EXPERTISE

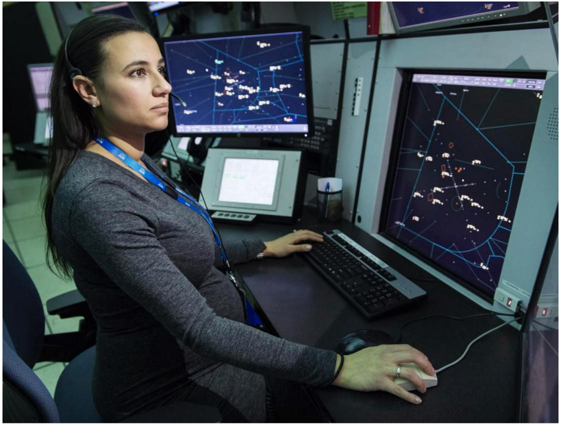
David Autor, MIT Stone Center, and Google Tech & Society Visiting Fellow
Neil Thompson, MIT CSAIL and MIT FutureTech

14.662 Spring 2026

March 9, 2026

What's the difference between these two occupations?

Crossing Guard
Median annual earnings $36,370



Air Traffic Controller
Median annual earnings $137,380

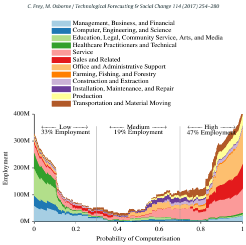
Defining expertise

- 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~~
Expert
NO ONE IS.
memegenerator.net

Economists habitually equate technology exposure / AI exposure with job loss



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

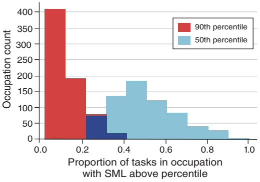


FIGURE 1. FREQUENCY COUNTS OF OCCUPATIONAL TASK PROPORTIONS ABOVE NINETIETH, SEVENTY-FIFTH, AND FIFTIETH PERCENTILES

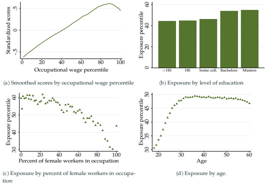
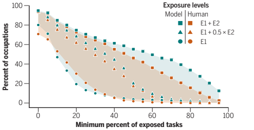
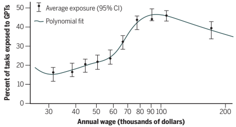


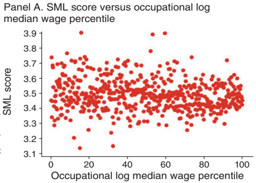
Figure 7: **Exposure to AI by demographic group**

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

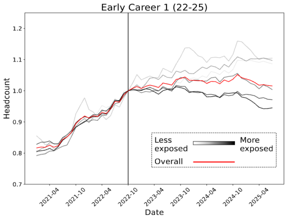




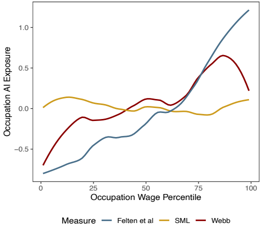
Eloundou, Manning, Mishkin & Rock 2024, "GPTs are GPTs: Labor market impact potential of LLMs"



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



Brynjolfsson, Chandar, Chen. 2025, "Canaries



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

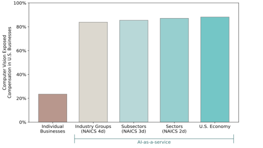


Figure 8 Fraction of vision task compensation economically-attractive to automate if single systems are deployed at this scope.

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

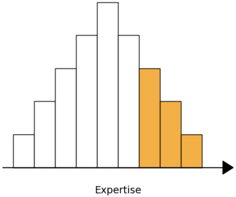
Is there ‘good exposure’ —
or is all exposure ‘bad exposure’?

Is there such thing as good automation exposure?

- **In canonical task models, automation is first-order bad, second-order okay**
  - Automation occurs when formerly labor-using tasks are reallocated to capital
  - First-order: This reduces labor demand and labor's share of national income
  - Second-order: *May* raise wages through Q-complementarity ...unless it is 'so-so'
  - New task creation—the opposite of automation—is unambiguously positive for labor
- **Adding occupations: bundles of related tasks performed together**
  - Tasks bundled in an occupation differ in their 'expertise' levels
  - Same task may be performed in many different occupations
  - When a task is automated, it's eliminated from all occupations that use it
  - But impact differs across occupations depending on where the task falls in each occ's expertise bundle
  - Eliminates "atomistic task assignment" feature/bug built from canonical task models

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

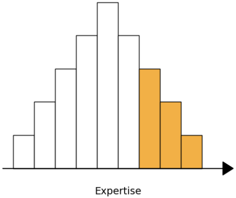
Consider an occupation that loses 25% of its tasks to automation



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

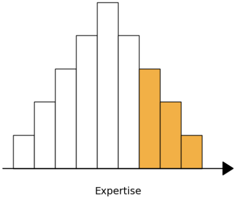


Expert tasks automated

	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

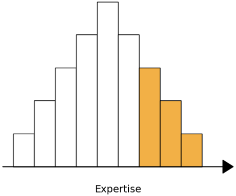


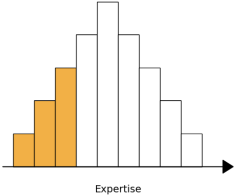
Expert tasks automated

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

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

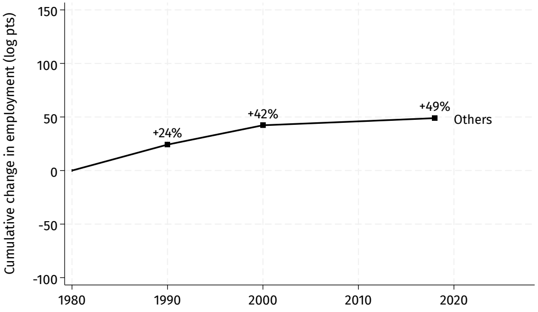
Consider an occupation that loses 25% of its tasks to automation



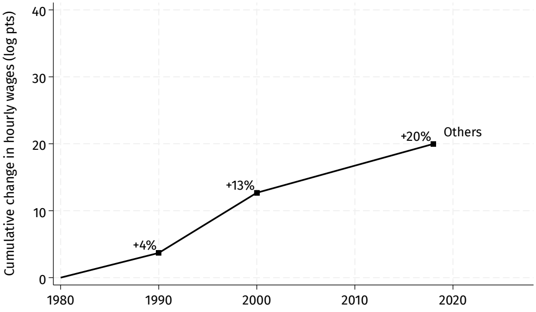


Expert tasks automated		Inexpert tasks automated
↑	Labor productivity	↑
↓	Average expertise	↑
↑	Employment	→ or ↓
→ or ↓	Wages	↑

