Expertise

David Autor & Neil Thompson (2025), JEEA

Reporter: Juncheng Jiang

Summer Seminar of Joint Workshop on Cities and Public Policy

2025.08.15

David Autor

MIT Department of Economics; Daniel (1972) and Gail Rubinfeld Professor, Margaret MacVicar Faculty Fellow

EDUCATION

- Ph.D., Public Policy, Harvard University, John F. Kennedy School of Government, June 1999.
- M,A.. Public Policy, Harvard University, John F. Kennedy School of Government, June 1994.
- B.A. Psychology (concentration in Computer Science), Tufts University, edford, A, 1989. (Summacum Laude. Phi Beta Kappa.)

FIELDS OF SPECIALIZATION

Human capital, skill demands, and earnings inequality;
Labor market and societal impacts of technological change and globalization;
Disability insurance and labor force participation.

Neil Thompson

Research Scientist, MIT
Computer Science & A.I. Lab
2018 –
Principal Investigator, MIT
Initiative on the Digital Econ.
2017 –

EDUCATION

- PhD in Business Public Policy (Berkeley, Haas) 2007 – 2012 (PhD Minor: Computational Science and Engineering)
- Masters in Statistics (Berkeley) 2010 – 2012
- Masters in Computer Science (Berkeley) 2008 – 2012
- Masters in Economics (London School of Economics) 2003 – 2004
- Bachelors in Economics / Int'n Development (Queen's) 1997 – 2001
- Bachelors in Physics (Queen's) 1997 – 2000

RESEARCH

Machine Learning and Algorithms;Tools that shapes innovation;

Abstract

Published

Journal of the European Economic Association 2025 0(0):1–69
https://doi.org/10.1093/jeea/jvaf023

Abstract
When job tasks are automated, does this augment or diminish the value of labor in the tasks that remain? We argue the answer depends on whether removing tasks raises or reduces the expertise required for remaining non-automated tasks. Since the same task may be relatively expert in one occupation and inexpert in another, automation can simultaneously replace experts in some occupations while augmenting expertise in others. We propose a conceptual model of occupational task bundling that predicts that changing occupational expertise requirements have countervailing wage and employment effects: automation that decreases expertise requirements reduces wages but permits the entry of less expert workers; automation that increases expertise requirements increases wages but reduces the set of qualified workers. We develop a novel, content-agnostic method for measuring job-task expertise, and we use it to quantify changes in occupational expertise demands over four decades attributable to job task removal and addition. We document that automation has raised wages and decreased employment in occupations where it eliminated inexpert tasks, but reduced wages and increased employment in occupations where it eliminated expert tasks. These effects are distinct from—and in the case of employment, opposite to—the effects of changing task quantities. The expertise framework resolves the puzzle of why routine task automation has decreased employment but often increased wages in routine task-intensive occupations. It provides a general tool for analyzing how task automation and new task creation reshape the scarcity value of human expertise within and across occupations. (JEL: E24, J11, J23, J24)

Claim

- Joseph R. Schumpeter lecture, presented to the European Economic Association on August 29, 2024 in Rotterdam, with lecture title "Does Automation Replace Experts or Complement Expertise? The Answer is Yes."
- You can find the lecture video through this link: https://eur.cloud.panopto.eu/Panopto/Pages/Viewer.aspx?id=090be602-d3f0-4194-9085-b1cb00dd29e3.
- To better understand this article, the following slides mainly come from the authors' copyright.

Does automation replace experts or augment expertise?

The answer is yes

David Autor, MIT Department of Economics and NBER
Neil Thompson, MIT CSAIL and MIT FutureTech

European Economic Association Annual Meeting
Joseph Schumpeter Lecture: Rotterdam, 29 Aug 2024

What's the difference between these two occupations?

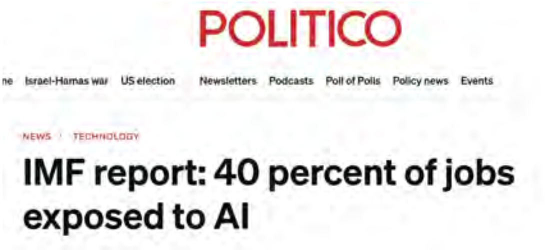
Crossing Guard

Median annual earnings $36,370

Air Traffic Controller

Median annual earnings $137,380

News headlines: ‘AI exposure’ threatens jobs, wages



POLITICO

ne Israel-Hamas war US election Newsletters Podcasts Poll of Polls Policy news Events

NEWS | TECHNOLOGY

IMF report: 40 percent of jobs exposed to AI

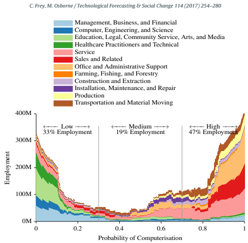
CNBC

AI IMPACT

AI IMPACT

‘AI exposure’ is the new buzz term to soften talk about job losses. Here’s what it means

Economists also equate ‘exposure’ with job loss



Frey & Osborne 2016, “The Future of Employment: How susceptible are jobs to computerisation”

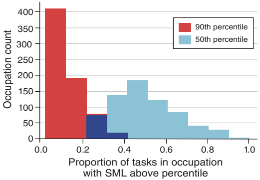


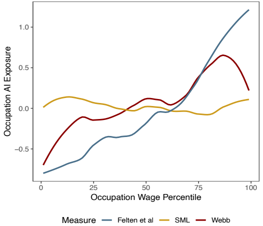
FIGURE 1. FREQUENCY COUNTS OF OCCUPATIONAL TASK PROPORTIONS ABOVE NINETIETH, SEVENTY-FIFTH, AND FIFTIETH PERCENTILES

Panel A. SML score versus occupational log median wage percentile

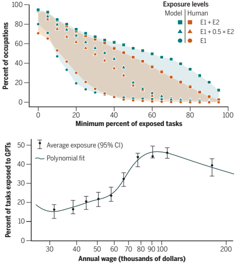
Brynjolfsson & Mitchell, 2018, "What Can Machines Learn and What Does It Mean for Occupations and the Economy?

Figure 7: **Exposure to AI by demographic group**

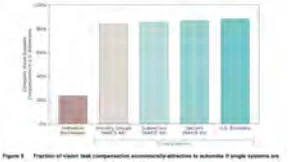
Webb 2020, "What Can Machines Learn and What Does It Mean for Occupations and the Economy?



Acemoglu, Autor, Hazell, & Restrepo 2022, “Artificial Intelligence and Jobs: Evidence from Online Vacancies”



Eloundou, Manning, Mishkin & Rock 2024, “GPTs are GPTs: Labor market impact potential of LLMs”



Svanberg, Li, Fleming, Goehring & Thompson 2024, “Beyond AI Exposure: Which Tasks are Cost-Effective to Automate with Computer Vision?”

This thinking is oversimplified

- Does automation or AI ‘exposure’ → Occupation, job, wages at risk?

1. Capital and labor are usually considered complements (Griliches ’68). Why not here?
2. An occupation or task might be exposed to *automation* or *augmentation* or both (Lin ’11; Acemoglu-Restrepo ’18; Atalay, Phongthiengtham, Sotelo, Tannenbaum ’20; Mann, Püttman ’23; Autor, Chin-Salomons, Seegmiller 24; Danieli ’24; Kim, Merritt, Peri ’24; Kogan, Papanikolaou, Schmidt, Seegmiller ’24)
3. Depending on **which tasks** are automated, automation could diminish or amplify the demand for human **expertise**

Defining expertise

- Expertise (*dictionary definition*)
  - **Domain-specific knowledge or competency required to accomplish a particular goal**
- Expertise (*economic relevance*)

1. The goal it enables must itself have market value
2. The expertise must be scarce


WHEN EVERYONE IS SPECIAL
NO ONE IS.
memegenerator.net

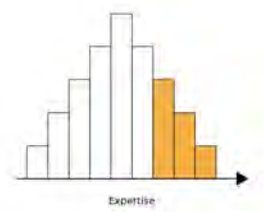
Expertise and automation: Not just how many tasks but which tasks

Consider an occupation that loses 25% of its tasks to automation

Expert tasks automated

Expertise and automation: Not just how many tasks but which tasks

Consider an occupation that loses 25% of its tasks to automation

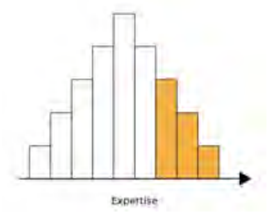


Expert tasks automated

	Labor productivity
	Average expertise
	Employment
	Wages

Expertise and automation: Not just how many tasks but which tasks

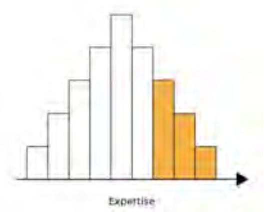
Consider an occupation that loses 25% of its tasks to automation

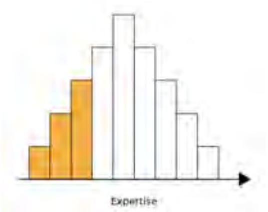


Expert tasks automated

$\uparrow$	Labor productivity
$\downarrow$	Average expertise
$\uparrow$	Employment
$\rightarrow$ or $\downarrow$	Wages

Consider an occupation that loses 25% of its tasks to automation

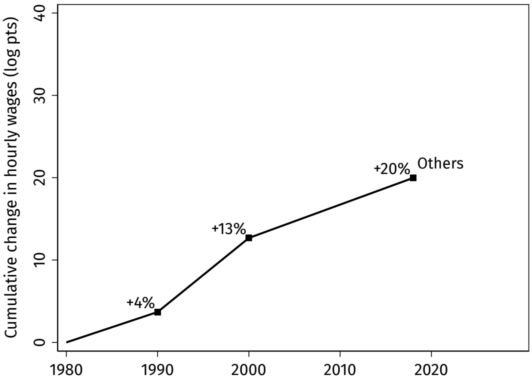




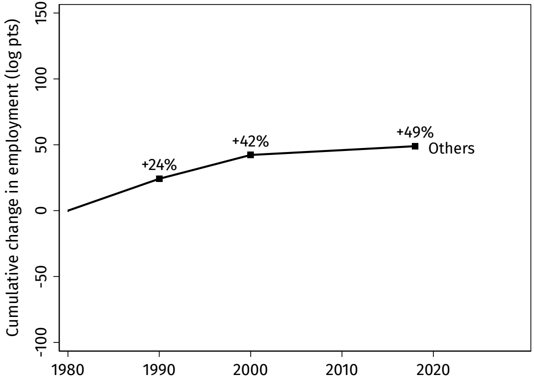
Expert tasks automated		Inexpert tasks automated
↑	Labor productivity	↑
↓	Average expertise	↑
↑	Employment	→ or ↓
→ or ↓	Wages	↑

