.272
Statistical Clerks	93.664	93.187
Clinical Laboratory Technologist & Technicians	74.926	72.267
Other Financial Specialists	77.206	75.284

- They follow Autor and Dorn (2013) methods to calculate Routine Index Percentile
- Correlation (Routine Index percentile, Complexity Index Percentile)=-0.3158

Caines, Hoffmann, and Kambourov (2017) RED

C-T BTC: Complexity index

Non-Routinizable Occupations with Low Complex Content

Occupation Title	Routine Index Percentile	Complexity Index Percentile
Waiters & Waitresses	12.041	3.624
Baggage Porters, Bellhops and Concierges	9.360	27.510
Recreation Facility Attendants	27.039	12.234
Taxi Cab Drivers & Chauffeurs	5.055	28.072
Personal Service Occupations	26.628	30.089
Door-to-door Sales, Street Sales, and News Vendors	26.858	6.423
Bus Drivers	3.777	12.119

Caines, Hoffmann, and Kambourov (2017) RED

C-T BTC: Employment change- Group Level

Dependent Variable: Change in Employment Share 1980-2005			
Independent Variable	(i)	(ii)	(iii)
Complexity Index	0.0000314***	0.0000226**	0.0000245**
	(3.07)	(2.30)	(2.38)
Routine Index		-0.0000247*	-0.0000252**
		(-1.94)	(-1.98)
Order of Wage Poly.	0	0	3
$N = 15177$			

- To show results are robust, they examine at both group and occupation levels
- Group: education, age, and race categories cells.

Caines, Hoffmann, and Kambourov (2017) RED

C-T BTC: Employment change- Occupation Level

Dependent Variable: Change in Employment Share 1980-2005					
	Complexity Variable: Complexity Index			Complexity Variable: Complex Indicator†	
Independent Variable	(i)	(ii)	(iii)	(iv)	(v)
Complexity Variable	0.00162	0.00135	0.00154	0.00000125	0.000875
	(1.44)	(1.19)	(1.34)	(0.00)	(1.55)
Routine Index		-0.000871	-0.000821	-0.000961	-0.000783
		(-1.44)	(-1.34)	(-1.57)	(-1.27)
Female Share	0.000156	0.000411	0.000212	0.000137	0.0000835
	(0.20)	(0.52)	(0.26)	(0.17)	(0.10)
College Share	0.000812	0.000424	0.000567	0.00136	0.000288
	(0.58)	(0.30)	(0.36)	(0.89)	(0.18)
High School Share	-0.00116	-0.000892	-0.000145	0.000481	0.000774
	(-0.50)	(-0.39)	(-0.06)	(0.20)	(0.33)

Caines, Hoffmann, and Kambourov (2017) RED

C-T BTC: Caines, Hoffmann, and Kambourov (2017)

Independent Variable	Dependent Variable: Log Wages	
	1980	2005
Complexity Index	0.351***	0.711***
	(7.12)	(14.12)
Routine Index	-0.0128	0.0172
	(-0.29)	(0.33)
N	3987067	949585

Caines, Hoffmann, and Kambourov (2017) RED

C-T BTC: Caines, Hoffmann, and Kambourov (2017)

Indep. Variable	(A) Dependent Variable: Log Wages in 1980				(B) Dependent Variable: Log Wages in 2005			
	Complexity Variable: Complexity Index		Complexity Variable: Complex Indicator†		Complexity Variable: Complexity Index		Complexity Variable: Complex Indicator†	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
Complexity Variable	0.102*	0.106*	0.00215	0.0233	0.400***	0.416***	0.115***	0.0863**
	(1.70)	(1.74)	(0.08)	(0.78)	(5.31)	(5.45)	(3.29)	(2.19)
Routine Index		0.0135	0.00476	0.00879		0.0512	0.0394	0.0317
		(0.42)	(0.15)	(0.27)		(1.28)	(0.95)	(0.76)
Female Share	-0.142***	-0.146***	-0.154***	-0.155***	-0.128**	-0.143***	-0.158***	-0.174***
	(-3.51)	(-3.51)	(-3.68)	(-3.71)	(-2.52)	(-2.75)	(-2.97)	(-3.24)
College Share	0.259***	0.265***	0.325***	0.295***	0.531***	0.554***	0.715***	0.676***
	(3.49)	(3.50)	(4.64)	(3.74)	(5.72)	(5.87)	(8.02)	(6.62)
High School Share	0.427***	0.423***	0.468***	0.478***	0.358**	0.342**	0.438***	0.565***
	(3.50)	(3.45)	(3.83)	(3.97)	(2.33)	(2.22)	(2.79)	(3.63)

Caines, Hoffmann, and Kambourov (2017) RED

C-T BTC: Caines, Hoffmann, and Kambourov (2017)

Independent Variable	Complexity Variable: Complexity Index (i)	(ii)	(iii)	Complexity Variable: Complex Indicator† (iv)	(v)
	Dependent Variable: Change in Log Wages 1980-2005				
Complexity Variable	0.304***	0.316***	0.347***	0.138***	0.0685**
	(4.94)	(5.07)	(5.74)	(5.02)	(2.19)
Routine Index		0.0394	0.0333	0.0260	0.0158
		(1.20)	(1.04)	(0.81)	(0.47)
Female Share	0.00628	-0.00519	-0.0293	-0.0263	-0.0498
	(0.15)	(-0.12)	(-0.70)	(-0.62)	(-1.14)
College Share	0.271***	0.288***	0.288***	0.350***	0.382***
	(3.57)	(3.74)	(3.53)	(4.39)	(4.36)
High School Share	-0.104	-0.116	0.0613	0.117	0.233*
	(-0.83)	(-0.93)	(0.48)	(0.92)	(1.79)

Caines, Hoffmann, and Kambourov (2017) RED

C-T BTC: Caines, Hoffmann, and Kambourov (2017)

Dependent Variable: Change in Log Wages 1980-2005			
Independent Variable	(i)	(ii)	(iii)
Complexity Index	0.258***	0.274***	0.349***
	(10.99)	(10.02)	(12.60)
Routine Index		0.0445	0.0458
		(1.42)	(1.55)
Order of Wage Poly.	0	0	3
$N = 15177$			

Caines, Hoffmann, and Kambourov (2017) RED

C-T BTC: Caines, Hoffmann, and Kambourov (2017)

What we get from this paper, when considering occupation complexity index:

- Routine index cannot explain both the level and the change of log wages from 1980 to 2005
- Routine index has very weak power to explain employment change at group level and cannot explain employment change at occupation level.
- Positive correlation between task complexity and wages and wage growth
- Positive correlation between task complexity and employment share change at group level not occupation level

Automation and New Tasks

Acemoglu and Restrepo propose a model to explain the changes of employment and wages with considering automation and new tasks.

In this framework, the effect of technology on the demand for skills and wages is not mediated via the elasticity of substitution.

In the canonical SBTC model, if there is no technological regress (and H/L increases as in the data), an increase in A_H/A_L changes wages by at least:

$$\Delta \ln w_L \geq s_H \frac{1}{\sigma} \Delta \ln \frac{A_H}{A_L}$$

whereas in the US, the real wages for unskill workers declined notably over the past four decades.

Automation and New Tasks

We summarize the sequence of works by Acemoglu and Restrepo to understand the key ideas of the role of automation and new tasks.

$$Y = (\frac{1}{M} \int_{\mathcal{T}} (My(x))^{\frac{\lambda-1}{\lambda}})^{\frac{\lambda}{\lambda-1}}$$

where $\lambda \geq 0$ is the elasticity of substitution between tasks. Tasks are performed by unskilled labor $\ell(x)$, skilled labor $h(x)$, or capital $k(x)$:

$$y(x) = \phi_L(x)\ell(x) + \phi_H(x)h(x) + \phi_K(x)k(x)$$

where $\phi_j(x) = A_j\gamma_j(x)$ for $j \in \{L, H, K\}$ denote the productivity of factor j at task x. ($\gamma_j(x)$: the measure of tasks produced by j)
They assum $k(x)$ is produced using $q(x)$ units of the final good.