Employment and wage changes across all U.S. occupations, 1980 – 2018

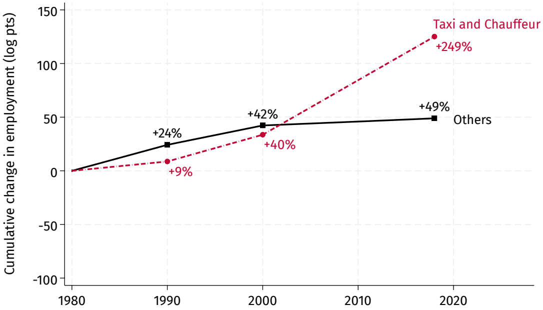


Cumulative Employment Change

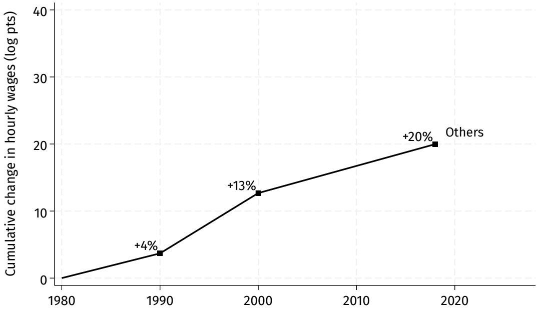


Cumulative Wage Change

Taxi driver employment rose by 209% between 2000 and 2018

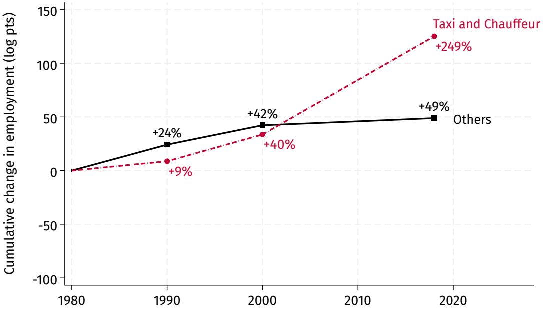


Cumulative Employment Change

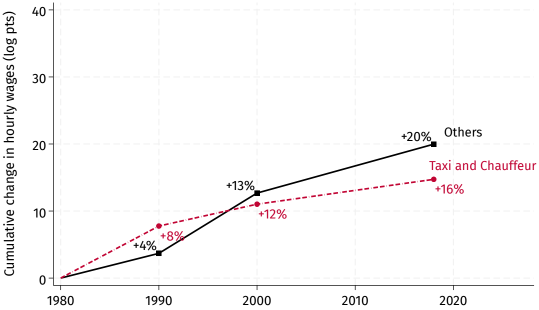


Cumulative Wage Change

Relative wages of taxi drivers fell by 5% between 2000 and 2018

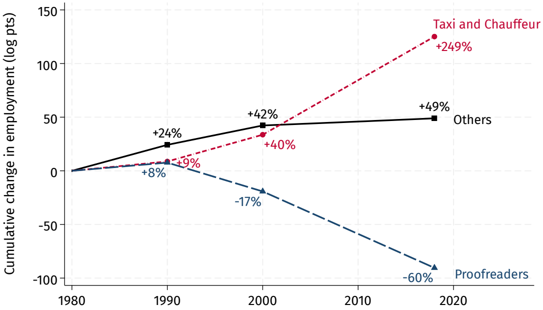


Cumulative Employment Change

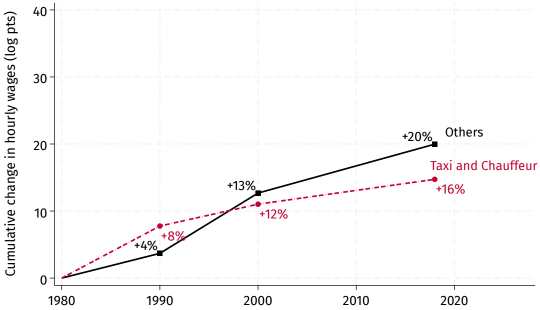


Cumulative Wage Change

Proofreader employment fell by 43% between 2000 and 2018

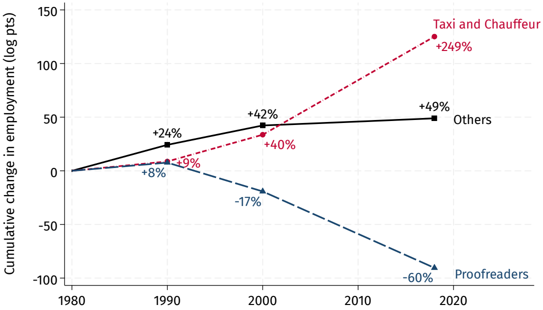


Cumulative Employment Change

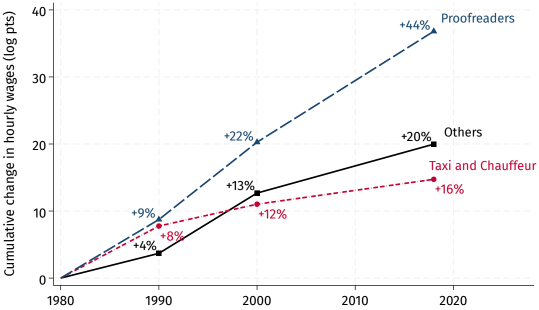


Cumulative Wage Change

Relative wages of proofreaders rose by 15% between 1980 and 2018



Cumulative Employment Change



Cumulative Wage Change

Related work that embraces a task bundling / expertise framework

Growing mini-literature

- Hampole, Papanikolaou, Schmidt, Seegmiller, "Artificial intelligence and the labor market" (NBER 2025)
- Althoff and Reichardt, "Task-specific technical change and comparative advantage" (2026)
- Freund and Mann (Lukas^2), "Job transformation, specialization, and the labor market effects of AI" (2026)
- Hosseini and Lichtenger, "Generative AI and occupational entry barriers: The labor-supply channel of technological change" (2026)

Replacing experts and augmenting expertise

A model of expertise and automation (sketch)

Expertise and automation: Foundations

1. The tasks comprising an occupation are indivisible → All must be performed
2. Accomplishing a specific task requires task-specific expertise
3. Expertise is hierarchical: More expert workers can do less expert tasks but not v.v
4. Automation displace labor in *some* expert tasks
5. All occupations contain generic, non-automatable tasks that any worker can perform

Task level production: Capital, labor, and occupations

- **Three categories of tasks:**
  1. **Generic:** $t \in (-\theta, 0]$ completed by labor of any expertise
  2. **Automated:** $t \in (0, I]$ completed by capital
  3. **Expert tasks:** $t \in (I, 1)$ completed by labor of sufficient expertise $e_i \geq t$

- **Occupations:** Which tasks a worker produces depends on her occupation
  - Occupations are indexed by $\phi \in (0, 1)$
  - Occupation ϕ requires tasks $t \in [\theta(\phi - 1), \phi]$ for production

- **Productive automation:** We assume that the relative productivity of capital to labor, η, is sufficiently high for producers to use capital whenever possible.