When expert tasks are eliminated — Free entry and angry incubments

Wage and employment change across all occupations

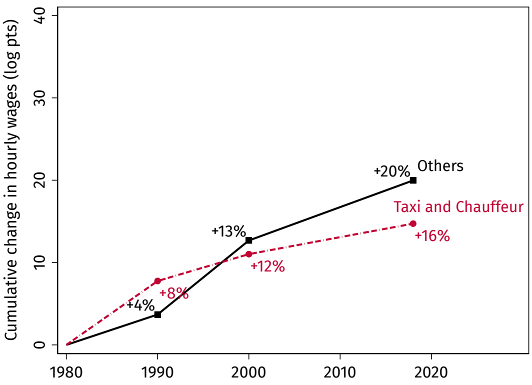


Cumulative Wage Change

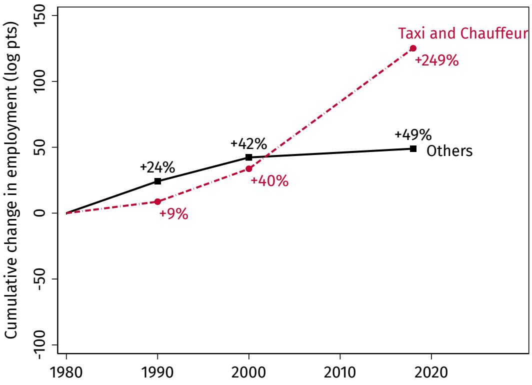


Cumulative Employment Change

Taxi drivers: Expertise, wages fell, employment rose

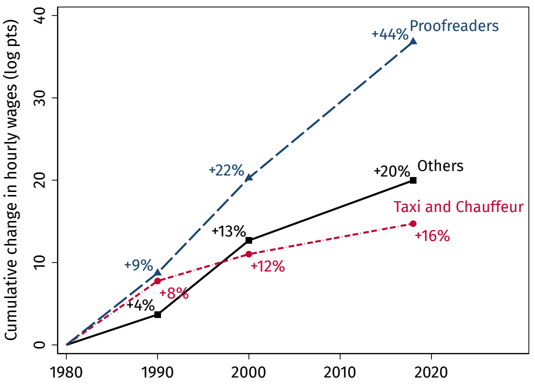


Cumulative Wage Change

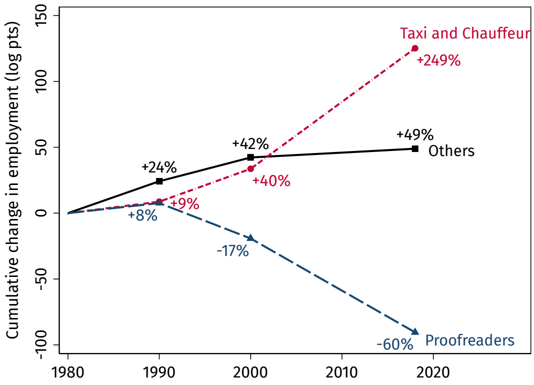


Cumulative Employment Change

Proofreaders: Expertise upgraded, wages rose, employment fell



Cumulative Wage Change



Cumulative Employment Change

Agenda

1. Conceptual framework
   - Foundations
   - A model of expertise, automation, and labor arbitrage
2. The measurement challenge
   - Measuring expertise
   - Measuring tasks removed and added
3. Main evidence: Changes in expertise demands, earnings and employment
   - Overall (net) changes in expertise requirements
   - Task removal and addition → Expertise downgrading *and* upgrading
   - Is it 'more expertise'—or just 'more tasks'
4. Implications and next steps

Agenda

1. Conceptual framework
   - Foundations
   - A model of expertise, automation, and labor arbitrage
2. The measurement challenge
   - Measuring expertise
   - Measuring tasks removed and added
3. Main evidence: Changes in expertise demands, earnings and employment
   - Overall (net) changes in expertise requirements
   - Task removal and addition → Expertise downgrading *and* upgrading
   - Is it 'more expertise'—or just 'more tasks'
4. Implications and next steps

Expertise and automation: Foundations

❶ The tasks comprising an occupation are **indivisible** → All must be performed

- Automating one set of tasks does not eliminate the need for the others (Acemoglu-Autor '11)

❷ Accomplishing a specific task requires **task-specific expertise**

- Air traffic controllers can be crossing guards—but the reverse is not true

❸ Automation displaces labor from some **expert tasks**

- Foundational notion in Task models (Autor Levy Murnane '03; Acemoglu Autor '11; Acemoglu Restrepo '18, '22)

❹ All occupations also have some **generic tasks**

- Can be done by all workers but are not subject to automation
- Generic tasks may require physical dexterity, multi-sensory interactions, common sense

Agenda

1. Conceptual framework
   - Foundations
   - A model of expertise, automation, and labor arbitrage
2. The measurement challenge
   - Measuring expertise
   - Measuring tasks removed and added
3. Main evidence: Changes in expertise demands, earnings and employment
   - Overall (net) changes in expertise requirements
   - Task removal and addition → Expertise downgrading *and* upgrading
   - Is it 'more expertise'—or just 'more tasks'
4. Implications and next steps

Model — Workers and expertise supply

Workers

- Each worker has one efficiency unit labor $\ell_i = 1$ that she can supply to one occupation
- Workers have different levels of expertise $j_i \in [0, 1]$
  - A worker of expertise j_i can perform any task $j^{'} \leq j_i$
  - All workers can also perform generic tasks
- Workers choose their occupation to maximize wages
  - They cannot subdivide ℓ_i across occupations
- There is a mass of workers uniformly distributed across all expertise levels
  - Expertise is not *exogenously* scarce—same number of experts as non-experts
  - But, intuitively, there are always more *potential* crossing-guards than air traffic controllers
  - Formally, expertise is *upwardly non-fungible*

Expertise be like... Russian stacking dolls

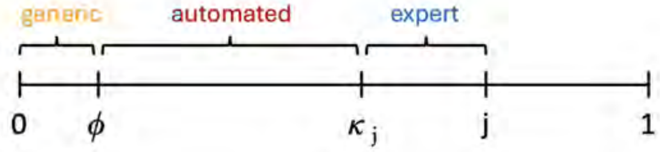
Occupations

- An occupation is defined by the tasks it employs
  - Occupation j requires expertise in tasks $[\phi, j]$
  - Tasks are ordered by increasing expertise
- Each occupation has both generic *and* expert tasks
  - Generic tasks: A task interval $[0, \phi)$, requires no expertise but cannot be automated
  - Remaining tasks are expert tasks, which can potentially be automated
- Indivisibility: Worker must be perform all *non-automated* tasks in her occupation
  - Air-traffic controller cannot ‘outsource’ speaking to pilots to less expert colleague

Model — Generic tasks, expert tasks, and automation

A worker in occ j produce y_j by completing continuum of tasks $x \in [0, j]$

- Generic versus expert tasks
  - Tasks $x \in [0, \phi)$ are generic: Every worker can do them and they can be done only by labor
  - Tasks $x \in [\phi, 1]$ require corresponding expertise but can potentially be automated
- State of automation is indexed by $\kappa \in [\phi, 1]$
  - Automation always raises output net of cost → Firms automate tasks if feasible
  - Once an expert task is automated, it no longer requires expertise
  - When *all* expert tasks in an occupation are automated, *any* worker can do that occupation
- Task continuum in an occupation has three segments



Model — Worker-level production function is Cobb-Douglas

Output of worker i supplying ℓ_i to occ j:

$$y_j = j \exp\left\{\frac{1}{j}\left[\underbrace{\int_0^{\phi} \ln\big(\ell_j(x)\big)dx}_{\text{generic}} + \underbrace{\int_{\phi}^{\kappa_j} \ln\left(\frac{k_j}{\kappa_j - \phi}\right)dx}_{\text{automated}} + \underbrace{\int_{\kappa_j}^{j} \ln\big(\ell_j(x)\big)dx}_{\text{expert}}\right]\right\} \tag{1}$$

- Firm's optimization problem ⏩ details
  - Seeks to maximize y_j (assume infinitesimal profits per unit of y_j)
  - Employs at most one machine per automated task ($k_j \leq \kappa_j - \phi$)
  - Efficiently distributes up to one unit of labor across non-automated tasks ($\ell_j(x)$ s.t. $\int_0^1 \ell_j(x)dx \leq 1$)
  - Automates up to $\min\{\kappa, j\}$ tasks ($\kappa_j \leq \min\{j, \kappa\}$)
- Labor and capital are both paid their marginal products ⏩ details

Model – Aggregate production and the price index

Occupational outputs are combined into aggregate good

- Occupation-level production is $Y_j := L_j y_j$ where L_j is the density of workers employed in occupation j
- Aggregate good Y is produced according to Dixit-Stiglitz CES production function:

$$Y = \left(\int_0^1 Y_j^{\frac{\sigma-1}{\sigma}} dj \right)^{\frac{\sigma}{\sigma-1}} \tag{2}$$

  where $\sigma > 1$ is the elasticity of substitution
- Price index for Y will be:

$$P = \left(\int_0^1 p_j^{1-\sigma} dj \right)^{\frac{1}{1-\sigma}} \tag{3}$$

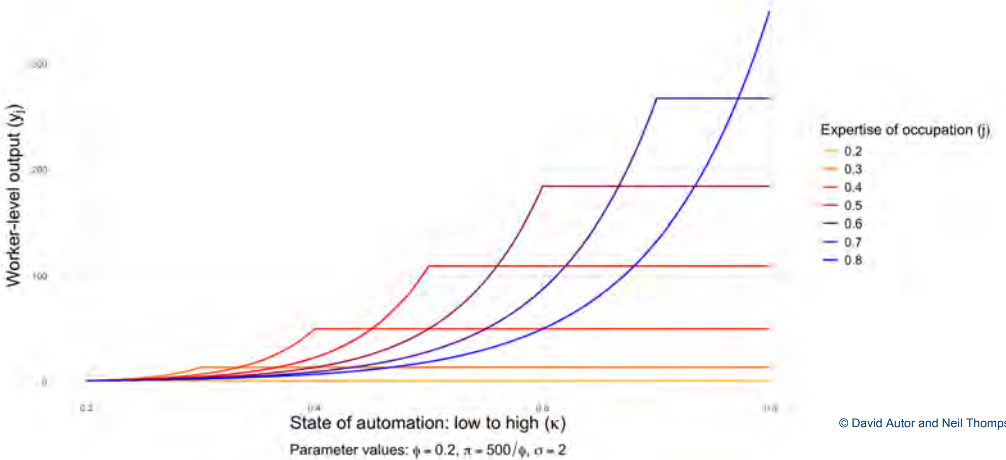
- Real occupational wage, prior to labor arbitrage, is $\tilde{w}_j = \frac{w_j}{P}$ details