Automation and New Tasks

They show that the competitive equilibrium to maximize the net output is represented by:

$$NY = (\Gamma_L^{\frac{1}{\lambda}}(A_L L)^{\frac{\lambda-1}{\lambda}} + \Gamma_H^{\frac{1}{\lambda}}(A_H H)^{\frac{\lambda-1}{\lambda}})^{\frac{\lambda-1}{\lambda}}$$

where the share parameters Γ_L and Γ_H are endogenously determined and represent the range of tasks performed by the two types of labor:

$$\Gamma_j = \frac{\frac{1}{M}\int_{\mathcal{T}_j} \gamma_j(x)^{\lambda-1}dx}{1 - \frac{1}{M}\int_{\mathcal{T}_K}(\frac{\phi_K(x)}{q(x)})^{\lambda-1}dx}$$

for $j \in \{L, H\}$

Automation and New Tasks

The effects of various technologies on the skill premium can be expressed as

$$d\ln(\frac{w_H}{w_L}) = -\frac{1}{\sigma}d\ln(\frac{H}{L}) + \frac{\sigma-1}{\sigma}d\ln(\frac{A_H}{A_L}) + \frac{1}{\lambda}d\ln(\frac{\Gamma_H}{\Gamma_L})|_{\frac{A_H H}{A_L L}}$$

The last term captures the effect of change in the allocation of tasks to factors on the skill premium. Also, they have:

$$\sigma = \lambda/(1 - \frac{\partial\ln(\Gamma_H/\Gamma_L)}{\partial\ln(A_H H/A_L L)}) \geq \lambda$$

the derived elasticity of substitution between skilled and unskilled labor which including two types of substitution: substitution between tasks, represented by λ, and substitution between unskilled labor and capital and skilled labor.

Automation and New Tasks

Automation: an increase in $\gamma_K(x)$ for a set of tasks currently not in $\mathcal{T}_K$, which will lead to an expansion in the set of tasks allocated to capital. Automation can displace skilled or unskilled labor. Consider an improvement in automation technologies such that the productivity of capital in a set of tasks in $A \subset \mathcal{T}_L$ increases to $\phi_K(x) > 0$. Then

$$d\ln(\frac{w_H}{w_L}) = \frac{1}{\sigma}\frac{\int_A \gamma_L(x)^{\lambda-1}dx}{\int_{\mathcal{T}_L} \gamma_L(x)^{\lambda-1}dx}$$

moreover, w_H increases, which w_L may increase or decrease. "displacement effects"
$w_L = \Gamma_L^{\frac{1}{\lambda}} A_L^{\frac{\lambda-1}{\lambda}} (\frac{NY}{L})^{\frac{1}{\lambda}}$ (Automation causes Γ_L decreases but net output NY may increase)

Automation and New Tasks

New tasks: suppose a small set of new tasks (expanding M) is introduced. If skilled workers have comparative advantage in these tasks (i.e., $w_H/\phi_H(x) < w_L/\phi_L(x)$) at current wages then the skill premium increases by

$$d\ln\left(\frac{w_H}{w_L}\right) = \frac{1}{\sigma}\frac{\int_{\mathcal{N}} \gamma_H(x)^{\lambda-1}dx}{\int_{\mathcal{T}_H} \gamma_H(x)^{\lambda-1}dx}$$

If unskilled workers have comparative advantage in these tasks (i.e., $w_H/\phi_H(x) > w_L/\phi_L(x)$) at current wages then the skill premium will decline by

$$d\ln\left(\frac{w_H}{w_L}\right) = \frac{1}{\sigma}\frac{\int_{\mathcal{N}} \gamma_L(x)^{\lambda-1}dx}{\int_{\mathcal{T}_L} \gamma_L(x)^{\lambda-1}dx}$$

"reinstatement effects"

Automation and New Tasks

$$\Delta \text{Skill Dem}_i = \beta_d \text{displacement}_i + \beta_r \textit{reinstatement}_i + \varepsilon_i$$

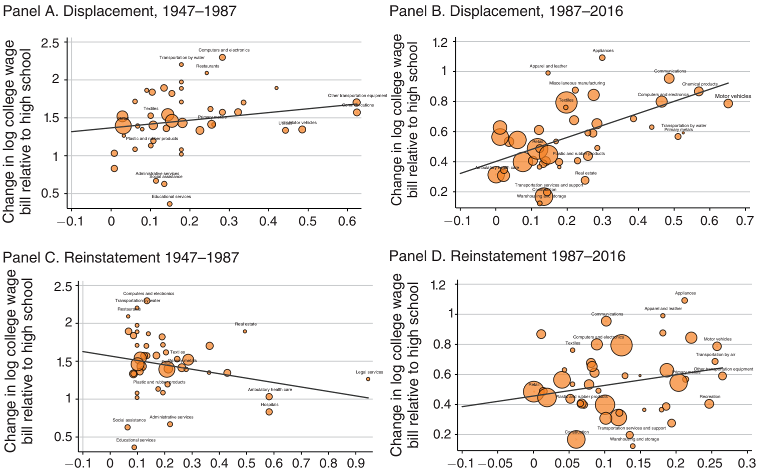


FIGURE 1. CHANGE IN RELATIVE DEMAND FOR SKILLS 1947–1987 AND 1987–2016 VERSUS DISPLACEMENT AND REINSTATEMENT

Dynamics: How to explain boom and bust periods?

Job Polarization and Jobless Recoveries

Job polarization and Jobless recoveries

In last 35 years, the U.S. labor market has been emergence of two new phenomena:

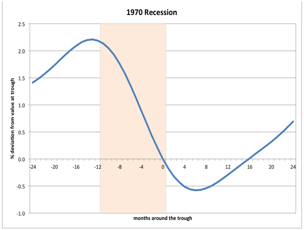
- **Job polarization**: Increasing concentration of employment in the highest and lowest wage occupations, as jobs in middle-skill occupations disappear
- **Jobless recoveries**: Post recession periods when aggregate output rebounds but aggregate employment recovers much slower.

Jaimovich and Siu (RES 2020)

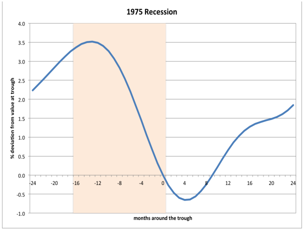
- Job polarization is not a gradual phenomenon: 88% of the job loss in routine occupations since mid of 1980s occurs within a 12 month window of recessions.
- Jobless recoveries in the aggregate can be explained by jobless recoveries in the routine occupations

Employment and Recessions I

Aggregate Employment around Early NBER Recessions (1970-1982)



(a) 1970 Recession

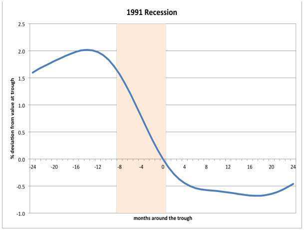


(b) 1975 Recession

(c) 1982 Recession

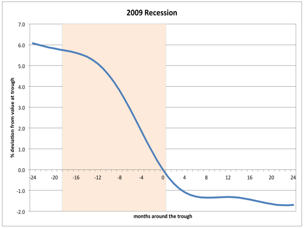
Employment and Recessions II

Aggregate Employment around Early NBER Recessions (1991-2009)



(d) 1991 Recession

(e) 2001 Recession



(f) 2009 Recession

Aggregate Employment and Output Recovery

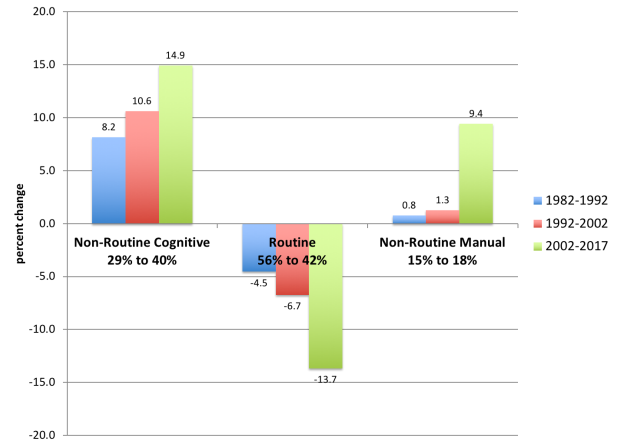
Table 1: Measures of Recovery following Early and Recent Recessions

	Early			*Recent*		
	1970	1975	1982	1991	2001	2009
A. Employment						
months to turn around	6	4	2	17	23	23
months to trough level	16	10	4	31	55	76
half-life (in months)	27	23	10	38	NA	NA
B. Output						
months to turn around	0	0	0	0	0	0
months to trough level	0	0	0	0	0	0
half-life (in months)	7	10	5	9	3	15

Notes: Data from the CPS; Bureau of Economic Analysis, National Income and Product Accounts (NIPA); and James Stock and Mark Watson. See Appendix A for details.