Task level production: Allocation of labor and capital

- Production function for tasks produced by labor

$$x_L(t, \ell_i(t)) = \begin{cases} \ell_i(t), & t \in (-\theta, e_i] \\ 0, & \text{otherwise} \end{cases}$$

- Production function for tasks produced by capital

$$x_K(t, \kappa_i(t)) = \begin{cases} \eta \kappa_i(t), & t \in (0, I] \\ 0, & \text{otherwise} \end{cases}$$

where $\eta > 1$ is the productivity of capital relative to labor

What workers produce: Occ level production function

- Each worker's output in an occupation is Cobb-Douglas

$$\ln\left(\frac{y_i(\phi)}{T(\phi)}\right) = T(\phi)^{-1}\left[\underbrace{\int_{\theta(\phi-1)}^{0} \ln(\ell_i(t))\,dt}_{\text{Generic}} + \underbrace{\int_{0}^{I(\phi)} \ln(\kappa_i(t)\eta)\,dt}_{\text{Automated}} + \underbrace{\int_{I(\phi)}^{\phi} \ln(\ell_i(t)\mathbf{1}\{e_i \geq\})\,dt}_{\text{Expert}}\right]$$

- Task bundling
  - Output is zero if i has insufficient expertise for any positive measure of tasks required in ϕ
- Expertise sufficiency
  - i can produce non zero-quantity of output in ϕ iff $\max\{e_i, I\} \geq \phi$
- Return to capital equated across all tasks
  - Each worker i in occupation ϕ subdivides k_i units of capital and 1 unit of labor across tasks in ϕ

Production of (final) consumption good: Combining occupational outputs

- Final consumption good is CES aggregate of occupation-level products:

$$Y = \left(\int_0^1 Y(\phi)^{\frac{\lambda-1}{\lambda}} \, d\phi \right)^{\frac{\lambda}{\lambda-1}}, \quad \lambda > 1.$$

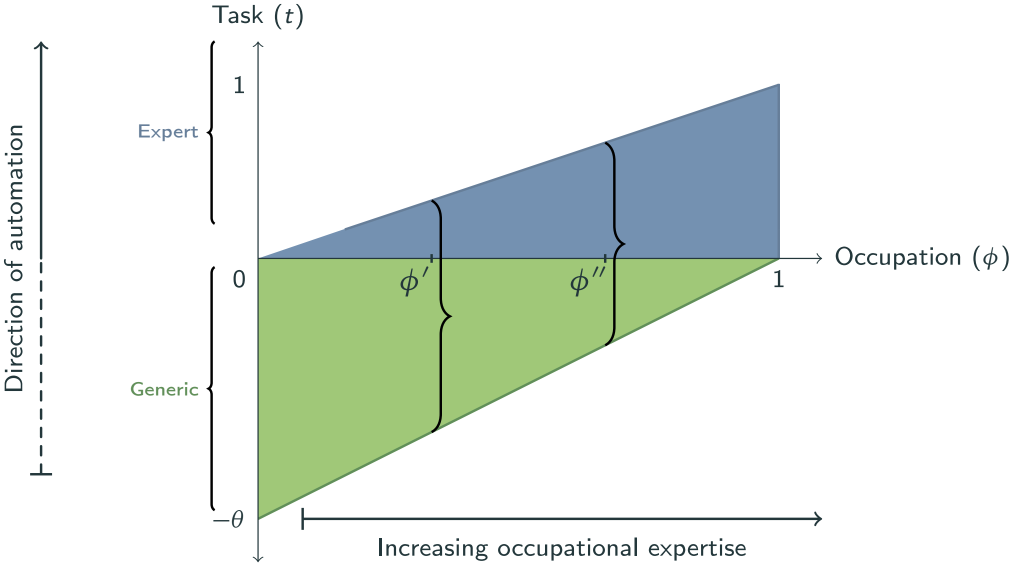
- $\lambda > 1 \rightarrow$ occupations are gross-substitutes in final good production
  - No 'immiserating' automation where productivity growth saturates demand for an occupation

- Total supplies of capital and labor are fixed: $\bar{L} = \int_0^1 L(\phi) d\phi, \quad \bar{K} = \int_0^1 K(\phi) d\phi$
  - Inelastic supply of capital $\rightarrow$ Wages do not automatically rise as automation advances

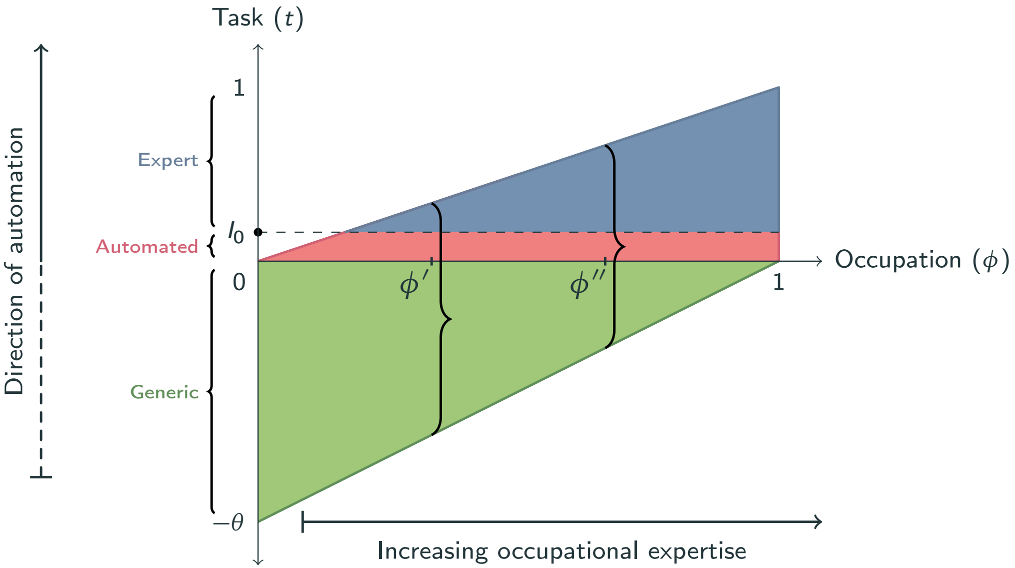
Key inputs linking assumptions to results