Model — Labor arbitrage, and the supply of inexpert and expert labor

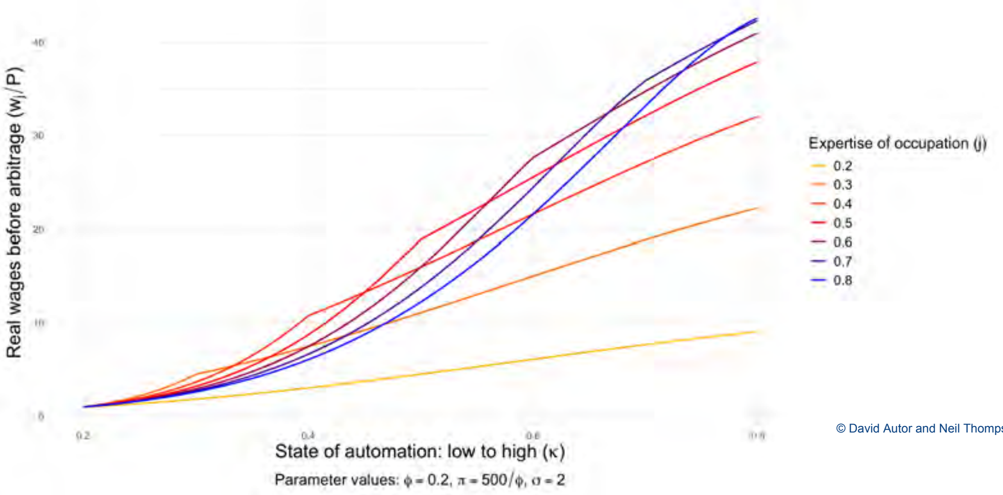
Workers arbitrage wage diffs, constrained by own expertise endowments

- Expertise replacement
  - More expert workers j can *always* flow into less expert occupations $j' < j$
  - If all expert tasks in an occ are automated, occ becomes generic → open to any worker
  - As occs go from expert to generic, their wages cannot exceed that in any expert occ, $j > \kappa$
  - *Cause — Inexpert labor is elastically supplied*
- Expertise augmentation
  - Less expert workers j' can *never* flow into more expert, non-automated tasks where $j' > j$
  - As κ rises, real value of more expert occs rises
  - Relative and real wages of remaining experts rise
  - *Cause — Expert labor supply is inelastically supplied*

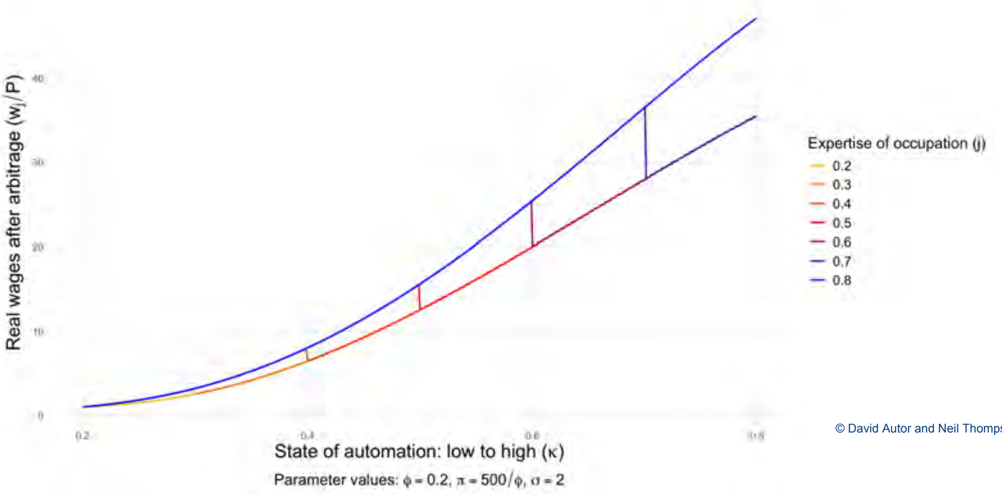
Automation first raises productivity in low-expertise occs, but ultimately raises it by more in high-expertise occs



Without expertise mobility: Wage growth by expertise is non-monotone in automation, reflecting productivity growth: Low, mid, high-expertise



Expertise mobility: Wage diffs arbitraged between high expertise vs mid-expertise occs (top); and between all fully generic occs (bottom)



Primary implications taken to the data

1. Expert work commands higher wages than generic work
   - Even within education groups
   - Even within white collar, blue collar, and service occupations
2. Changes in set of tasks in an occupation may raise or lower expertise demands
   - Adding tasks may lower expertise demands — *if added tasks are inexpert*
   - Removing tasks may raise expertise — *if removed tasks are inexpert*
3. Change in occ's expertise demands will have opposing effects on wages, employment
   - Increase in expertise demand will raise wages, reduce employment (relative)
   - Fall in expertise demand will reduce wages, raise employment (relative)
   - Labor arbitrage is key: *Inexpert labor supply is elastic; Expert labor supply is inelastic*
4. What matters: Not only *quantity* of tasks added/removed but *expertise* of those tasks

Agenda

1. Conceptual framework
   - Foundations
   - A model of expertise, automation, and labor arbitrage
2. The measurement challenge
   - Measuring expertise
   - Measuring tasks removed and added
3. Main evidence: Changes in expertise demands, earnings and employment
   - Overall (net) changes in expertise requirements
   - Task removal and addition → Expertise downgrading *and* upgrading
   - Is it 'more expertise'—or just 'more tasks'
4. Implications and next steps

Empirical approach

What we will measure

1. How much expertise a job requires
2. Which tasks have been removed from and added to an occupation
3. Quantify change in expertise requirements due to task removal and addition
4. Distinguish *quantity* of tasks added/removed from the *expertise* of these tasks
5. Wage and employment changes by occupation 1980 – 2018

Agenda

1. Conceptual framework
   - Foundations
   - A model of expertise, automation, and labor arbitrage
2. The measurement challenge
   - Measuring expertise
   - Measuring tasks removed and added
3. Main evidence: Changes in expertise demands, earnings and employment
   - Overall (net) changes in expertise requirements
   - Task removal and addition → Expertise downgrading *and* upgrading
   - Is it 'more expertise'—or just 'more tasks'
4. Implications and next steps

Measuring expertise by harnessing Zipf's Law of Abbrevation

Zipf's Law of Abbreviation (Zipf 1945)—known in linguistics as the Brevity Law

- Linguistic regularity: frequently used words tend to be shorter than rare words
  - Known in neuroscience as the Efficient Coding Hypothesis (Barlow 1961)
  - Empirically verified for almost a thousand languages of 80 different linguistic families
- Related to the *principle of least effort*
  - Language finds path of least resistance
  - Trades off the cost of verbalizing against the benefit of maximizing transmission success
  - *Specialized words—such as those used by experts—will be longer, less-frequent than words* denoting generic, common tasks
- Relevance to measuring expertise demands of job tasks
  - **Familiar terms are short and simple** → Non-expert
  - **Job tasks characterized by rare, complex words** → (More) Expert

Measuring expertise

Calculate Dale-Chall *readability* to measure expertise requirements of jobs

- Dale-Chall score is numeric gauge of the comprehension difficulty of a corpus of text (Dale & Chall '45, '95)
- Calculate **Dale-Chall Complexity** as

$$DCC \equiv 1 - \frac{N^{dc}_{words}}{N_{words}}$$

  - N^{dc}_{words} is N words found in the Dale-Chall vocabulary, N_{words} is the total word count

No

Yes

Edgar Dale

Jeanne Chall

Measuring expertise: Job task descriptions from DOT 1977, O*Net 2018

Ingredients for measuring Dale-Chall task scores

1. Textual job descriptions from the 1977 *Dictionary of Occupational Titles*, limited to $\approx 4,000$ titles detected in National Academy of Sciences, 1984
2. Textual job descriptions from the 2018 O*NET, linked to 1977 DOT

Measuring expertise – Examples

Examples of *high expertise* (high DCC) job tasks

- Initiates promotions within department (Production supervisors or foremen, 1977, $DCC = 100\%$)
- Disassembles unit to locate defects (Mechanics and repairers, 1977, $DCC = 80\%$)
- Operate Magnetic Resonance Imaging (MRI) scanners (Radiologic technologists and technicians, 2018, $DCC = 100\%$)
- Install network software, including security or firewall software (Computer systems analysts, 2018, $DCC = 88\%$)

Examples of *low expertise* (low DCC) job tasks

- Empties trash collecting box or bag at end of each shift (Janitors, 1977, $DCC = 9\%$)
- Print and make copies of work (Typists, 2018, $DCC = 0\%$)
- Butters bread and places meat or filling and garnish, such as chopped or sliced onion and lettuce, between bread slices (Food preparation workers, 1977, $DCC = 5\%$)
- Announce stops to passengers (Bus drivers, 2018, $DCC = 0\%$)

Linking to wage and employment changes by occupation, 1980 – 2018

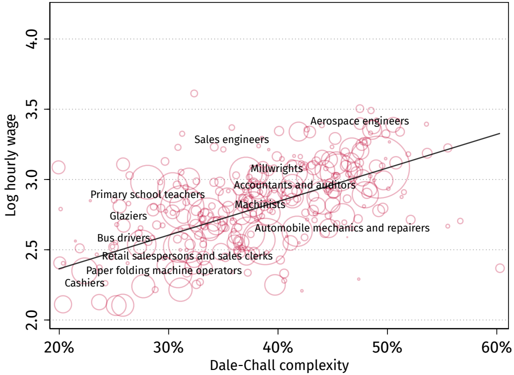
Source for employment and earnings data

- Harmonized US Census employment and earnings data for 1980, 2000, 2018 from Autor Chin Salomons Seegmiller '24
- 306 consistent, comprehensive occupations (`occ1990dd18`)
- We also use the ACSS '24 measure of the *addition of new titles to occupations* ("new work"), which builds on (Lin '11), to validate our new task measure