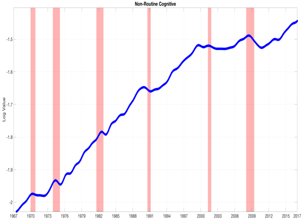
Aggregate Employment Changes by Occupation Group

Figure 3: Percent Change in Employment Shares by Occupation Group

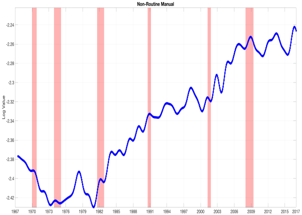


Aggregate Employment Changes by Occupation Group

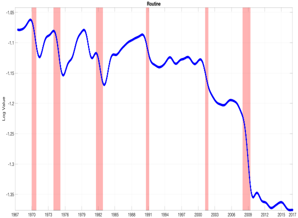
Aggregate Employment in Occupational Groups



(g) Non-Routine Cognitive



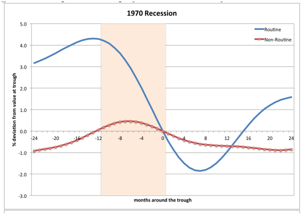
(h) Non-Routine Manual



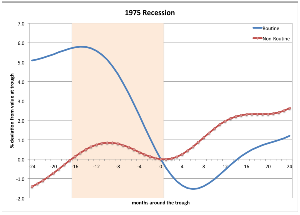
(i) Routine

Employment and Recessions by Occupational Grou pd I

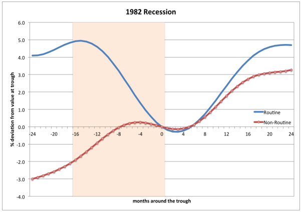
Occupational Employment round Recessions



(j) 1970 Recession



(k) 1975 Recession

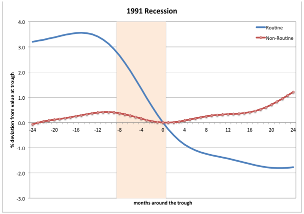


(l) 1982 Recession

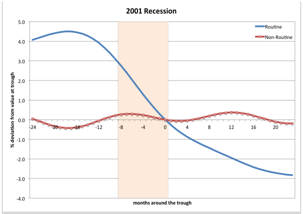
(Bule: Routine; Red: Non-Routine)

Employment and Recessions by Occupational Groupd II

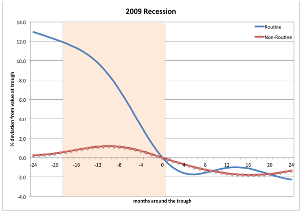
Occupational Employment round Recessions



(m) 1991 Recession



(n) 2001 Recession

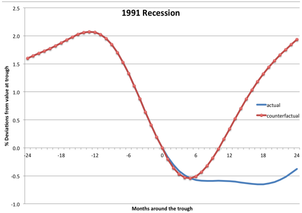


(o) 2009 Recession

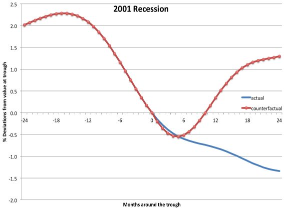
(Bule: Routine; Red: Non-Routine)

Employment and Recessions Counterfactual

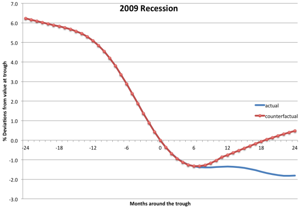
Actual and Counterfactual Employment around Recessions



(p) 1991 Recession



(q) 2001 Recession



(r) 2009 Recession

(Bule: actual; Red: counterfactual)

Skill vs. Task

Skill vs. Tasks

So far we document main streams of ideas (RBTC and "C-T" BTC) and automation and new tasks to explain the aggregate findings about employment and wages in recent decades.

There are several questions we should consider

- How important are occupations?
- What is the role of skill?
- What is the interaction between skill and occupations?

Skill Demand Changes: Evidence from Vacancy Postings I (Hershbein and Kahn, AER 2018)

Buring Glass Technologies Data (BG data)

- Covers only vacancies posted on the Internet
- Rothwell (2014) finds that health care support, transportation, maintenance, sales, and food service workers are underrepresented
- Including the characteristics of vacancies
- contain 70 possible standardized fields for each vacancy (e.g., stated education skill requirement, occupation, geography, firm identifiers)
- This paper restricts main sample to ads with non-missing employers that posted at least 10 ads over the sample 2007 and 2010-2015

Figure A1: Industry Distributions: BG, JOLTS: 2007, 2010-2014

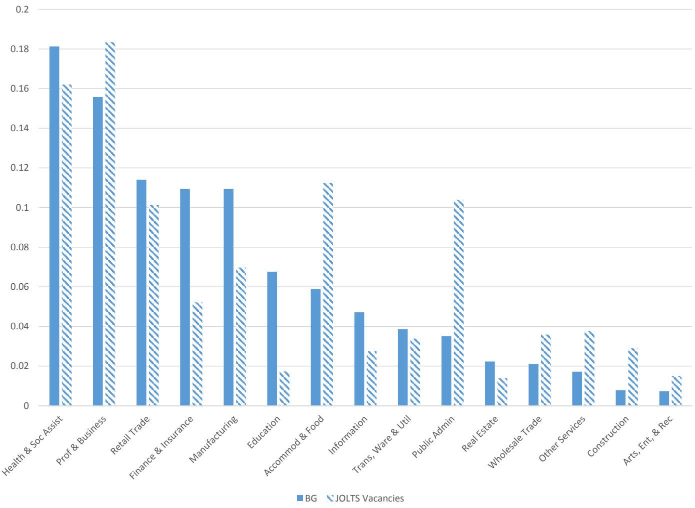


Figure A2: Occupation Distributions: BG, New Jobs (CPS) and Employment (OES)

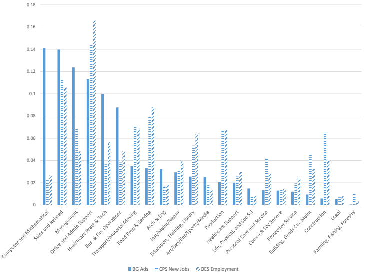
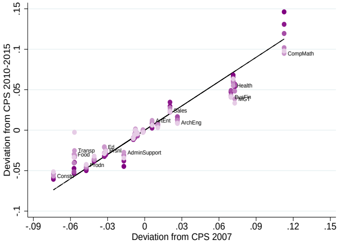


Figure A3: Representativeness of BG Occupations, Relative to New Jobs (CPS)



The x-axis is the BG ad share in an occupation in 2007 minus the CPS new job share in the same occupation in 2007.
The y-axis is these differences for each year from 2010-2015. Darker shades are earlier years, lighter shades are later.

Skill requirements in BG data

- stated education level
- experience requirements
- stated demand for skills that were classified as "cognitive" (Contains: research, analysis, decision, or thinking)
- stated demand for computer skills (Contains: common Excel, PowerPoints, AutoCAD, less common Java, SQL, Python)

BG data Summary Statistics I

TABLE 1—SUMMARY STATISTICS

	Mean (SD)		
	2007	2010–2015	Change
Panel A. Ad characteristics			
Education requirements			
Any	0.34	0.57	0.23
	(0.06)	(0.05)	
HS	0.09	0.20	0.10
	(0.03)	(0.05)	
BA	0.17	0.27	0.10
	(0.05)	(0.08)	
>BA	0.03	0.05	0.02
	(0.01)	(0.01)	
Years, conditional on any	14.84	14.67	−0.18
	(0.40)	(0.44)	
Experience requirements			
Any	0.32	0.52	0.20
	(0.06)	(0.07)	
0–3	0.13	0.24	0.11
	(0.03)	(0.03)	
3–5	0.14	0.21	0.07
	(0.03)	(0.04)	
>5	0.05	0.08	0.03
	(0.02)	(0.04)	
Years, conditional on any	3.52	3.34	−0.18
	(0.47)	(0.54)	
Skill requirements			
Any stated skills	0.73	0.91	0.18
	(0.05)	(0.04)	
Cognitive, conditional on any	0.22	0.34	0.11
	(0.05)	(0.06)	

BG data Summary Statistics II

	Mean	Min	Max
Panel B. Share of ads in 2010–2015 matching to 2007 and to other datasets			
Missing ACS match	0.08		
Continuing firm	0.65		
In Harte-Hanks, among continuing	0.78		
In Compustat, among continuing	0.40		
Panel C. Cell counts			
Number MSAs	381		
Posts per MSA-year	21,779	132	1,231,417
Number occupations (four-digit)	108		
Posts per occupation-MSA-year	228	1	194,558
Number firms	170,809		
Posts per Firm-MSA-year	13	1	16,413

Methodology

$$outcome_{gmt} - outcome_{gm2007} = \alpha_0 + [shock_m \times I^t]\alpha_1 + I^t + controls + \epsilon_{gmt}$$

- $outcome_{gmt}$ are measures associated with changes in labor skill demand in MSA m, year t, and subgroup g (occupation or firm)
- $t \in [2010, 2015]$
- $shock_m$ is a measure of the local employment shock generated by the Great Recession
- I^t are years dummies
- α_1 captures the effect across metro areas in the employment shock not the national shock over time

Construct $shock_m$

$$\Delta \hat{E}_{mt} = \sum_{k=1}^{K} \phi_{m,k,\tau}(\ln E_{kt} - \ln E_{k,t-1}), \quad shock_m = \Delta \hat{E}_{m2009} - \Delta \hat{E}_{m2006}$$