- Absent automation, experts are not scarcer or higher paid than non-experts
  - Experts can always substitute for non-experts but not vice-versa
  - Creates no-arbitrage condition: Non-experts cannot earn more than experts
- Demand for each occupation is elastic ($\sigma > 1$)
  - No 'immiserating' automation where productivity growth saturates occupation demand
- Inelastic capital supply
  - If capital supply elastic, all benefits of automation ultimately accrue to workers
  - Nothing interesting about that
- Labor complementarity and expertise substitution
  - Automation always complements labor
  - But automation also substitutes for expertise
  - Advancing automation renders some expertise generic, complements remaining expertise

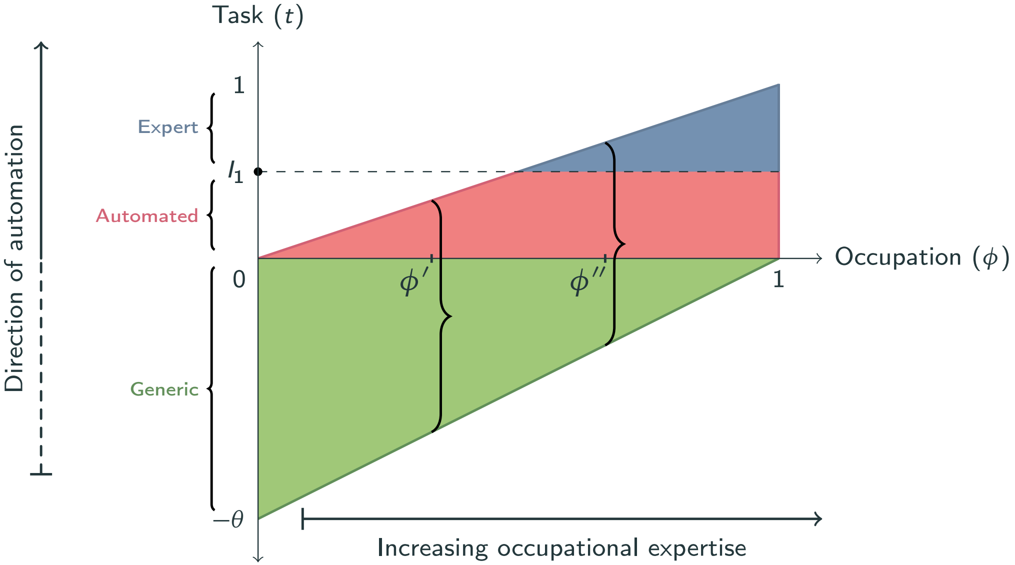
Space of tasks and occupations: Occupations on x-axis, tasks on y-axis



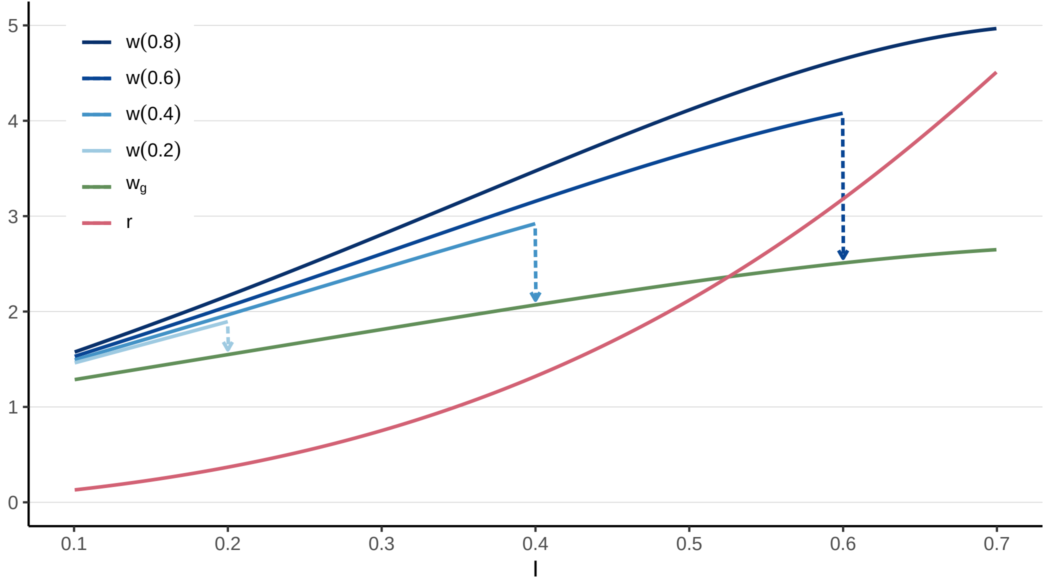
Visualization automation ⟶ Rising I



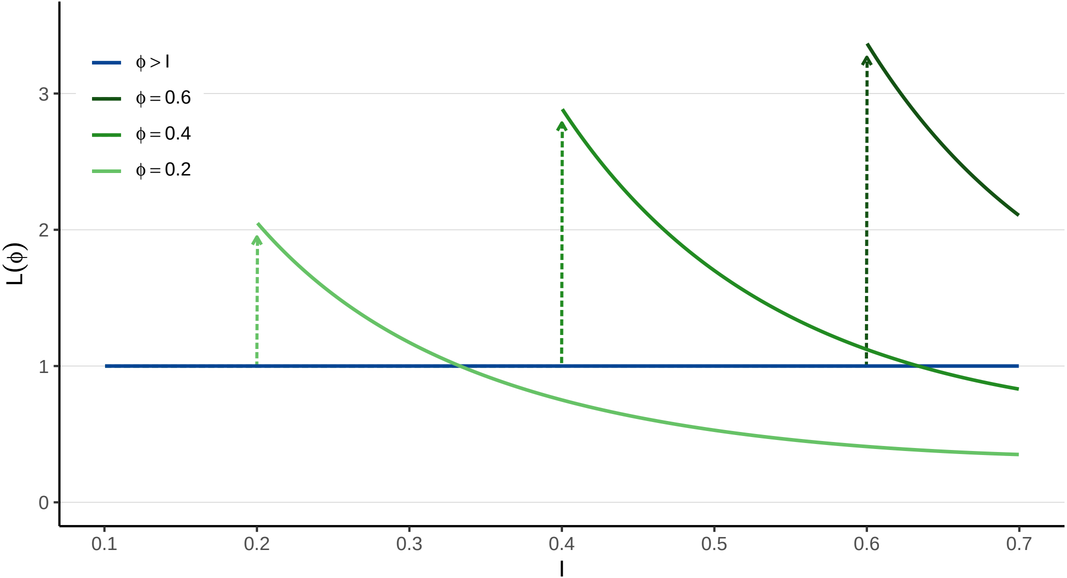
Further automation: Rise in I from $I_0 \rightarrow I_1$