Expertise and log wages by occupation, 1980 and 2018

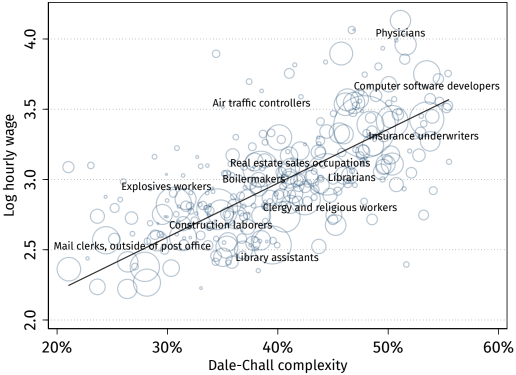
$$\ln(\text{Wage})_{jt} = \alpha_t + \beta_t \text{DCC}_{jt} + \epsilon_{jt}$$

1980



Slope: 2.39 (0.17), R2: 0.39, N: 306

2018

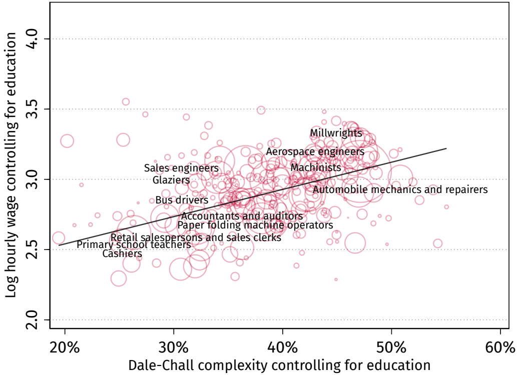


Slope: 3.84 (0.18), R2: 0.60, N: 305

Expertise and log wages by occupation, conditional on education

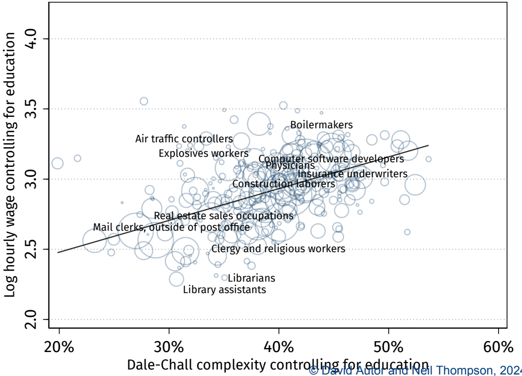
$$\ln(\text{Wage})_{jt} = \alpha_t + \beta_t \text{DCC}_{jt} + \sum_{g=1}^{4} \theta_{gt} \text{ShareEdu}_{jgt} + \epsilon_{jt}$$

1980



Slope: 1.94 (0.17), Partial R2: 0.29, N: 306

2018



Slope: 2.26 (0.19), Partial R2: 0.32, N: 305

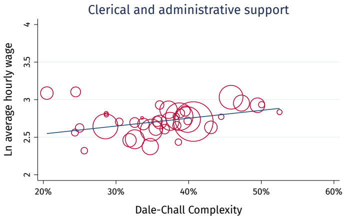
High and low expertise occupations by broad category

	Low Expertise			High Expertise			
	Occupation	DCC	Wage (hr)	Occupation	DCC	Wage (hr)	diff
Services: Personal	Food preparation workers	26%	$9.26	Recreation and fitness workers	44%	$13.53	46%
Services: Cleaning and protective	Housekeepers and cleaners	26%	$9.68	Cleaning and building service supervisors	45%	$16.19	67%
Farm and mining	Farm workers and managers	29%	$10.04	Inspectors of agricultural products	46%	$16.54	65%
Sales minus financial/advertising	Cashiers	25%	$10.06	Sales promoters and models	38%	$14.27	42%
Services: Health	Health and nursing aides	35%	$11.43	Dental Assistants	57%	$13.14	15%
Clerical and administrative support	Mail clerks, outside of post office	24%	$12.98	Insurance adjusters	49%	$18.80	45%
Transportation	Bus drivers	26%	$14.87	Vehicle transportation supervisors	42%	$19.26	30%
Production and operative	Butchers and meat cutters	27%	$15.08	Production supervisors or foremen	48%	$21.74	44%
Technicians, fire, and police	Licensed practical nurses	37%	$15.21	Engineering technicians	51%	$21.91	44%
Construction and mechanics	Locksmiths and safe repairers	24%	$17.51	Construction supervisors	48%	$23.24	33%
Managers and executives	Purchasing agents of farm products	39%	$20.46	HR and labor relations managers	52%	$27.04	32%
Professionals	Advertising and related sales jobs	37%	$23.84	Economists and market researchers	50%	$29.85	25%

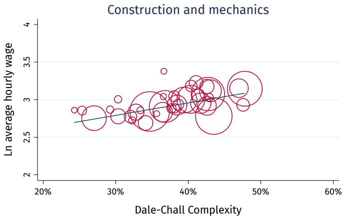
High and low expertise occupations by broad category—A few examples

	Low Expertise			High Expertise			
	Occupation	DCC	Wage (hr)	Occupation	DCC	Wage (hr)	diff
Services	Housekeepers and cleaners	26%	$9.68	Cleaning and building supervisors	45%	$16.19	67%
Clerical	Mail clerks, outside of post office	24%	$12.98	Insurance adjusters	49%	$18.80	45%
Technicians	Licensed practical nurses	37%	$15.21	Engineering technicians	51%	$21.91	44%
Professionals	Advertising and related sales jobs	37%	$23.84	Economists and market researchers	50%	$29.85	25%

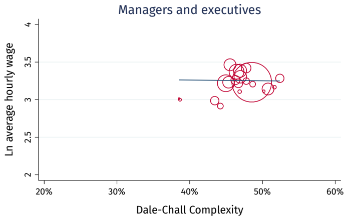
Expertise/wage scatterplots by broad occupation



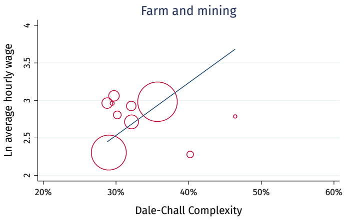
Slope: 1.05 (0.41), adj-R2: 0.13, N: 39



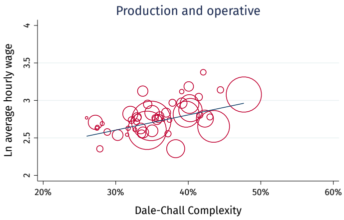
Slope: 1.66 (0.33), adj-R2: 0.40, N: 37



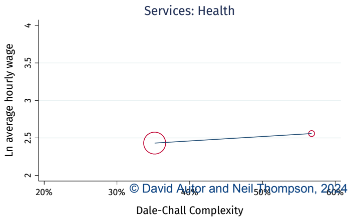
Slope: -0.10 (1.17), adj-R2: -0.05, N: 21



Slope: 7.02 (2.28), adj-R2: 0.48, N: 10

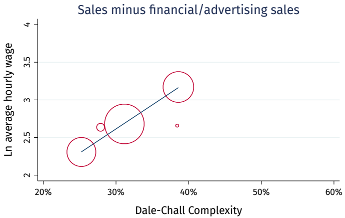


Slope: 2.03 (0.43), adj-R2: 0.30, N: 49

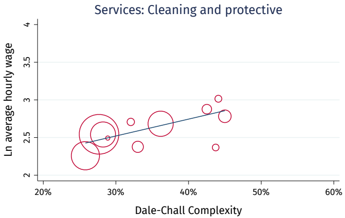


Slope: 0.59 (0.00), adj-R2: ., N: 2

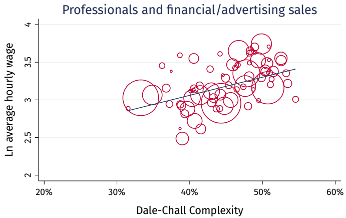
Expertise/wage scatterplots by broad occupation



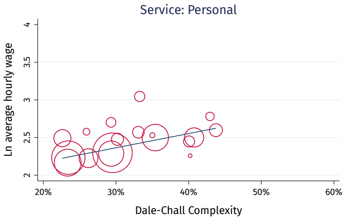
Slope: 6.39 (0.40), adj-R2: 0.98, N: 5



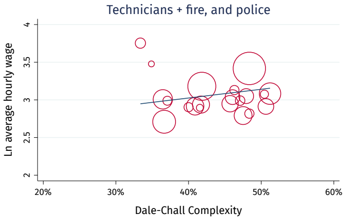
Slope: 2.24 (0.71), adj-R2: 0.47, N: 11



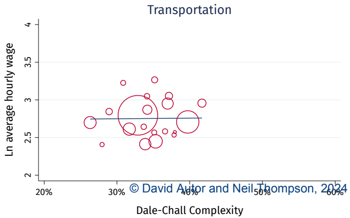
Slope: 2.40 (0.47), adj-R2: 0.26, N: 73



Slope: 1.88 (0.53), adj-R2: 0.40, N: 18



Slope: 1.16 (1.03), adj-R2: 0.01, N: 21



Slope: 0.09 (1.08), adj-R2: -0.06, N: 20

Agenda

1. Conceptual framework
   - Foundations
   - A model of expertise, automation, and labor arbitrage
2. The measurement challenge
   - Measuring expertise
   - Measuring tasks removed and added
3. Main evidence: Changes in expertise demands, earnings and employment
   - Overall (net) changes in expertise requirements
   - Task removal and addition → Expertise downgrading *and* upgrading
   - Is it 'more expertise'—or just 'more tasks'
4. Implications and next steps

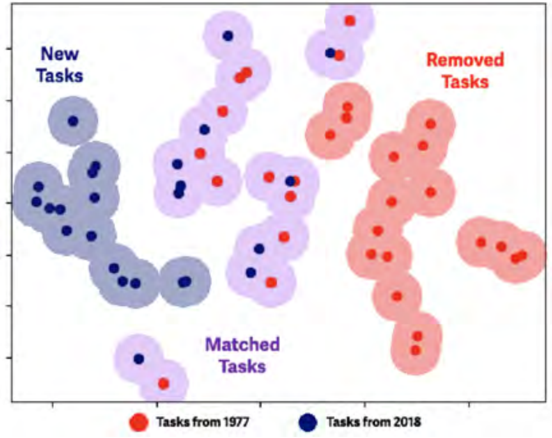
How we measure tasks removed and added

❶ **Encode tasks**: Transform each task description to 1,536 dimensional vector (OpenAI `text-embedding-3-small`)

❷ **Identify nearest tasks**: For each task in 1977 (2018), identify the nearest task from 2018 (1977)