- $shock_m$ is the MSA-specific change in projected annual employment growth between 2006 and 2009 (Bartik shock)
- $\phi_{m,k,\tau}$ is the employment share of industry k in MSA m at time τ (the average of 2004 and 2005)
- They normalized the shock so that a one unit change is equal to the difference between the tenth and ninetieth percentile MSAs

The Bartik shock measure

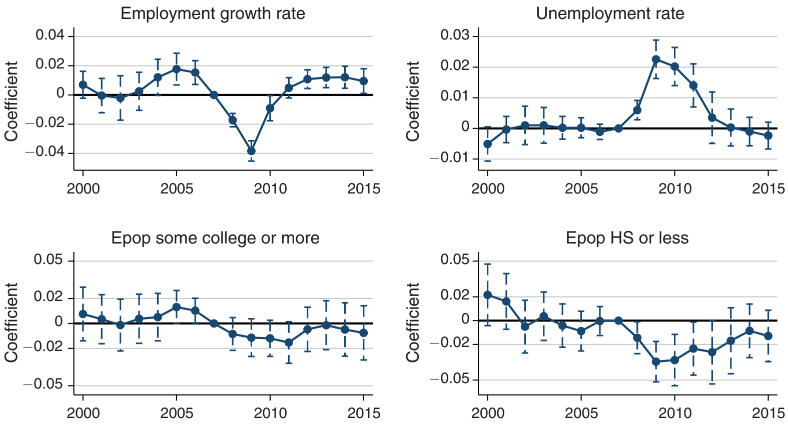


Figure 1. Labor Market Variables and the MSA-Specific Employment Shock

Notes: We regress the MSA-level change in local labor market variables from 2007 on an exhaustive set of MSA employment shock-by-year interactions, controlling for year fixed effects (see equation (1)). Graph plots the coefficients on Bartik shock $\times$ year, as well as 95 percent CI bars. Unemployment and employment growth rates are from the BLS. Employment-to-population ratios (Epops) are author calculations based on the CPS.

Main Results

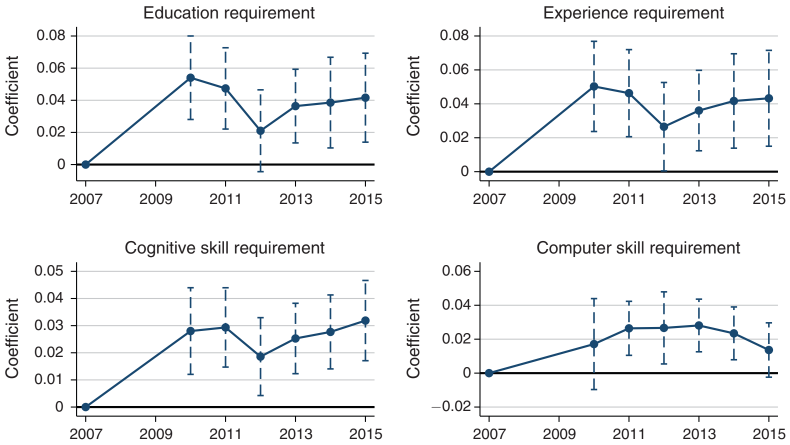


FIGURE 2. SKILL REQUIREMENTS AND THE MSA-SPECIFIC EMPLOYMENT SHOCK

Notes: We regress the MSA-level change in BG skill requirements from 2007 on an exhaustive set of MSA employment shock-by-year interactions, controlling for year fixed effects and MSA characteristics (see equation (1)). Graph plots the coefficients on Bartik shock × year and 95 percent confidence intervals.

Main Results

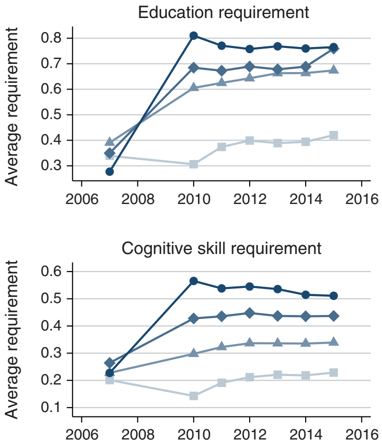


FIGURE 3. SKILL REQUIREMENTS BY FIRM, 2007–2010 CHANGE

Notes: Graph plots average BG skill requirement by year and quartile of 2007–2010 firm-level skill change. Circles, diamonds, triangles, and squares indicate skill change quartile from largest to smallest, respectively.

Main Results

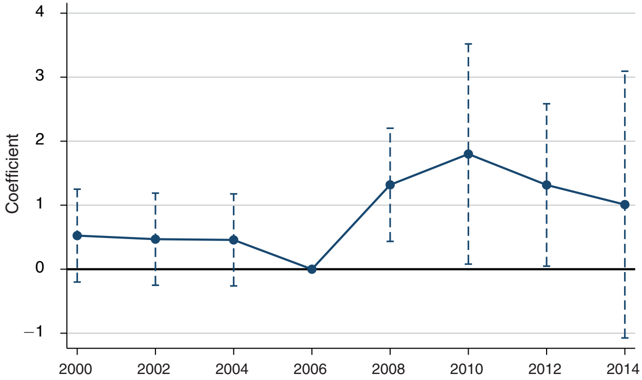


FIGURE 4. PC ADOPTION AND THE MSA-EMPLOYMENT SHOCK

Notes: We regress the MSA-level change in IT investment from 2006 on an exhaustive set of MSA employment shock-by-year interactions, controlling for year fixed effects and MSA characteristics (see equation (1)). Graph plots the coefficients on Bartik shock $\times$ year, as well as 95 percent confidence intervals. MSA-year IT investment is the employment-weighted average of site-level PCs per pre-recession employment from Harte-Hanks.

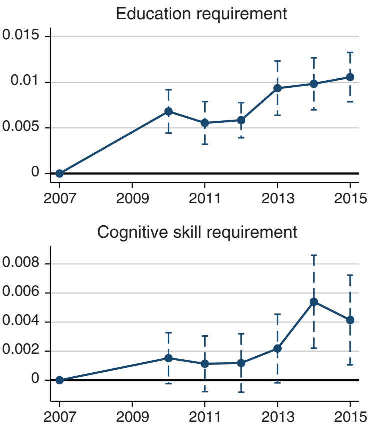
Capital Investment

$$
\begin{aligned}
outcome_{fmt} \quad - \quad & outcome_{fm2007} = \alpha_0 + [shock_m \times I^t]\alpha_1 \\
& + [shock_m \times I^t \times Capital_f]\alpha_2 + I^t + X_m\beta + \epsilon_{fmt}
\end{aligned}
$$

- Want to examine how IT investment and general capital respond to demand shocks
- Link BG data to HH data (PCs per worker)
- Link BG data to Compustat data (Capital holdings)

Capital Investment

Panel A. PCs (HH)



Capital Investment

Panel B. Capital holdings (Compustat)

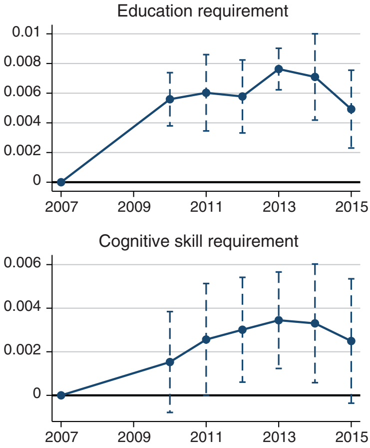


FIGURE 5. DIFFERENTIAL UPSKILLING BY 90–10 CHANGE IN FIRM CAPITAL INVESTMENTS

Routine Occupations

- So far, they show the evidence that MSAs more severely affected by the Great Recession experienced persisitent increases in the skill demand of job postings and greater increases in capital.
- Now they want to examine whether the upskilling is more prevalent in routine occupations

$$
\begin{aligned}
outcome_{omt} \quad - \quad & outcome_{om2007} = \alpha_0 + [shock_m \times I^t]\alpha_1 + \\
& [shock_m \times I^t \times Routine_o^i]\alpha_2 + I^t + X_m\beta + \epsilon_{fmt}
\end{aligned}
$$

- $Routine_o^i$ is an indicator equal to 1 if occupation o is in the top quartile of categorization
- $i \in \{cognitive, manual\}$

Routine Occupations

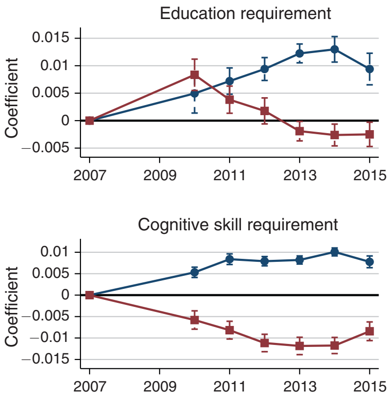


FIGURE 6. DIFFERENTIAL UPSKILLING FOR ROUTINE OCCUPATIONS

blue: (routine cognitive); red(routine manual)