Wages: Automation raises expert wages — until expertise becomes generic



Labor arbitrage: Occupations grow when their expertise is made generic



General Equilibrium: Wages and employment

1. The wage in expert occupations is strictly greater than that in generic ones
2. Wages fall in occupations that were previously expert as they are rendered generic by a small increase in I
3. There is a sudden influx of inexpert labor into those occupations

Implications

Primary implications taken to the data

1. **Wage levels:** Expert work commands higher wages than generic work
   - Even within education groups
   - Even within white collar, blue collar, and service occupations
2. **Task $\Delta' s \longleftrightarrow$ Expertise:** Adding/removing tasks may raise or lower expertise demands
   - Adding tasks may lower expertise demands — *if tasks added are inexpert*
   - Removing tasks may raise expertise — *if tasks removed are inexpert*
3. **Wages v emp:** Δ Expertise demands have countervailing effects on occ wages v emp
   - Increase in expertise demand will raise wages, reduce employment (both relative)
   - Fall in expertise demand will reduce wages, raise employment (both relative)

What's ahead

I. Measurement

1. Building a content-agnostic index of task expertise
2. Measuring changes in occupations' expertise requirements

II. Results

1. Does ΔExpertise predict ΔWages?
2. Does ΔExpertise predict ΔEmployment with opposite sign?
3. Are ΔExpertise levels distinct from ΔTask quantities?
4. Causal test: Using routine task removal to identify quasi-exogenous ΔExpertise, ΔTasks
5. Pre-release beta: in-progress work w/Lucy Hampton, Neil Thompson, & Can Yeșildere

Measurement I of (II) —

A content-agnostic index of task expertise requirements

Expertise and the Efficient Coding Hypothesis (ECH)

- Natural language speakers face a tradeoff between **brevity** and **clarity**
  - Brevity — minimizing bandwidth utilization (or effort)
  - Clarity — minimizing miscommunication risk
- Familiar words: profit, inflation
  - Sophisticated ideas, but frequently encountered, so commonly understood
  - Used by experts and non-experts in everyday conversation
- Expert words: elasticity, arbitrage
  - Equally sophisticated ideas, **not** frequently encountered
  - Used by domain experts but few others encounter them
  - Expert could say, "percent change in one variable caused by a percent change in another"
- Tradeoff leads to 'efficient coding' — trading off between brevity and clarity

Building a content-agnostic measure of job task expertise requirements

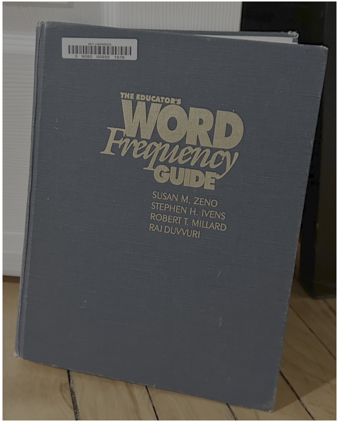
Efficient coding explains why experts use distinct vocabularies (AKA, jargon)

- Implication: Experts develop and use precise words for events that are common within the expert's domain but not otherwise (e.g., elasticity, arbitrage, hyper-parameter)

Measuring expertise of job tasks by leveraging efficient coding hypothesis

- Non-expert tasks will use words/concepts that are familiar to most adults
- Expert tasks will use words that are
  - Infrequent among non-experts
  - Low-entropy — found in a small subset of corpora
- **Empirical counterpart**
  - Task expertise is decreasing in both commonality and entropy of task descriptive words

Frequency & entropy: The Educator's Word Frequency Guide (Zeno '95)



Use the SFI *(Standard Frequency Index)* to capture entropy and frequency

- Data from the *Educator's Word Frequency Guide*
- A compilation of frequency statistics for 160,000 words
- Using texts from 1st grade to college level (Zeno '95)

$$SFI \equiv -10 \cdot (\log_{10}(F/D) + 4)$$

- Where F is raw frequency, D is entropy
- We take $100 - SFI$ so it is *increasing* in expertise

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

Source for occupational task enumerations

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

Source for employment and earnings data

- Harmonized US Census employment and earnings data for 1980 and 2018 from Autor Chin Salomons Seegmiller (ACSS) '24
- 306 consistent, comprehensive occupations (`occ1990dd18`)

Measuring expertise of job tasks: Examples

Examples of high expertise job tasks

- Reinstalls plumbing and electrical and rigging connections (Mechanics, 1977, $XPT = 9.11$)
- May operate punchcard tabulating machines, such as sorters and collators (Office machine operators, 1977, $XPT = 11.31$)
- Sing a cappella or with musical accompaniment (Musicians, 2018, $XPT = 11.25$)
- Monitor the arrival, parking, refueling, loading, and departure of all aircraft. (Air traffic controllers, 2018, $XPT = 4.15$)

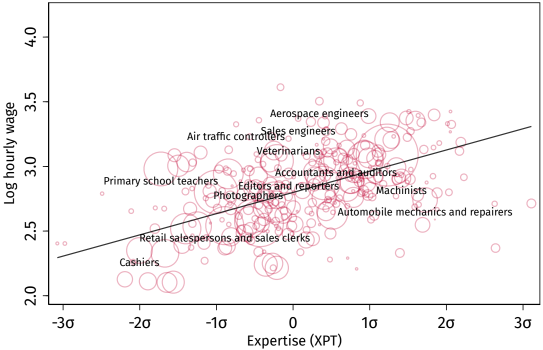
Examples of low expertise job tasks

- Makes beds (Housekeepers, 1977, $XPT = -10.93$)
- Print and make copies of work (Typists, 2018, $XPT = -8.06$)
- Transport mail from one work station to another (Postal clerks, 2018, $XPT = -7.28$)
- Guards street crossings during hours when children are going to or coming from school (Crossing guards, 1977, $XPT = -8.13$)