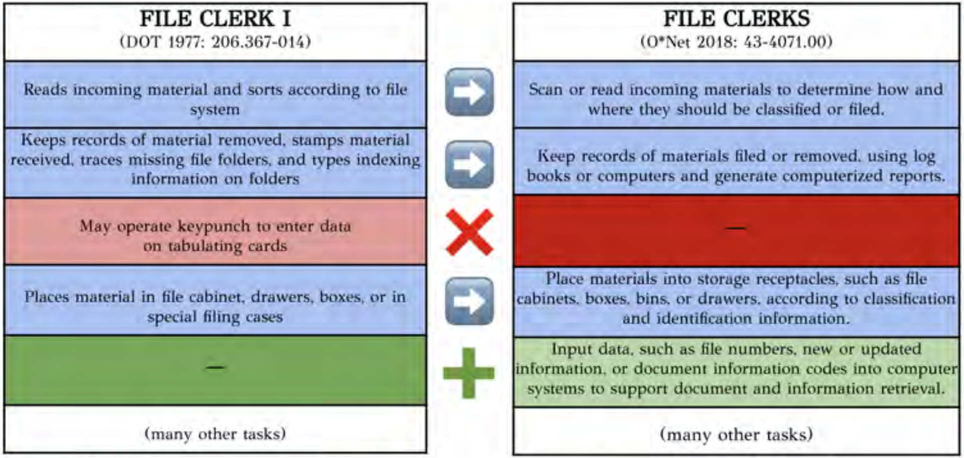
❸ **Identify unmatched tasks**:

- Found in 1977 not 2018→**Task removed**
- Found in 2018 not 1977→**Task added**



Stylized representation of task matching, with 1,536-dimensional neighbourhood reduced to 2-d using `t-SNE`

Tasks removed and added: File Clerk occupation, 1977–2018



FILE CLERK I (DOT 1977: 206.367-014)	FILE CLERKS (O*Net 2018: 43-4071.00)
Reads incoming material and sorts according to file system	Scan or read incoming materials to determine how and where they should be classified or filed.
Keeps records of material removed, stamps material received, traces missing file folders, and types indexing information on folders	Keep records of materials filed or removed, using log books or computers and generate computerized reports.
May operate keypunch to enter data on tabulating cards	—
Places material in file cabinet, drawers, boxes, or in special filing cases	Place materials into storage receptacles, such as file cabinets, boxes, bins, or drawers, according to classification and identification information.
—	Input data, such as file numbers, new or updated information, or document information codes into computer systems to support document and information retrieval.
(many other tasks)	(many other tasks)

Share of removed tasks: 12.5%
Average DCC in 1977: 34.6%
DC of removed: 31.8%, Net Effect + 0.6%

Share of removed tasks: 5.2%
Average DCC in 2018: 36.9%
DC of removed: 33.9%, Net Effect -1.3%

How we calculate changes in expertise

❶ **Measure share of tasks added and removed, 1980–2018**

$$\Delta\tau_{\text{add}},\ \Delta\tau_{\text{remove}}$$

$$\Delta\tau_{\text{net}} = \Delta\tau_{\text{add}} + \Delta\tau_{\text{remove}}$$

❷ **Calculate the change in expertise due to task addition**

$$\Delta\text{DCC}_{\text{add}} = \Delta\tau_{\text{add}} \times (\text{DCC}_{\text{2018,added}} - \text{DCC}_{1980})$$

❸ **Calculate the change in expertise due to task removal**

$$\Delta\text{DCC}_{\text{remove}} = \Delta\tau_{\text{remove}} \times (\text{DCC}_{1980} - \text{DCC}_{\text{1980,removed}})$$

❹ **Calculate the net change in expertise due to task addition and removal**

$$\Delta\text{DCC}_{\text{net}} = \Delta\text{DCC}_{\text{add}} + \Delta\text{DCC}_{\text{remove}}$$

Consider tasks removed and retained by Typists, 1977 – 2018

Expertise downgrading

Tasks Removed

- Types message heard through earphones
- Reads chart prepared by dictator to determine length of message
- Presses button to stop tape or to mark end of tape section
- Pastes messages received on tape on paper forms
- Reads incoming messages to detect errors and presses lever to stop transcription

Tasks Retained

- Types letters, reports, stencils, forms, addresses
- Compiles data and operates typewriter in performance of routine clerical duties to maintain business records and reports
- May operate duplicating machines to reproduce copy
- May sort mail

Expertise upgrading

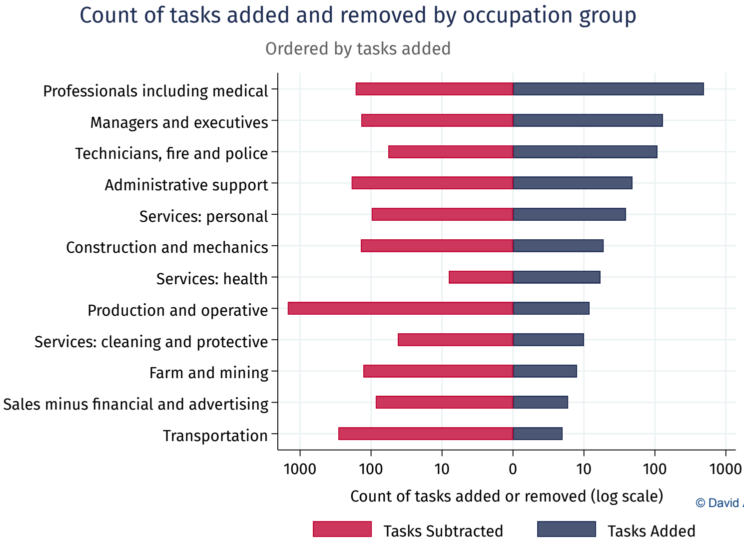
Tasks Removed

- Compiles names, addresses, vital statistics, and other facts or opinions from business subscribers or persons in communities or cities
- Records figures shown on dial and measuring wheels of planimeter at beginning and ending of tracing and subtracts figures from each other to determine acreage
- Posts and files charts

Tasks Retained

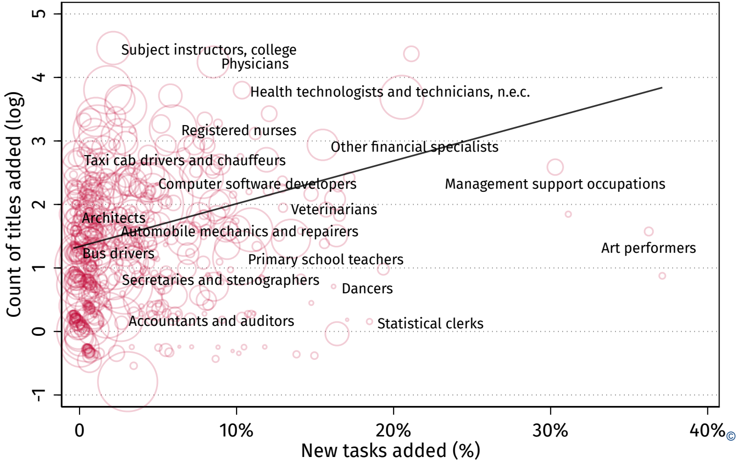
- Applies standardized mathematical formulas, principles, and methodology to technological problems... in relation to specific industrial and research objectives
- Confers with professional, scientific, and engineering personnel to plan projects
- Analyzes processed data to detect errors

Task subtraction is concentrated in blue collar jobs; addition in white collar



New titles added and new tasks added

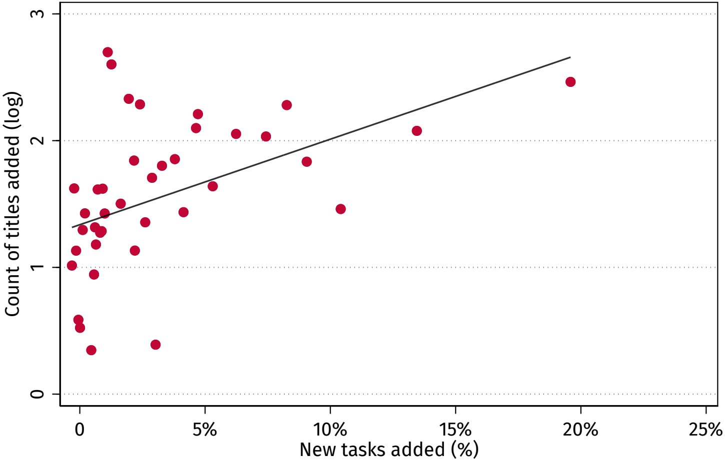
$$\ln(\text{New Titles})_{jt} = \alpha + \beta \Delta_{\text{add},jt} + \epsilon_{tj}$$



Slope: 6.75 (1.83), Partial R2: 0.07, N: 534

New titles added and new tasks added

$$\ln(\text{New Titles})_{jt} = \alpha + \beta \Delta\tau_{\text{add},jt} + \epsilon_{jt}$$



Slope: 6.75 (1.83), Partial R2: 0.07, N: 534

Agenda

1. Conceptual framework
   - Foundations
   - A model of expertise, automation, and labor arbitrage
2. The measurement challenge
   - Measuring expertise
   - Measuring tasks removed and added
3. Main evidence: Changes in expertise demands, earnings and employment
   - Overall (net) changes in expertise requirements
   - Task removal and addition → Expertise downgrading *and* upgrading
   - Is it 'more expertise'—or just 'more tasks'
4. Implications and next steps

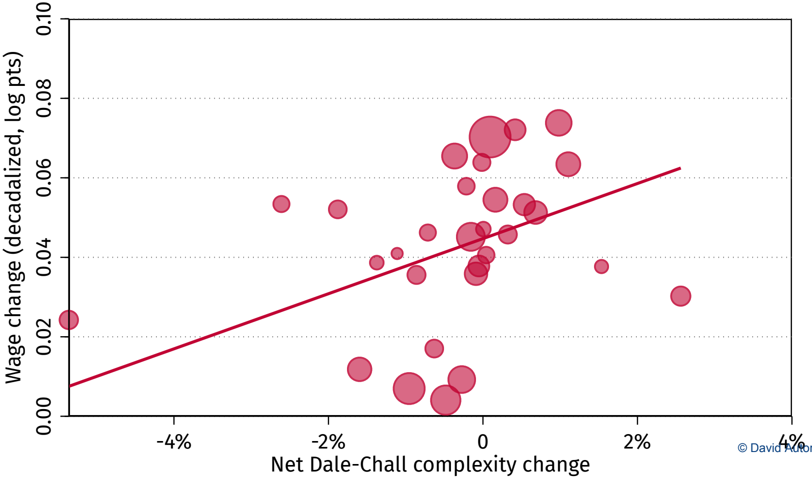
Agenda

1. Conceptual framework
   - Foundations
   - A model of expertise, automation, and labor arbitrage
2. The measurement challenge
   - Measuring expertise
   - Measuring tasks removed and added
3. Main evidence: Changes in expertise demands, earnings and employment
   - Overall (net) changes in expertise requirements
   - Task removal and addition → Expertise downgrading *and* upgrading
   - Is it ‘more expertise’—or just ‘more tasks’
4. Implications and next steps

Change in occupational wage and ΔDCC (expertise), 1980–2018

$$\Delta \ln(\text{Wage})_{1980\text{–}2018,j} = \alpha + \beta \Delta \text{DCC}_{\text{net},j} + \epsilon_j$$

▸ table



Slope: 0.69 (0.20), Partial R2: 0.03, N: 305

Do occupational wage changes reflect changes in expertise demands?