Routine Occupations

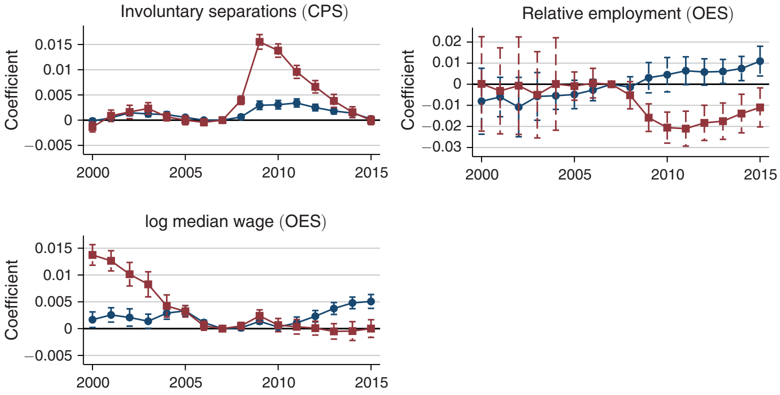


FIGURE 7. DIFFERENTIAL EMPLOYMENT AND WAGE EFFECTS FOR ROUTINE OCCUPATIONS

blue: (routine cognitive); red(routine manual)

Hershbein and Kahn (2018) Conclusion

- Job posting in harder-hit MSAs experienced larger increases in education, experience, cognitive, and computer requirements
- The increase in skill requirements are accompanied by increases in capital investments
- Upskilling is relatively concentrated in routine-cognitive occupations

Skill Demand: Multiple Skills

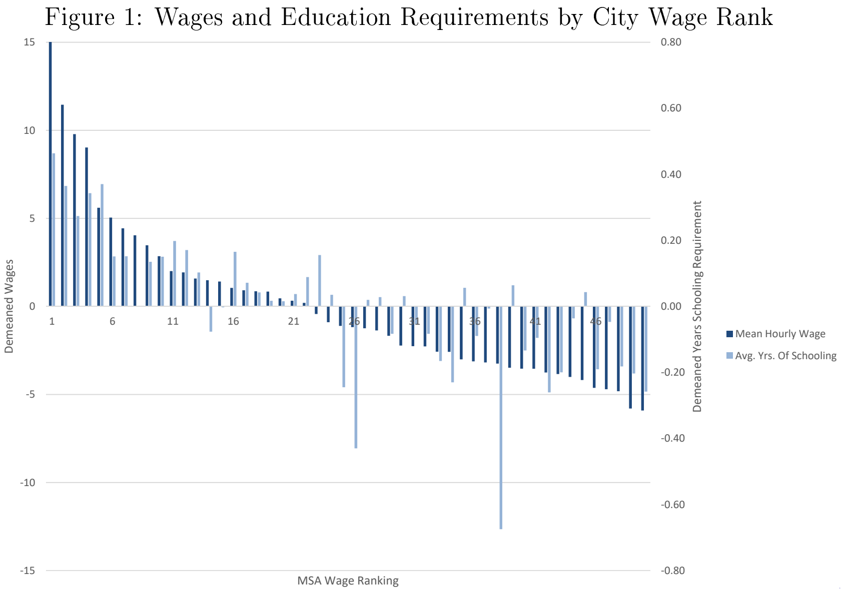
Skill Demand Changes: Evidence from Vacancy Postings II (Deming and Kahn, JOLE 2018)

- A large economics literature links rising wage inequality in U.S. to technological change, specifically the computerization of the labor market.
- One empirical limitation in the study of technological change is the measure variation is across occupations but not within them.
- This paper studies variation in skill demands for professional across firms and labor markets
- Also, this paper examines the correlations between each skill and external measures of pay and firm performance.

BG Data

- Professional occupations: management, business and financial operation, computer and mathematical, legal, education, etc.
- Ads with a nonmissing firm (Some firms do not wish to reveal their information) (63%)
- 13% of ads includes offered wage information
- Average wages for MSA-occupation cells from OES program, which is a large survey produced by BLS
- Firm performance data is from Compustat (30% of ads)
- MSA demographic characteristics are from ACS data.

Wage and Education Correlation



Skill Category

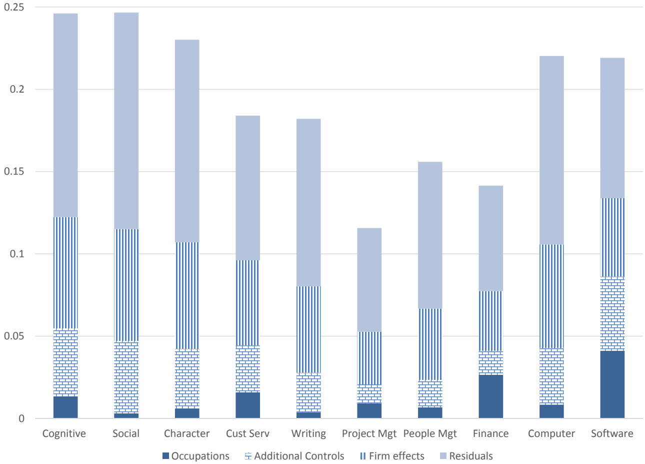
Table 1
Description of Job Skills

Job Skills	Keywords and Phrases
Cognitive	Problem solving, research, analytical, critical thinking, math, statistics
Social	Communication, teamwork, collaboration, negotiation, presentation
Character	Organized, detail oriented, multitasking, time management, meeting deadlines, energetic
Writing	Writing
Customer service	Customer, sales, client, patient
Project management	Project management
People management	Supervisory, leadership, management (not project), mentoring, staff
Financial	Budgeting, accounting, finance, cost
Computer (general)	Computer, spreadsheets, common software (e.g., Microsoft Excel, PowerPoint)
Software (specific)	Programming language or specialized software (e.g., Java, SQL, Python)

NOTE.—Shown is the authors categorization of open text fields in Burning Glass Technologies data.

Skill Variation

Figure 2: Variances of Skill Requirements



NOTES: Based on the firm sample. We regress an indicator for whether an ad has the skill requirement on occupation (6 digit) fixed effects, additional controls (MSA fixed effects and education and experience requirements) and firm fixed effects. Bars plot variances of fitted values based on specified controls or the residuals.

Skill Variation

Table 2
Correlations of Skill Requirements

	Education	Experience	Cognitive	Social	Character	Writing	Customer Service	Project Mgmt	People Mgmt	Financial	Computer	Software
Years of education required	1.00											
Years of experience required	.30	1.00										
Cognitive	.20	.37	1.00									
Social	.05	.25	.64	1.00								
Character	−.06	.14	.59	.69	1.00							
Customer service	−.27	−.38	−.03	.17	.14	1.00						
Writing	.12	.24	.57	.52	.52	−.07	1.00					
Project mgmt	.20	.57	.55	.45	.39	−.20	.39	1.00				
People mgmt	−.05	.01	.35	.34	.38	.13	.30	.27	1.00			
Financial	.02	.21	.43	.35	.37	−.04	.36	.38	.39	1.00		
Computer (general)	−.06	.27	.52	.52	.54	−.02	.50	.40	.24	.41	1.00	
Software (specific)	.26	.61	.36	.25	.11	−.33	.24	.50	−.06	.02	.27	1.00

NOTE.—The table shows ad-weighted bivariate correlations across all skill measures at the firm level using the firm sample. See table 1 for skills definitions. mgmt = management.

Correlation between wage and skill requirements

$$log(Wage)_{om} = \alpha + \bar{Skill}_{om}\beta' + Controls + \varepsilon_{om}$$

Table 3
Average Wages and Skill Requirements

	Dependent Variable: Log(Mean Wages) in MSA-Occupation Cells					
	(1)	(2)	(3)	(4)	(5)	(6)
Cognitive	.113***	−.413***	.245***	.181***	.0792***	.0465***
	(.00908)	(.0166)	(.00784)	(.0139)	(.00873)	(.0122)
Social	.429***	−.0919***	.301***	.236***	.0517***	.0202
	(.0155)	(.0206)	(.0121)	(.0167)	(.00966)	(.0127)
Both required		1.319***		.157***		.0760***
		(.0349)		(.0278)		(.0198)
Years of education	.131***	.129***	.0764***	.0765***	.00865***	.00873***
	(.000770)	(.000763)	(.000844)	(.000844)	(.000995)	(.000995)
Years of experience	.160***	.161***	.0848***	.0849***	.0318***	.0318***
	(.00120)	(.00118)	(.00120)	(.00120)	(.00102)	(.00102)
Base controls			X	X		
Detailed controls					X	X
F-statistic (cognitive and social)	553.1	855.0	1,004	680.4	69.66	51.35
F-statistic (all 10 skills)	1,874	2,054	612.6	560.1	59.93	55.83
MSA-occupation cells	56,611	56,611	56,611	56,611	56,611	56,611
R^2	.702	.710	.846	.846	.940	.941