Expertise and log wages by occupation, 1980 and 2018

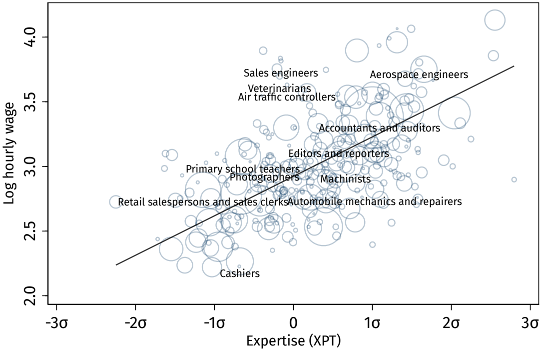
$$\ln(\text{Wage})_{jt} = \alpha_t + \beta_t \text{XPT}_{jt} + \epsilon_{jt}$$

1980



Slope: 0.16 (0.01), R2: 0.32, N: 303

2018

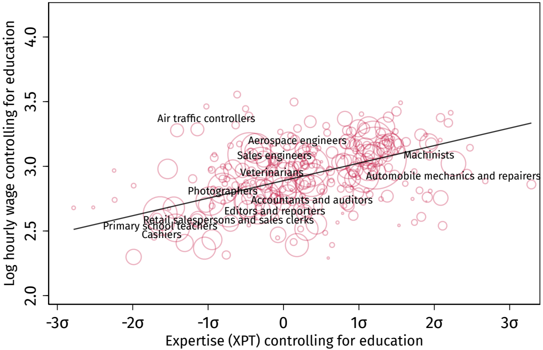


Slope: 0.31 (0.02), R2: 0.49, N: 303

Expertise and log wages by occupation, conditional on education

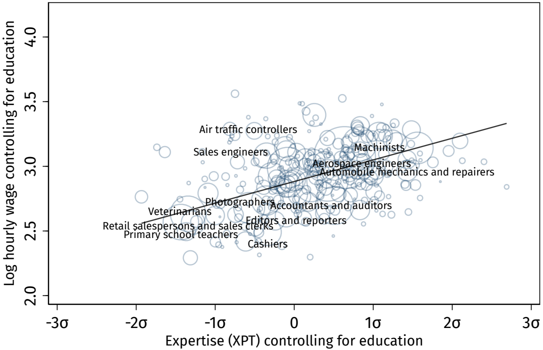
$$\ln(\text{Wage})_{jt} = \alpha_t + \beta_t \text{XPT}_{jt} + \sum_{g=1}^{4} \theta_{gt} \text{ShareEdu}_{jgt} + \lambda_{occ} + \epsilon_{jt}$$

1980



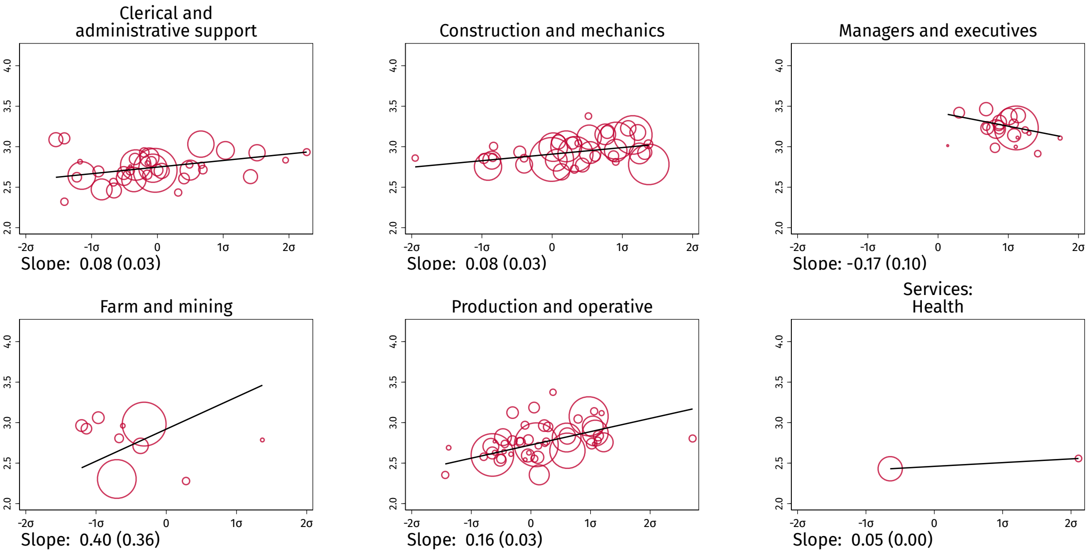
Slope: 0.14 (0.01), Partial R2: 0.31, N: 303