Calculate expected change in occ's wages due to measured compositional shifts

- Estimate cross-section log wage regression in each Census/ACS year—saturated for sex, race, ethnicity, education level, all interacted w/ age quadratic

$$w_{i,jt} = \alpha_t + X_{ij}\beta_t + \epsilon_{ijt}$$

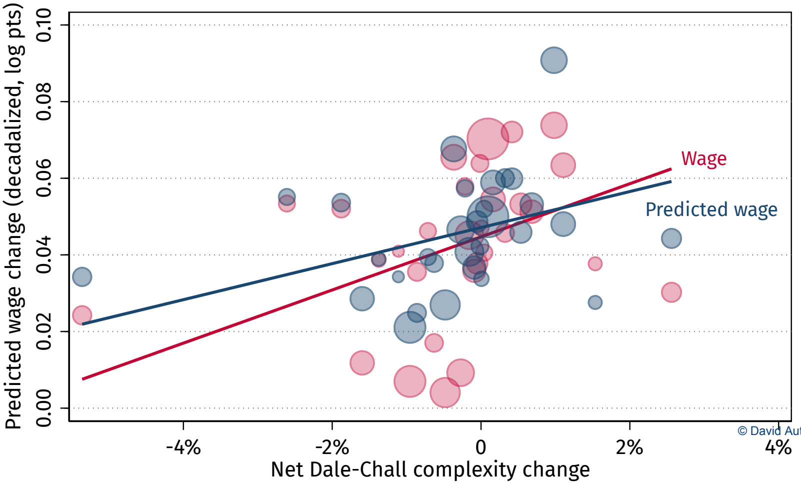
- Calculate predicted log wage $\hat{w}_{ijt} = E\left[w_{ijt} | X_{ij}, t\right]$ for each worker
- Collapse to occupation-year cells $\bar{\hat{w}}_{jt}$
- Wage components are
  - $\Delta\bar{\hat{w}}_{jt}$ is the change in mean log wages in occupation j attributable to changes in education, experience, and demographics of workers
  - $\Delta\hat{w}_{jt} - \Delta\bar{\hat{w}}_{jt}$ is observed wage change *not* attributable to Δ worker composition
- Finally, regress change in expected wage on change in expertise requirements, $\Delta\text{DCC}_{net,j}$

$$\Delta\bar{\hat{w}}_{j\tau} = \alpha_0 + \beta_0\Delta\text{DCC}_{net,j\tau} + e_{jt}$$

Change in occupational skill and ΔDCC (expertise), 1980–2018

$$\Delta \ln(\mathrm{E}[\mathrm{Wage}])_{1980\text{–}2018,j} = \alpha + \beta \Delta \mathrm{DCC}_{\mathrm{net},j} + \epsilon_j$$

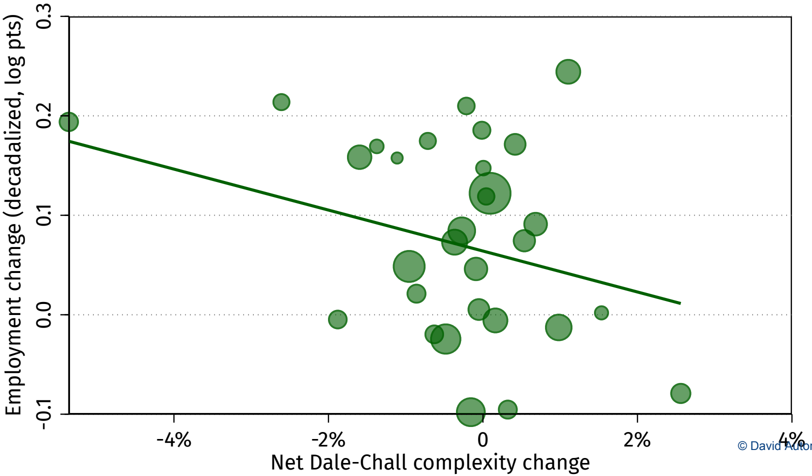
table



Change in occupational employment and ΔDCC (expertise), 1980–2018

$$\Delta \ln(\text{Emp})_{1980\text{–}2018,j} = \alpha + \beta \Delta \text{DCC}_{\text{net},j} + \epsilon_j$$

table



Slope: -1.88 (0.86), Partial R2: 0.01, N: 305

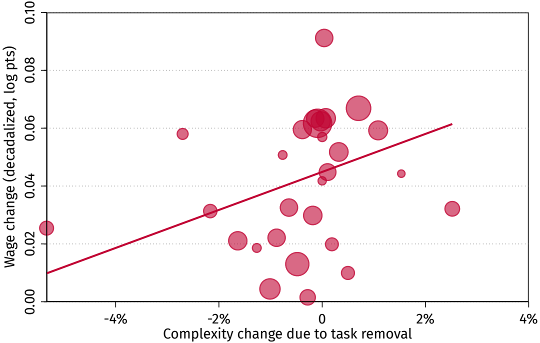
Agenda

1. Conceptual framework
   - Foundations
   - A model of expertise, automation, and labor arbitrage
2. The measurement challenge
   - Measuring expertise
   - Measuring tasks removed and added
3. Main evidence: Changes in expertise demands, earnings and employment
   - Overall (net) changes in expertise requirements
   - Task removal and addition → Expertise downgrading *and* upgrading
   - Is it 'more expertise'—or just 'more tasks'
4. Implications and next steps

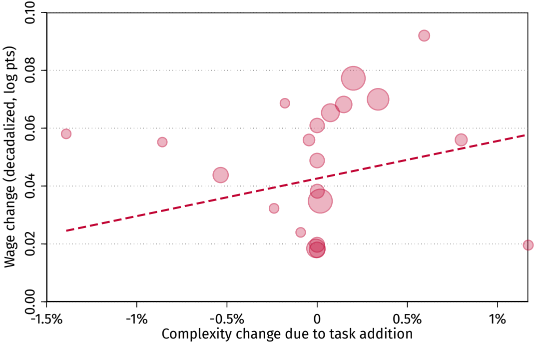
Removing inexpert tasks and adding expert tasks: Both raise wages

$$\Delta \ln(\text{Wage})_{1980-2018,j} = \alpha + \beta \Delta \text{DCC}_{\text{remove/add},j} + \epsilon_j$$

table



Slope: 0.63 (0.20), Partial R2: 0.03, N: 305



Slope: 1.24 (0.77), Partial R2: 0.01, N: 305

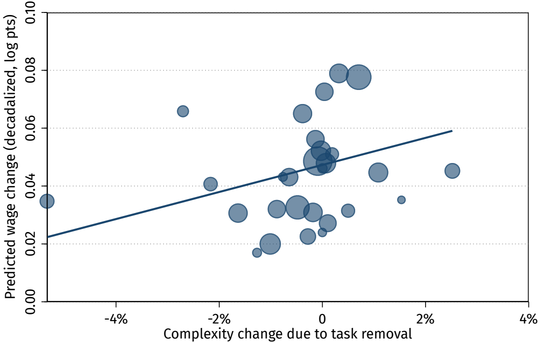
Δ Dale-Chall Complexity: Removal

Δ Dale-Chall Complexity: Addition

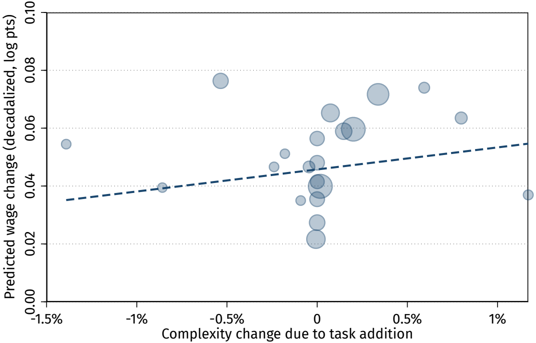
Removing inexpert tasks and adding expert tasks: Both raise skill

$$\Delta \ln(\mathrm{E[Wage]})_{1980-2018,j} = \alpha + \beta \Delta \mathrm{DCC}_{\mathrm{remove/add},j} + \epsilon_j$$

▸ table



Slope: 0.50 (0.15), Partial R2: 0.03, N: 305



Slope: 0.56 (0.55), Partial R2: 0.00, N: 305

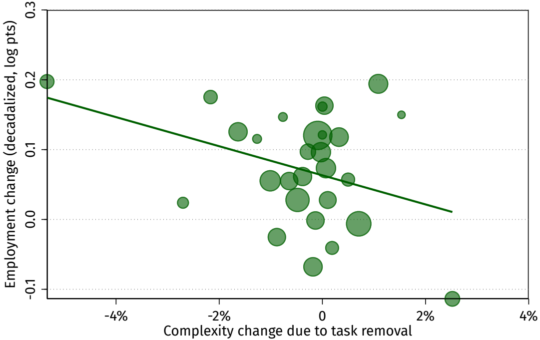
Δ Dale-Chall Complexity: Removal

Δ Dale-Chall Complexity: Addition

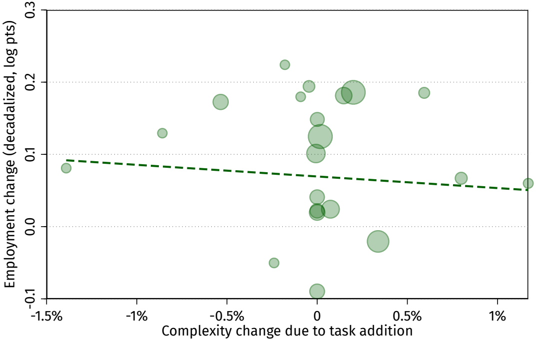
Removing inexpert tasks and adding expert tasks: Both lower employment

$$\Delta \ln(\text{Emp})_{1980\text{–}2018,j} = \alpha + \beta \Delta \text{DCC}_{\text{remove/add},j} + \epsilon_j$$