Correlation between Skill requirements and firm performance

$$FirmPerf_f = \alpha_o + \bar{Skill}_f \beta' + \bar{I}_f^o + \bar{X}_f \gamma' + \theta_n + \varepsilon_f$$

Table 4
Firm Outcomes and Average Skill Requirements

	Publicly Traded				Log(Revenue per Worker)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cognitive	.0131	−.170***	.0318**	−.136***	.469***	.624***	.379***	.0761
	(.0122)	(.0180)	(.0129)	(.0185)	(.117)	(.190)	(.136)	(.218)
Social	.162***	.0165	.0934***	−.0364**	.218**	.348**	.239*	−.00813
	(.0114)	(.0115)	(.0115)	(.0154)	(.105)	(.164)	(.123)	(.185)
Both required		.365***		.328***		−.268		.531*
		(.0262)		(.0260)		(.259)		(.298)
Years of education	−.00212	−.00141	−.00242*	−.00203	.00423	.00312	.00979	.00974
	(.00134)	(.00134)	(.00135)	(.00135)	(.0222)	(.0222)	(.0266)	(.0266)
Years of experience	.0236***	.0239***	.0125***	.0128***	.0851***	.0839***	.119***	.120***
	(.00150)	(.00150)	(.00157)	(.00157)	(.0144)	(.0145)	(.0182)	(.0182)
Base controls	X	X			X	X		
Detailed controls			X	X			X	X
F-statistic (cognitive and social)	110.2	138.1	41.93	81.19	12.43	8.644	6.560	5.432
F-statistic (all 10 skills)	181.6	183.1	130.3	133.2	10.96	10.06	4.072	3.993
Number of firms	85,695	85,695	85,695	85,695	3,622	3,622	3,622	3,622
R^2	.246	.248	.330	.332	.511	.511	.736	.737

NOTE.—Observations are at the firm level, weighted by number of ads posted by the firm. All regressions control for the share of ads with each of the eight other job skill, education, and experience requirements. Years of education and experience equal 0 if the firm has no ads that specify requirements. In col. 1–4, the dependent variable is an indicator equal to 1 if the firm can be matched to Compustat; in col. 5–8, it is equal to the log of revenue per worker, conditional on being matched to Compustat. Base controls include two-digit North American Industry Classification System industry fixed effects and the ad-weighted distributions of four-digit occupation fixed effects and metropolitan statistical area (MSA) characteristics from the American Community Survey. Detailed controls include industry fixed effects and the ad-weighted distributions of MSA and six-digit Standard Occupational Classification occupation fixed effects. See table 1 for skills definitions.

Heterogeneity across Firms and Skill Demand

$$log(Wage)_{omf} = \beta_f + Controls + \varepsilon_{omf}$$

Table 5
Standard Deviations of Firm Effects in Outcomes and Skills

	No Controls (1)	Base Controls (2)	Detailed Controls (3)
Log hourly wages	.190	.101	.027
Publicly traded	.459		
Log revenue per worker	.827		
Cognitive	.203	.176	.168
Social	.201	.190	.186
Cognitive and social	.162	.149	.145
Character	.188	.172	.167
Customer service	.180	.160	.149
Writing	.154	.143	.140
Project management	.106	.098	.081
People management	.125	.122	.116
Financial	.141	.101	.091
Computer (general)	.185	.168	.163
Software (specific)	.244	.172	.136

NOTE.—We regress the variable in each row on firm fixed effects and specified controls. The table reports standard deviations of the firm fixed effects, weighted by the number of postings to each firm. Base controls include metropolitan statistical area (MSA) characteristics, four-digit occupation fixed effects, and industry fixed effects. Detailed controls include MSA, six-digit occupation, and industry fixed effects. Specifications including controls are omitted for "Publicly traded" and "Log revenue per worker," since they vary only at the firm level.

Heterogeneity across Firms and Skill Demand

$$\beta_f = \bar{Skill}_f \alpha' + \delta \nu_f$$

Table 6
Decomposing Firm Effects in Wages on Skill Demands

	Log(Wages)			
	(1)	(2)	(3)	(4)
Total standard deviation of firm effect	.190	.190	.084	.025
Share attributed to skills (%):				
Total	11.6	33.9	20.9	6.3
Social and cognitive skills	11.6	5.5	4.7	1.3
Other skills		11.3	7.3	.6
Education and experience		17.1	8.9	4.5
Residual	88.4	66.1	79.1	93.7
Additional skills		X	X	X
Base controls			X	
Detailed controls				X
Number of firms	85,695			

Note.—Base controls are metropolitan statistical area (MSA) characteristics and four-digit occupation fixed effects. Detailed controls are MSA and six-digit occupation fixed effects. Social and cognitive skills include requirements for each and the share of ads specifying both. Other skills include the eight additional job skills listed in table 1. Education and experience include both years required and the share of ads that have any requirement. We regress the firm fixed effect in wages on the firm fixed effect for each of the skill measures (and controls if included). We use coefficients and the variance-covariance matrix of the skills to fit the share of the variance in wages that can be attributed to various components (by fitting variances with the other coefficients set to 0).

Heterogeneity across Firms and Skill Demand

Table 7
Decomposing Firm Performance Outcomes on Skill Demands

	Publicly Traded		Log(Revenue per Worker)	
	(1)	(2)	(3)	(4)
Total standard deviation of firm effect	.459	.459	.685	.685
Share attributed to skills (%):				
Total	7.2	13.2	14.8	21.4
Social and cognitive skills	7.2	1.7	14.8	9.4
Other skills		3.8		3.1
Education and experience		7.7		8.9
Residual	92.8	86.8	85.2	78.6
Additional skills		X		X
Number of firms	85,695		3,622	

NOTE.—See table 6.

Take away

- Large skill variation within occupations
- There are positive correlation between wage and firm performance and skill requirements
- Cognitive and Social skill complementarity

Heterogeneous Human Capitals (Skills)

Heterogeneous human capitals (skills):

- Heckman and Sedlacek (1985), Keane and Wolpin (1997), and many subsequent papers are based on the Roy model, in which heterogeneous human capital play a central role.
- Since they use tasks as bundle of skills, they find the price of skills are not the same across different occupations

Why and how skills are differently rewarded and transferable across occupation?

- For these papers, occupations are treated as different categories, we cannot measure similarity of tasks across occupations (Notice, we still can measure skills across occupations)
- It is hard to estimate the model, since when the number of occupation increases, the number of parameters and state variables are also increasing sharply.

Yamaguchi (2012)

The key idea of this paper is to examine how tasks (occupations) and skills can explain individuals' wage composition and wage growth.

To answer this question, he

- constructs task complexity measures to map task bundles with occupations and make tasks transferable across occupations
- allows the returns to skills change with task complexity. It is helpful to examine why returns to skills are different across occupations and how important occupations are (We can consider the case that workers cannot unbundle their skills (Heckman and Scheinkman, 1987))

Wage Function

The products of each firm can be characterized by a task complexity vector.

- The marginal value product of a worker with skill s_t in an occupation with task complexity x_t is

$$w_t = \pi(x_t)q(x_t, s_t)\exp(\eta_t), \tag{1}$$

- Here, he assumes occupation can be mapping to cognitive Task and motor task complexity index
- $\pi(x_t)$ denotes the price of the product.
- $q(x_t, s_t)$ is the productivity of a worker with skill s_t in a job with task complexity x_t
- He said "As in the Roy model, skills are rewarded differently across occupations." Then he assumes $q(x_t, s_t) = \theta'(x_t)s_t$
- (1) is *assumed* – not derived from some underlying model.