2018

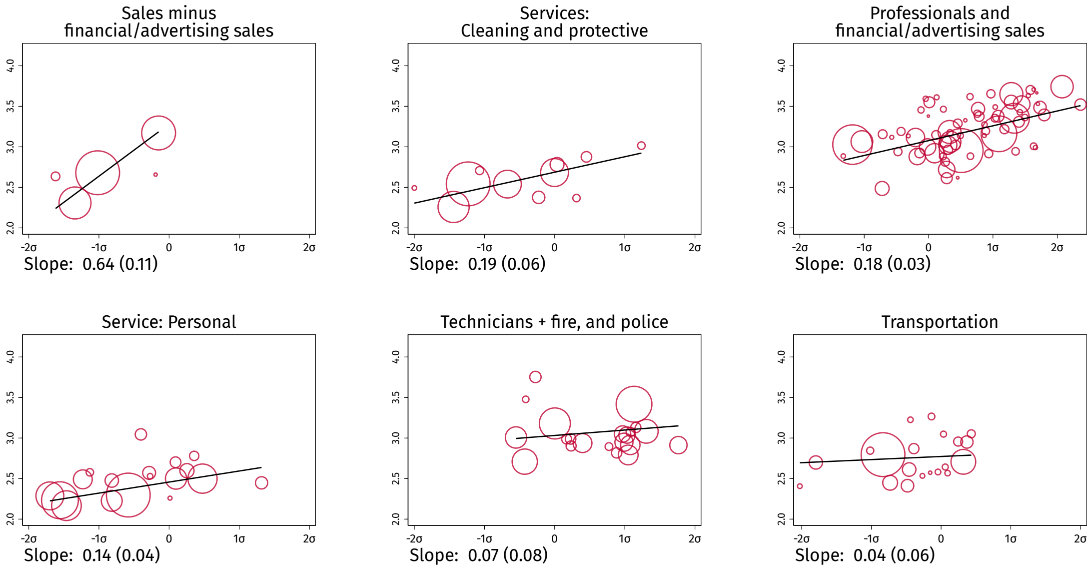


Slope: 0.17 (0.01), Partial R2: 0.32, N: 303

Expertise/wage scatterplots by broad occupation



Expertise/wage scatterplots by broad occupation



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

	25th Percentile			75th Percentile		
Occupation	**Title**	**XPT**	**ln(Wage)**	**Title**	**XPT**	**ln(Wage)**
Professionals	Social workers	0.09	2.92	Computer scientists	1.33	3.35
Technicians	Machine Programmers	0.17	2.99	Chemical technicians	1.08	3.08
Clerical	Bank tellers	-0.66	2.46	Weighers and measurers	0.49	2.78
Services	Janitors	-1.23	2.54	Landscaping supervisors	0.45	2.88

Within-occupation evidence: Person-level variation in expertise and wages

Within *detailed* occupations, are workers with more expert tasks paid more?

- Survey data taken from the PDII (*Princeton Data Improvement Initiative*), 2008
- Workers summarize 'the general duties of their job' in their own words
  e.g., "dumping trash", "I sit all day and make decisions"
- We clean these task statements and calculate expertise
- The dataset also contains educational attainment, gender, ethnicity and experience

$$\ln w_{ij} = \alpha + \beta_1 xpt_{ij} + \delta_1 X_i + \gamma_j + \epsilon_{ij},$$

where	X_i	is a vector of human capital and demographic controls,
	γ_j	are SOC occupation fixed effects.

Within-occupation evidence: Person-level variation in expertise and wages

	(1)	(2)	(3a)	(3b)	(4)
Expertise	0.0229***	0.0178***	0.0066**	0.0085***	0.0055*
	(0.0036)	(0.0034)	(0.0032)	(0.0029)	(0.0031)
Demographic dummies	No	Yes	Yes	Yes	Yes
Education/experience	No	No	No	Yes	Yes
Occupation dummies	No	No	Yes	No	Yes
# of occ dummies	0	0	240	0	240
Observations	1,295	1,295	1,295	1,295	1,295
R-squared	0.0301	0.1497	0.6185	0.4016	0.6486

In each specification, $\ln(w)$ is the dependent variable.

Measurement II of (II) —

Changes in occupations' expertise requirements

Measuring tasks added/removed: DOT & O*Net created 40 years apart

Dictionary of Occupational Titles, 1977

078.361-014 MEDICAL TECHNOLOGIST (medical ser.)
Performs chemical, microscopic, serologic, hematologic, immunohematologic, parasitic, and bacteriologic tests to provide data for use in treatment and diagnosis of disease: Receives specimens for laboratory, or obtains such body materials as urine, blood, pus, and tissue directly from patient, and makes quantitative and qualitative chemical analyses. Cultivates, isolates, and identifies pathogenic bacteria, parasites, and other micro-organisms. Cuts, stains, and mounts tissue sections for study by PATHOLOGIST (medical ser.). Performs blood tests for transfusions, studies morphology of blood. Groups or types blood and cross-matches that of donor and recipient to ascertain compatibility. Engages in medical research to further control and cure disease. May calibrate and use equipment designed to measure glandular and other bodily activity [NUCLEAR MEDICAL TECHNOLOGIST (medical ser.)]. May take electrocardiograms. May train and supervise MEDICAL-LABORATORY TECHNICIAN (medical ser.) and student MEDICAL TECHNOLOGISTS (medical ser.). May be designated according to field of specialization as BLOOD-BANK TECHNOLOGIST (medical ser.); HEMATOLOGY TECHNOLOGIST (medical ser.); SEROLOGY TECHNOLOGIST (medical ser.).

O*NET Database v30.0, 2025

Medical and Clinical Laboratory Technologists

Tasks

All 16 displayed

- Analyze samples of biological material for chemical content or reaction.
- Analyze laboratory findings to check the accuracy of the results.
- Conduct chemical analysis of body fluids, including blood, urine, or spinal fluid, to determine presence of normal or abnormal components.
- Enter data from analysis of medical tests or clinical results into computer for storage.
- Collect and study blood samples to determine the number of cells, their morphology, or their blood group, blood type, or compatibility for transfusion purposes, using microscopic techniques.
- Set up, clean, and maintain laboratory equipment.
- Operate, calibrate, or maintain equipment used in quantitative or qualitative analysis, such as spectrophotometers, calorimeters, flame photometers, or computer-controlled analyzers.
- Establish or monitor quality assurance programs or activities to ensure the accuracy of laboratory results.
- Supervise, train, or direct lab assistants, medical and clinical laboratory technicians or technologists, or other medical laboratory workers engaged in laboratory testing.
- Select and prepare specimens and media for cell cultures, using aseptic technique and knowledge of medium components and cell requirements.
- Obtain, cut, stain, and mount biological material on slides for microscopic study and diagnosis, following standard laboratory procedures.
- Provide technical information about test results to physicians, family members, or researchers.
- Develop, standardize, evaluate, or modify procedures, techniques, or tests used in the analysis of specimens or in medical laboratory experiments.
- Cultivate, isolate, or assist in identifying microbial organisms or perform various tests on these microorganisms.
- Harvest cell cultures at optimum time, based on knowledge of cell cycle differences and culture conditions.
- Conduct blood typing and antibody screening.

How we measure tasks removed and added

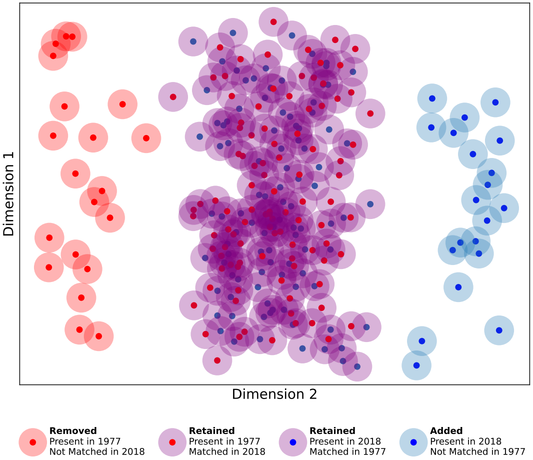
❶ **Encode tasks**: Transform each task description to 1,536 dimensional vector (OpenAI `text-embedding-3-small`)