▸ table



Slope: -1.89 (0.88), Partial R2: 0.01, N: 305



Slope: -0.93 (3.30), Partial R2: -0.00, N: 305

△ Dale-Chall Complexity: Removal

△ Dale-Chall Complexity: Addition

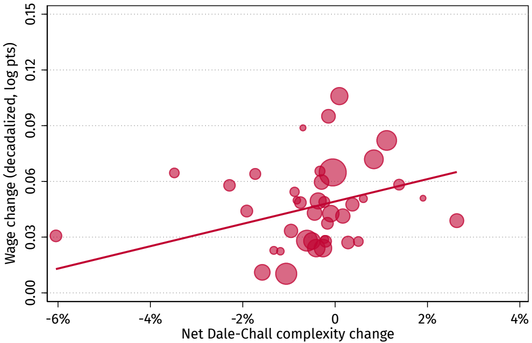
Agenda

1. Conceptual framework
   - Foundations
   - A model of expertise, automation, and labor arbitrage
2. The measurement challenge
   - Measuring expertise
   - Measuring tasks removed and added
3. Main evidence: Changes in expertise demands, earnings and employment
   - Overall (net) changes in expertise requirements
   - Task removal and addition → Expertise downgrading *and* upgrading
   - Is it 'more expertise'—or just 'more tasks'
4. Implications and next steps

How many tasks or which tasks: Wage regressions

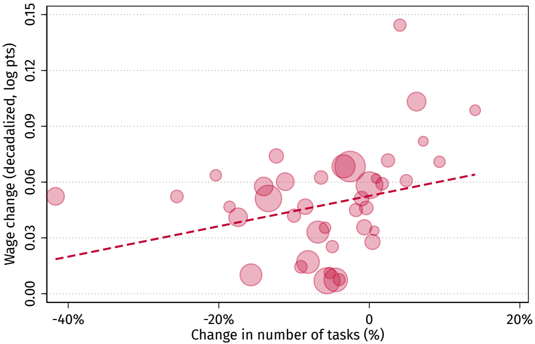
$$\Delta \ln(\text{Wage})_{1980\text{–}2018,j} = \alpha + \beta_1 \Delta \text{DCC}_{\text{net},j} + \beta_2 \Delta \tau_{\text{net},j} + \epsilon_j$$

▸ table



Slope: 0.61 (0.20), Partial R2: 0.03, N: 305

△ Dale-Chall Complexity



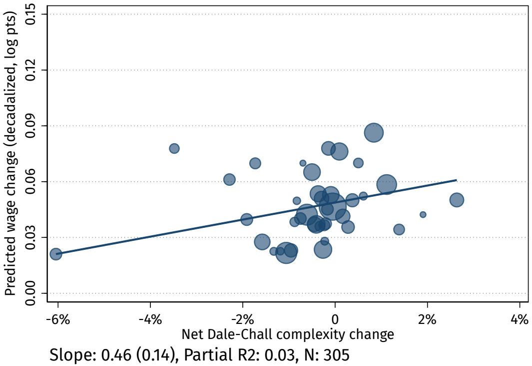
Slope: 0.08 (0.03), Partial R2: 0.03, N: 305

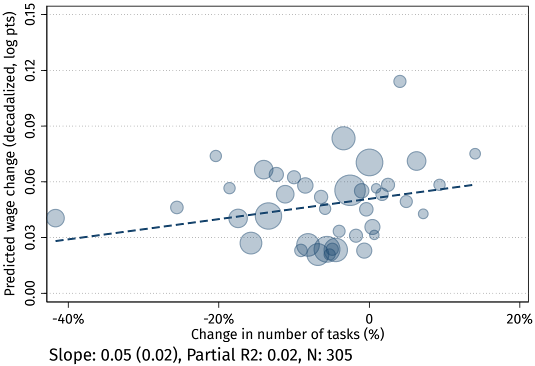
△ Task Count

How many tasks or which tasks: Skill regressions

$$\Delta \ln(\mathrm{E}[\mathrm{Wage}])_{1980-2018,j} = \alpha + \beta_1 \Delta \mathrm{DCC}_{\mathrm{net},j} + \beta_2 \Delta \tau_{\mathrm{net},j} + \epsilon_j$$

▸ table





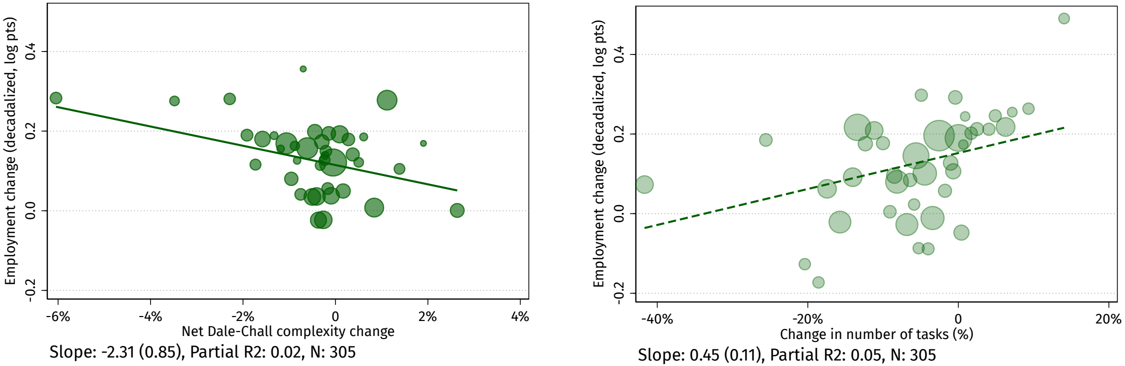
△ Dale-Chall Complexity

△ Task Count

How many tasks or which tasks: Employment regressions

$$\Delta \ln(\text{Emp})_{1980\text{–}2018,j} = \alpha + \beta_1 \Delta \text{DCC}_{\text{net},j} + \beta_2 \Delta \tau_{\text{net},j} + \epsilon_j$$

▸ table



△ Dale-Chall Complexity

△ Task Count

Agenda

1. Conceptual framework
   - Foundations
   - A model of expertise, automation, and labor arbitrage
2. The measurement challenge
   - Measuring expertise
   - Measuring tasks removed and added
3. Main evidence: Changes in expertise demands, earnings and employment
   - Overall (net) changes in expertise requirements
   - Task removal and addition → Expertise downgrading *and* upgrading
   - Is it 'more expertise'—or just 'more tasks'
4. Implications and next steps

Does automation replace experts or augment expertise? The answer is yes

1. Automation both replaces and augments expertise
   - Relevant questions is not *how many tasks* but *which tasks*

2. Focus on 'exposure' to automation/AI is misplaced
   - Why don't grocery cashiers make high wages given huge productivity gains?
   - Why doesn't everyone apply to pediatric oncology jobs, given the high pay?
   - One-way fungibility of expertise is central to the answer

3. Most theories of job 'exposure' fail to predict the past
   - They are therefore ill-equipped to predict the AI future
   - Applying the expertise approach, we hope to do better

Acknowledgements – Essential contributors

- **Lucy Hampton**, Bennett Institute for Public Policy, University of Cambridge
- **Yongyin (Joanne) Liang**, MIT Shaping the Future of Work Initiative
- **Anna Salomons**, Utrecht University
- **Christian Vogt**, MIT Shaping the Future of Work Initiative
- **Can Yesledire**, MIT Shaping the Future of Work Initiative

APPENDIX SLIDES

Model Appendix — Production function algebra

Firm optimization

- Due to Cobb-Douglas form, worker/firm will distribute labor ℓ_j equally across non-automated tasks, i.e. $\ell_j(x) = \frac{l_j}{j+\phi-\kappa_j}, \forall x \in [0,\phi] \cup (\kappa_j, 1]$ and $\ell_j(x) = 0, \forall x \in (\phi, \kappa_j]$ for some $l_j \leq 1$.
- Tech-monopolist sells k_j and can perfectly price-discriminate between occupations
  - Labor and capital paid their marginal products:

$$\frac{w_j}{p_j} = \frac{\mathrm{d}y_j}{\mathrm{d}l_j} = \frac{j+\phi-\kappa_j}{j}\frac{y_j}{l_j} \tag{4}$$

$$\frac{r_j}{p_j} = \frac{\mathrm{d}y_j}{\mathrm{d}k_j} = \frac{\kappa_j-\phi}{j}\frac{y_j}{k_j} \tag{5}$$

- Firms will choose $l_j = 1$ and $k_j = \kappa_j - \phi$ since y_j increases in l_j and k_j.

Simplifications of worker-level production and wages after firm choices

- y_j is monotone increasing in κ_j (since $\pi > \phi^{-1}$). Firms will choose $\kappa_j = \min\{j, \kappa\}$.
- worker-level production and wages simplify to:

$$y_j = j\left(\frac{1}{j+\phi-\kappa_j}\right)^{\frac{j+\phi-\kappa_j}{j}} \pi^{\frac{\kappa_j-\phi}{j}} \tag{6}$$

$$\frac{w_j}{p_j} = [(j+\phi-\kappa_j)\pi]^{\frac{\kappa_j-\phi}{j}} \tag{7}$$

Model Appendix — Real wages before arbitrage

Factors in (before arbitrage) real wage expression reflect channels of operation

$$\frac{w_j}{P} = \frac{p_j}{P}\frac{w_j}{p_j} = Y_j^{-\frac{1}{\sigma}}\left(\int_0^1 Y_i^{\frac{\sigma-1}{\sigma}} di\right)^{\frac{1}{\sigma-1}} \frac{w_j}{p_j} \tag{8}$$

- $\frac{w_j}{P}$ is non-monotone in κ: Labor-share falls, productivity increases
- $Y_j^{-\sigma}$ decreases in κ (until $\kappa = j$): Occupational output rises, lowering output price
  - But occupational revenue (price × quantity) always increases with output since $\sigma > 1$
- $\left(\int_0^1 Y_i^{\frac{\sigma-1}{\sigma}} di\right)^{\frac{1}{\sigma-1}}$ increases in automation κ: Economic growth

Model Appendix — Simulation procedure

Finite occupations for simulations

- For computational reasons we replace the continuous CES aggregate production function with a discrete one with occupations $j \in \Omega \subseteq [0,1]$ and $J := |\Omega| < \infty$:

$$Y = \frac{1}{J}\left(\sum_{i \in \Omega} Y_i^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} \tag{9}$$

- Denote by L_j^0 the mass of workers of type j. We let $\sum_{j \in \Omega} L_j = 1$.
- We simulate J occupations uniformly distributed on $[0,1]$ and let L_j^0 be uniform on $[0,1]$ as well, i.e. $L_j^0 = 1/J, \forall j \in \Omega$.