Wage Function

- Labor productivity:

$$\ln q(x_t, s_t) = \theta'(x_t)s_t, \tag{2}$$

In Heckman and Sedlacek (1985)

$$\ln t_i(s) = c_i s_t, \tag{3}$$

- $\theta(x_t)$ is a K-dimensional vector of implicit skill prices and represents the contribution of skills s_t to an occupation with task x_t.
- Skills are more intensely used and contribute to productivity more, when the corresponding tasks are complex $\partial\theta_k(x)/\partial x_k > 0$, where subscript k is an index for the task dimension.
- Notice: in his setting, since task complexity is transferable, it is possible to explain why experience in one occupation is rewarded in others

Model

The Bellman equation for an individual is given by

$$V_t(s_t, \bar{x}_t, \tilde{\nu}_t, \eta_t; d) = \max_{x_t} \ln w(x_t, s_t, \eta_t) + v(x_t, \bar{x}_t, s_t, \tilde{\nu}_t; d) + \beta E V_{t+1}(s_{t+1}, \bar{x}_{t+1}, \tilde{\nu}_{t+1}, \eta_{t+1}; d),$$

- $\bar{x}_t$ is work habits, $\tilde{\nu}_t$ is preferences shocks
- $v(x_t, \bar{x}_t, s_t, \tilde{\nu}_t; d)$ is job preferences
- skill s_{t+1} is linear function of previous skills s_t, tasks x_t, and ability d

$$s_{t+1} = D s_t + a_0 + A_1 x_t + A_2 d + \varepsilon_{t+1},$$

Main Results

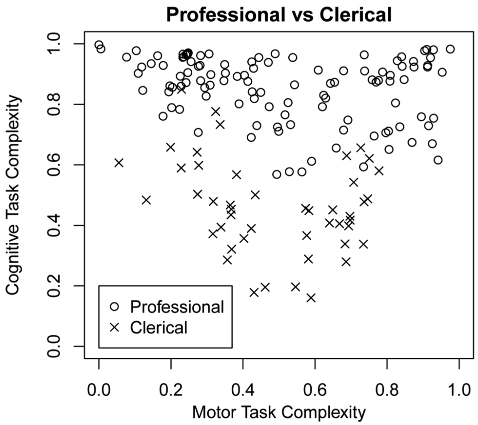
Table: Task Complexity by Occupation at One-Digit Classification

	Cognitive Task		Motor Task		
	Mean	SD	Mean	SD	No. Observations
Professional	.85	.14	.45	.33	7,522
Manager	.79	.15	.21	.21	5,538
Sales	.57	.17	.23	.15	3,748
Clerical	.49	.16	.56	.22	9,270
Craftsmen	.52	.20	.82	.20	6,557
Operatives	.20	.18	.58	.20	5,824
Transport	.28	.15	.63	.10	1,774
Laborer	.15	.16	.46	.13	2,818
Farmer	.68	.19	.78	.14	1,117
Farm laborer	.18	.19	.53	.16	882
Service	.32	.22	.44	.24	6,834
Household service	.20	.11	.24	.23	1,469
All occupations	.49	.29	.50	.29	53,353

Note: Sample consists of all working individuals in the 1971 April Current Population Survey augmented with occupational characteristics variables from the revised fourth edition of the Dictionary of Occupational Titles (1991). Sample size is 53,353. Task complexity measures are percentile scores divided by 100.

Main Results

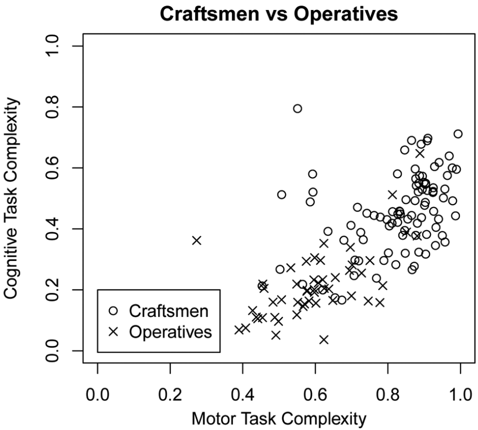
Figure: Task complexity comparison



Task complexity measures are percentile scores divided by 100.
Source: 1971 April Current Population Survey augmented with occupational characteristics variables from the revised fourth edition of the Dictionary of Occupational Titles (1991).

Main Results

Figure: Task complexity comparison



Task complexity measures are percentile scores divided by 100.
Source: 1971 April Current Population Survey augmented with occupational characteristics variables from the revised fourth edition of the Dictionary of Occupational Titles (1991).

Main Results

Table: Log Wage Variance When Initial Conditions Are Homogeneous

		Homogeneous			
Year	Benchmark	Preference	Initial Skills	Learning Ability	All
1	.206	.204	.061	.206	.061
10	.292	.260	.234	.241	.190
20	.359	.297	.335	.257	.232

Note: Author's estimates from the National Longitudinal Survey of Youth 1979–2000. Sample consists of 2,417 men.

- In year 1, about 70% $1 - 0.061/0.206$ of the log wage variance is explained by differences in initial skills
- In year 10, about 20% of log wage variance is explained by initial skills, 35% explained by all initial conditions
- In year 20, about 7% explained by initial skills; about 35% explained by all initial conditions

Main Results

Table: Mean Skill Profiles by Education

Year	All Men	High School Dropouts	High School	College
Cognitive skills:				
1	.000	−.813	−.269	.498
10	.631	−.650	.206	1.405
20	.996	−.539	.489	1.923
Motor skills:				
1	.000	.731	.240	−.448
10	−.066	.871	.240	−.637
20	−.108	.950	.238	−.750

Note: Author's estimates from the National Longitudinal Survey of Youth 1979–2000. Sample consists of 325 high school dropouts, 1,009 high school graduates, and 1,083 college workers.

- Cognitive skills grow faster for the educated workers (higher learning ability, and work in high task complexity occupations)
- Motor skills grow in high school dropouts, constant in high school graduates, and decrease for college graduates

Table: Accumulated Wage Growth by Skill Type and Education

	Benchmark				All Men	
Years since Entry	Dropouts (1)	High School (2)	College (3)	All Men (4)	CF 1 (5)	CF 2 (6)
Cognitive skills:						
5	.068	.209	.416	.282	.276	.271
10	.124	.362	.716	.487	.472	.454
15	.166	.472	.927	.634	.612	.580
20	.197	.549	1.074	.737	.710	.665
Motor skills:						
5	.061	.003	−.069	−.021	−.026	−.027
10	.098	.003	−.120	−.038	−.045	−.044
15	.124	.002	−.156	−.052	−.059	−.055
20	.141	.000	−.183	−.063	−.071	−.062
Total:						
5	.129	.212	.347	.261	.249	.244
10	.222	.365	.596	.448	.427	.410
15	.291	.474	.771	.582	.552	.525
20	.337	.549	.892	.674	.639	.603

- Cognitive skills are the main source of wage growth, motor skills only for dropouts
- If no change of task complexity, wage decreases 4 to 7 percentage points
- If no change of task complexity but with the same skills, wage dropped by 3 percentage points

Lise and Postel-Vinay (2020)

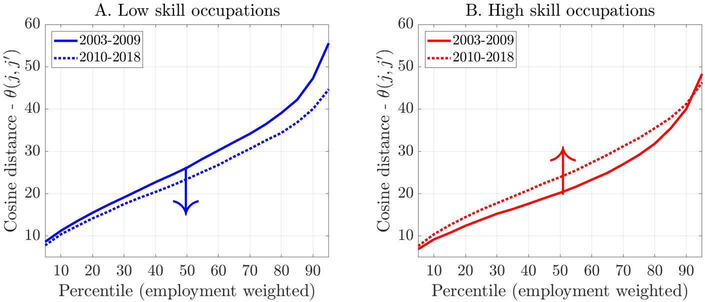
Lise and Postel-Vinay (2020) extend Yamaguchi (2012) work by

- including the labor market frictions (job search)
- wage growth not only through skill accumulation but also through job-shopping

Unbundling Labor (Edmond and Mongey, 2021)

- Heterogeneity in skill requirements across occupations: Low skill jobs (↓), high skill jobs (↑)
- Inequality in wages within occupations Low skill jobs (↓), high skill jobs (↑)

Fact: High skill jobs have become more different; low skill jobs have become more similar

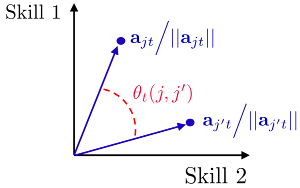


- E.g. median distance between low skill occupations down ≈ 5 degrees

Unbundling Labor (Edmond and Mongey, 2021)

Approach

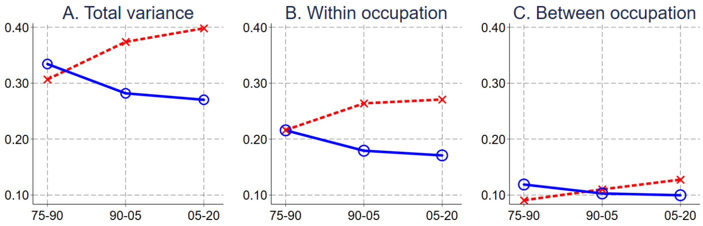
1. O*NET data on 250+ skills and J occupations. Split: 2003-09, 2010-18
2. Reduce to $4 \times J$ matrix of skills $\mathbf{A}_t = \left[\mathbf{a}_{1t}, \ldots, \mathbf{a}_{Jt}\right]$ (Lise Postel-Vinay, 2020)
3. Distance between occupations (Gathmann Schönberg, 2010)



4. Compare the distribution of these distances $\theta(j, j')$ across periods

Unbundling Labor (Edmond and Mongey, 2021)

Wages in high skill jobs have become more different; wages in low skill jobs have become more similar



Variance of residuals. Red = High wage occupations, Blue = Low wage occupations

Robust across {All,Male,Female}×{Fix occupations in 1980, 2010}

- Log annual earnings from the CPS
- Residuals after controlling for observables ($Year_t$, edu, race, sex, firm size, exp hours, etc)