Model Appendix — Simulation procedure

Labor arbitrage algorithm

- We say *wages are equalized* between occupations j and i if L_j/L_i is set s.t. wages are equal in both occupations. Let $j_1 := \min\{\Omega \cap (\kappa, 1]\}$, $j_2 := \min\{\Omega \cap (j_1, 1]\}$, etc. and do the following steps:

1. Wages between fully automated occupations (all $j \in \Omega \cap [0, \kappa]$) are equalized.
2. If wages in occupation j_1 are lower than in fully automated occupations, wages between all $j \in \Omega \cap [0, j_1]$ are equalized.
3. If wages in occupation j_2 are lower than in occupation j_1, wages are equalized. If wages in j_1 are now lower than in fully automated occupations, wages between all $j \in \Omega \cap [0, j_2]$ are equalized.
4. If wages in occupation j_3 are lower than in occupation j_2, wages are equalized. If wages in j_2 are now lower than in j_1, wages are equalized between j_1,j_2 & j_3. If wages in j_1 are now lower than in fully automated occupations, wages between all $j \in \Omega \cap [0, j_3]$ are equalized.
5. …

Model Appendix — Key condition governing labor arbitrage

Algorithm relies on ratio L_j/L_i s.t. wages are equal in occupations j & i

$$\frac{w_j}{P} \geq \frac{w_i}{P} \tag{10}$$

$$\Longleftrightarrow \frac{w_j}{w_i} = \left(\frac{L_j y_j}{L_i y_i}\right)^{-\frac{1}{\sigma}} \left(\frac{w_j/p_j}{w_i/p_i}\right) \geq 1 \tag{11}$$

$$\Longleftrightarrow \frac{L_j}{L_i} \leq \frac{y_i}{y_j}\left(\frac{w_j/p_j}{w_i/p_i}\right)^{\sigma} \tag{12}$$

Results Appendix — Main evidence table

Dependent Variable = Δ log Wage, 80-18 decadalized				
	(1)	(2)	(3)	(4)
DCC_{net}	0.69***			0.61**
	(0.20)			(0.20)
DCC_{remove}		0.63**		
		(0.20)		
DCC_{add}			1.24	
			(0.77)	
$Task_{net}$				0.08**
				(0.03)
N	305	306	305	305
R2	0.04	0.03	0.01	0.07

back

Results Appendix — Main evidence table

Dependent Variable = Δ log Emp, 80-18 decadalized				
	(1)	(2)	(3)	(4)
DCC_{net}	-1.88*			-2.31**
	(0.86)			(0.85)
DCC_{remove}		-1.89*		
		(0.88)		
DCC_{add}			-0.93	
			(3.30)	
$Task_{net}$				0.45***
				(0.11)
N	305	306	305	305
R2	0.02	0.01	0.00	0.06

back

Recent News

SUCCESS· CAREERS

Microsoft researchers have revealed the 40 jobs most exposed to AI—and even teachers make the list

BY **PRESTON FORE**
STAFF WRITER, EDUCATION

July 31, 2025 at 11:31 AM EDT

Sorry, Gen Z: AI is coming for safe and secure teaching jobs, as well as grad roles.
GETTY IMAGES—DEMAERRE

Listen to the article now
00:00 06:37 1.0x

Powered by: Trinity Audio

- **Microsoft's list of 40 jobs that have high crossover with AI** is going viral—and professionals are warning that it highlights the careers "most at risk," with historians, translators, and sales reps high on the list. While Microsoft says high applicability doesn't automatically mean those roles will be killed by AI, employers have been putting a pause on hiring and cutting roles to make way for enhanced productivity.

As companies like Amazon publicly announce AI-driven workforce reductions, workers are scrambling to understand which careers might soon disappear and be outsourced to technology.

Extension

There is a paper behind the news named "Working with AI: Measuring the Occupational Implications of Generative AI" written by several research scientists. (Online on Microsoft and Arxiv)

Working with AI:
Measuring the Occupational Implications of Generative AI*

Kiran Tomlinson[1], Sonia Jaffe[1], Will Wang[1], Scott Counts[2], and Siddharth Suri[1]

[1]Microsoft Research
[2]Microsoft

This study reveals the 40 jobs AI is most likely to impact — and 40 that are safe (for now).

The following two tables list the detail job title and I guess it can be explained by "Expertise" to some extent...

Table 3: Top 40 occupations with highest AI applicability score.

Job Title (Abbrv.)	Coverage	Cmpltn.	Scope	Score	Employment
Interpreters and Translators	0.98	0.88	0.57	0.49	51,560
Historians	0.91	0.85	0.56	0.48	3,040
Passenger Attendants	0.80	0.88	0.62	0.47	20,190
Sales Representatives of Services	0.84	0.90	0.57	0.46	1,142,020
Writers and Authors	0.85	0.84	0.60	0.45	49,450
Customer Service Representatives	0.72	0.90	0.59	0.44	2,858,710
CNC Tool Programmers	0.90	0.87	0.53	0.44	28,030
Telephone Operators	0.80	0.86	0.57	0.42	4,600
Ticket Agents and Travel Clerks	0.71	0.90	0.56	0.41	119,270
Broadcast Announcers and Radio DJs	0.74	0.84	0.60	0.41	25,070
Brokerage Clerks	0.74	0.89	0.57	0.41	48,060
Farm and Home Management Educators	0.77	0.91	0.55	0.41	8,110
Telemarketers	0.66	0.89	0.60	0.40	81,580
Concierges	0.70	0.88	0.56	0.40	41,020
Political Scientists	0.77	0.87	0.53	0.39	5,580
News Analysts, Reporters, Journalists	0.81	0.81	0.56	0.39	45,020
Mathematicians	0.91	0.74	0.54	0.39	2,220
Technical Writers	0.83	0.82	0.54	0.38	47,970
Proofreaders and Copy Markers	0.91	0.86	0.49	0.38	5,490
Hosts and Hostesses	0.60	0.90	0.57	0.37	425,020
Editors	0.78	0.82	0.54	0.37	95,700
Business Teachers, Postsecondary	0.70	0.90	0.52	0.37	82,980
Public Relations Specialists	0.63	0.90	0.60	0.36	275,550
Demonstrators and Product Promoters	0.64	0.88	0.53	0.36	50,790
Advertising Sales Agents	0.66	0.90	0.53	0.36	108,100
New Accounts Clerks	0.72	0.87	0.51	0.36	41,180
Statistical Assistants	0.85	0.84	0.49	0.36	7,200
Counter and Rental Clerks	0.62	0.90	0.52	0.36	390,300
Data Scientists	0.77	0.86	0.51	0.36	192,710
Personal Financial Advisors	0.69	0.88	0.52	0.35	272,190
Archivists	0.66	0.88	0.49	0.35	7,150
Economics Teachers, Postsecondary	0.68	0.90	0.51	0.35	12,210
Web Developers	0.73	0.86	0.51	0.35	85,350
Management Analysts	0.68	0.90	0.54	0.35	838,140
Geographers	0.77	0.83	0.48	0.35	1,460
Models	0.64	0.89	0.53	0.35	3,090
Market Research Analysts	0.71	0.90	0.52	0.35	846,370
Public Safety Telecommunicators	0.66	0.88	0.53	0.35	97,820

Table 4: Bottom 40 occupations with lowest AI applicability score.

Job Title (Abbrv.)	Coverage	Cmpltn.	Scope	Score	Empl.
Phlebotomists	0.06	0.95	0.29	0.03	137,080
Nursing Assistants	0.07	0.85	0.34	0.03	1,351,760
Hazardous Materials Removal Workers	0.04	0.95	0.35	0.03	49,960
Helpers–Painters, Plasterers, ...	0.04	0.96	0.38	0.03	7,700
Embalmers	0.07	0.55	0.22	0.03	3,380
Plant and System Operators, All Other	0.05	0.93	0.38	0.03	15,370
Oral and Maxillofacial Surgeons	0.05	0.89	0.34	0.03	4,160
Automotive Glass Installers and Repairers	0.04	0.93	0.34	0.03	16,890
Ship Engineers	0.05	0.92	0.39	0.03	8,860
Tire Repairers and Changers	0.04	0.95	0.35	0.02	101,520
Prosthodontists	0.10	0.90	0.29	0.02	570
Helpers–Production Workers	0.04	0.93	0.36	0.02	181,810
Highway Maintenance Workers	0.03	0.96	0.32	0.02	150,860
Medical Equipment Preparers	0.04	0.96	0.31	0.02	66,790
Packaging and Filling Machine Op.	0.04	0.91	0.39	0.02	371,600
Machine Feeders and Offbearers	0.05	0.89	0.36	0.02	44,500
Dishwashers	0.03	0.95	0.30	0.02	463,940
Cement Masons and Concrete Finishers	0.03	0.92	0.39	0.01	203,560
Supervisors of Firefighters	0.04	0.88	0.39	0.01	84,120
Industrial Truck and Tractor Operators	0.03	0.94	0.28	0.01	778,920
Ophthalmic Medical Technicians	0.04	0.89	0.33	0.01	73,390
Massage Therapists	0.10	0.91	0.32	0.01	92,650
Surgical Assistants	0.03	0.78	0.29	0.01	18,780
Tire Builders	0.03	0.93	0.40	0.01	20,660
Helpers–Roofers	0.02	0.94	0.37	0.01	4,540
Gas Compressor and Gas Pumping Station Op.	0.01	0.96	0.47	0.01	4,400
Roofers	0.02	0.94	0.38	0.01	135,140
Roustabouts, Oil and Gas	0.01	0.95	0.39	0.01	43,830
Maids and Housekeeping Cleaners	0.02	0.94	0.34	0.01	836,230
Paving, Surfacing, and Tamping Equipment Op.	0.01	0.96	0.29	0.01	43,080
Logging Equipment Operators	0.01	0.95	0.36	0.01	23,720
Motorboat Operators	0.01	0.93	0.39	0.00	2,710
Orderlies	0.00	0.76	0.18	0.00	48,710
Floor Sanders and Finishers	0.00	0.94	0.34	0.00	5,070
Pile Driver Operators	0.00	0.98	0.24	0.00	3,010
Rail-Track Laying and Maintenance Equip. Op.	0.00	0.96	0.27	0.00	18,770
Foundry Mold and Coremakers	0.00	0.95	0.36	0.00	11,780
Water Treatment Plant and System Op.	0.00	0.92	0.44	0.00	120,710
Bridge and Lock Tenders	0.00	0.93	0.39	0.00	3,460

The End