Model

- Workers $i \in [0,1]$ endowed with two skills $k \in \{x, y\}$: $(x(i), y(i)) \sim H(x, y)$
- Final Good: $U(C_1, C_2)$
- Task/Occupation j technology $\alpha_1 = 1 - \alpha_2 > 0.5$; $C_j = F_j(X_j, Y_j) = [\alpha_j X_j^{\sigma} + (1-\alpha_j) Y_j^{\sigma}]^{\frac{1}{\sigma}}$, $X_j = \int x(i)\phi_j(i)di$, $Y_j = \int y(i)\phi_j(i)di$, $\phi_j(i) \in \{0, 1\}$

Bundled: Worker i must allocate (x(i),y(i)) to the same task j

Efficient Allocation

$$\max_{\phi_{1x}(i)\in\{0,1\},\phi_{1y}(i)\in\{0,1\}} U\Big(F_1(X_1,Y_1),F_2(X_2,Y_2)\Big)$$

subject to

Let λ_{jX} be the shadow price of X_j

$$X_1 = \int \phi_{1x}(i)\,x(i)\,di \longrightarrow \lambda_{1X} = U_1 F_{1X}$$

$$X_2 = \int \Big[1-\phi_{1x}(i)\Big]\,x(i)\,di \longrightarrow \lambda_{2X} = U_2 F_{2X}$$

$$Y_1 = \int \phi_{1y}(i)\,y(i)\,di \longrightarrow \lambda_{1Y} = U_1 F_{1Y}$$

$$Y_2 = \int \Big[1-\phi_{1y}(i)\Big]\,y(i)\,di \longrightarrow \lambda_{2Y} = U_2 F_{2Y}$$

and person-by-person bundling constraints

$$\phi_{1x}(i) = \phi_{1y}(i) \qquad \text{for all} \quad i \in [0,1]$$

Feasible allocations

- Given X_1 what is *minimum* and *maximum* Y_1 bundled along with it?

$$\text{Bundling constraint:} \quad Y_1 \in \left[\underline{B}(X_1)\,,\,\overline{B}(X_1)\right]$$

- Construct X_1 using workers with highest $x(i)\big/y(i)$ first

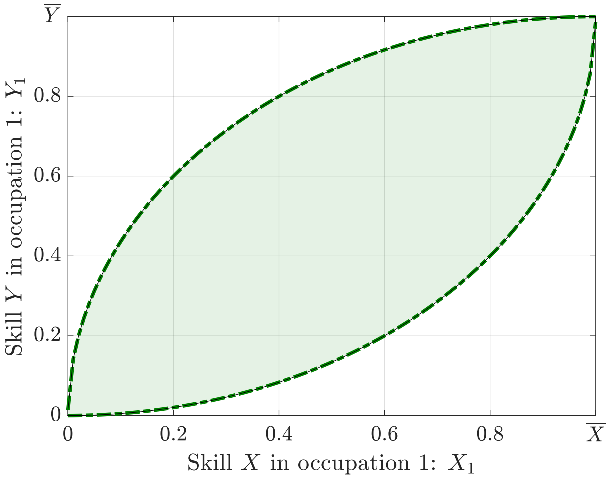
$$X_1 = \int_0^{i^*} x(i)\,di \quad , \quad \underline{B}(X_1) = \int_0^{i^*} y(i)\,di$$

Result - *If the skill distribution H has no mass points, then*

1. $\underline{B}$ *is strictly increasing, strictly convex*
2. $\overline{B}$ *is strictly increasing, strictly concave*
3. *Continuously differentiable, with derivative* $\underline{B}'(X_1) = \dfrac{y(i^*)}{x(i^*)}$

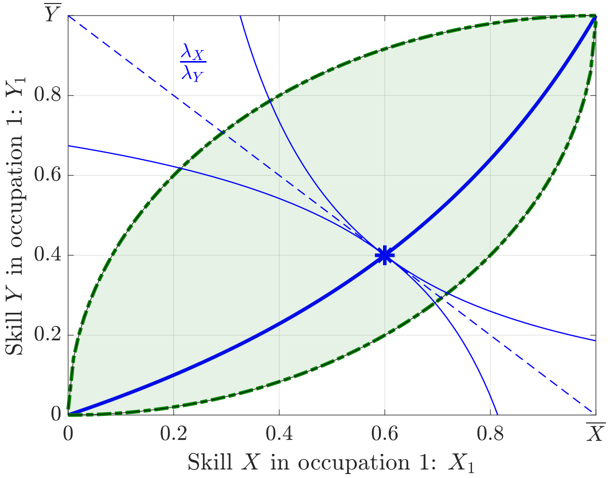
Feasible allocations

Feasible allocations must satisfy aggregate *bundling constraint* $Y_1 \in [\underline{B}(X_1), \overline{B}(X_1)]$.
Determined by distribution of skill endowments only. Example: $x(i) \sim$ *Fréchet*(θ).



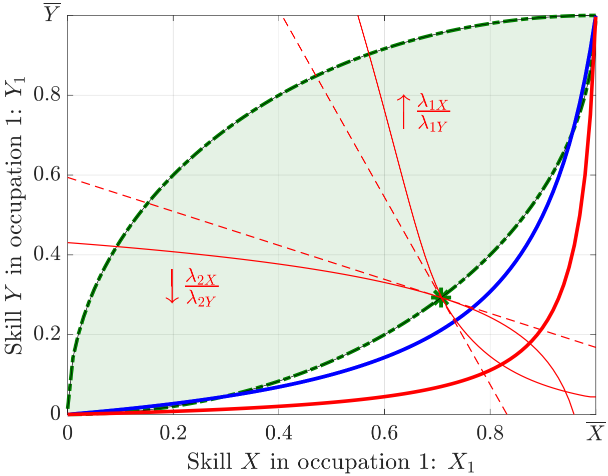
Unbundled allocation

'Contract curve' equates marginal rates of technical substitution: $F_{1X}/F_{1Y} = F_{2X}/F_{2Y}$.
Unbundled allocation ($*$) equates U_1/U_2 to marginal rate of transformation F_{2k}/F_{1k}.



Wages

$$\log w_1(i) = \log \lambda_{1Y} + \log y(i) + \log\left(1 + \uparrow\left(\frac{\lambda_{1X}}{\lambda_{1Y}}\right)\left(\frac{x(i)}{y(i)}\right)\right)$$



Symmetric Frechet example

1. Skills

$$x(i) \sim \mathit{Frechet}(\theta) \quad , \quad y(i) \sim \mathit{Frechet}(\theta) \quad , \quad \text{Tail: } 1/\theta \, , \, \theta > 1$$

2. Technology

$$F_1 = \left[\alpha X_1^\sigma + (1-\alpha) Y_1^\sigma\right]^{1/\sigma} \quad , \quad F_2 = \left[(1-\alpha)\Big(1-X_1\Big)^\sigma + \alpha\Big(1-Y_1\Big)^\sigma\right]^{1/\sigma}$$

- Bundling constraint

$$\underline{B}\Big(X_1\Big) = 1 - \left(1 - X_1^{\frac{\theta}{\theta-1}}\right)^{\frac{\theta-1}{\theta}} \quad , \quad \lim_{\theta\to\infty} \underline{B}(X_1) = X_1 \quad , \quad \lim_{\theta \searrow 1} \underline{B}(X_1) = 0$$

- If $\alpha < \alpha^*$ then *unbundled equilibrium*

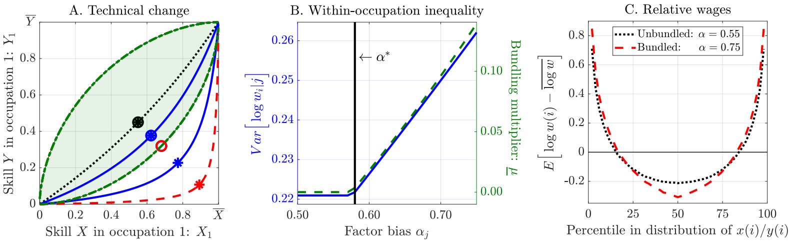
$$\uparrow\alpha^* = \frac{\uparrow\psi^{1-\sigma}}{1 + \uparrow\psi^{1-\sigma}} \quad , \quad \uparrow\psi = \frac{1}{2^{1-\uparrow 1/\theta} - 1} \in \left[\frac{1}{2}, 1\right]$$

1. More dispersion of skills $\uparrow (1/\theta)$, increase $\alpha^* \to$ Unbundled

2. More complementary skills $\downarrow \sigma$, increase $\alpha^* \to$ Unbundled

Skill bias and inequality

Varying $\alpha \in \{0.50, \ldots, 0.75\}$. As occupations become more different, bundling constraint binds and *primary* skill prices increase relative to *secondary* skill prices.



Skill bias and inequality

Varying $\alpha \in \{0.50, \ldots, 0.75\}$. As occupations become more different, bundling constraint binds and *primary* skill prices increase relative to *secondary* skill prices.