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**

task added v.s. new titles



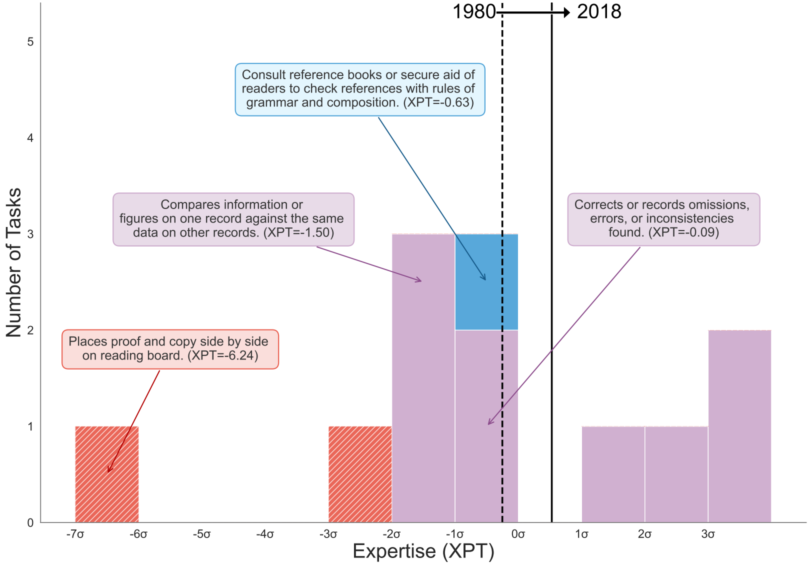
Tasks removed and added: File Clerk occupation, 1977–2018

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 : 13.16%
Average exp in 1977: 0.22
exp of removed: -1.53, Effect: +0.23

Share of added tasks : 5.26%
Average exp in 1977: 0.22
exp of added: -4.74, Effect: -0.26

Expertise upgrading due to task removal: Proofreaders



Calculating changes in task counts and expertise requirements

- **Change in expertise due to task addition or removal**

$$\Delta \mathrm{XPT}_j^{sub} \equiv \mathrm{XPT}_{j,1977}^{ret} - \mathrm{XPT}_{j,1977}$$
$$\Delta \mathrm{XPT}_j^{add} \equiv \mathrm{XPT}_{j,2018} - \mathrm{XPT}_{j,2018}^{ret}$$
$$\Delta \mathrm{XPT}_j^{net} \equiv \Delta \mathrm{XPT}_j^{sub} + \Delta \mathrm{XPT}_j^{add}.$$

- **Share of tasks added and removed, 1980–2018**

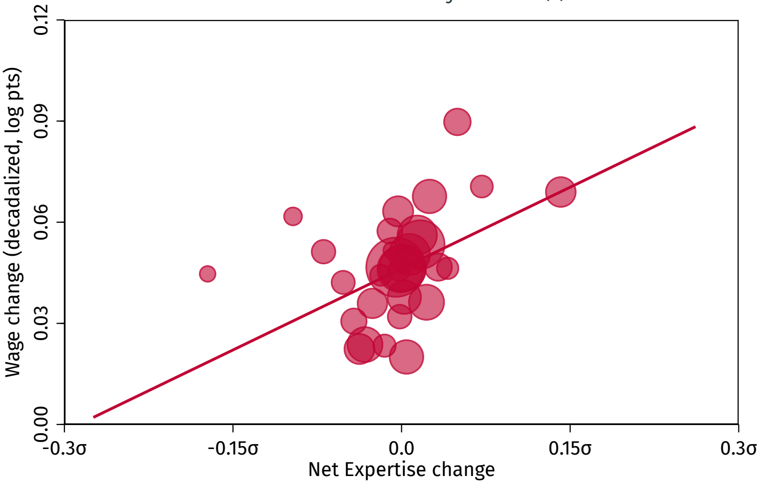
$$\Delta \mathrm{TASK}_j^{sub} \equiv 1 - {}^{N_{j\in ret}^{1977}}/_{N_j^{1977}}$$
$$\Delta \mathrm{TASK}_j^{add} \equiv 1 - {}^{N_{j\in ret}^{2018}}/_{N_j^{2018}}$$
$$\Delta \mathrm{TASK}_j^{net} \equiv \Delta \mathrm{TASK}_j^{add} - \Delta \mathrm{TASK}_j^{sub}$$

Evidence I of IV —

Does ΔExpertise predict ΔWages?

Change in occupational wages and ΔXPT (expertise), 1980–2018

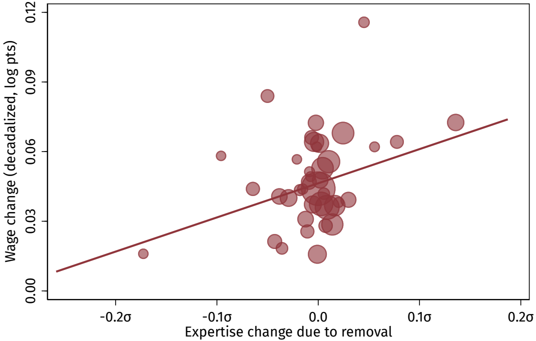
$$\Delta \ln w_j = \alpha + \beta \Delta \mathrm{XPT}_j^{net} + \gamma_{J(j)} + \epsilon_j$$



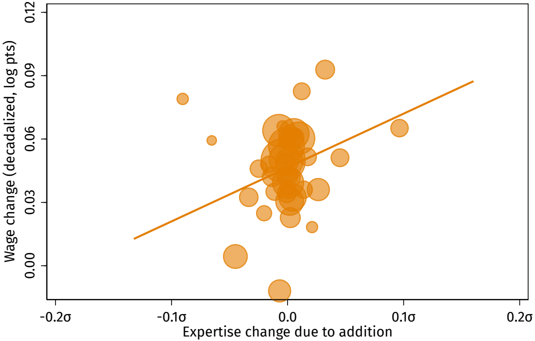
Slope: 0.16 (0.05), Partial R2: 0.04, N: 303

Removing inexpert tasks and adding expert tasks: Both ↑ wages

$$\Delta \ln w_j = \alpha + \beta_1 \Delta \mathrm{XPT}_j^{sub} + \beta_2 \Delta \mathrm{XPT}_j^{add} + \gamma_{J(j)} + \epsilon_j$$



Slope: 0.15 (0.05), Partial R2: 0.43, N: 303



Slope: 0.26 (0.09), Partial R2: 0.43, N: 303

Δ Expertise: Task Removal

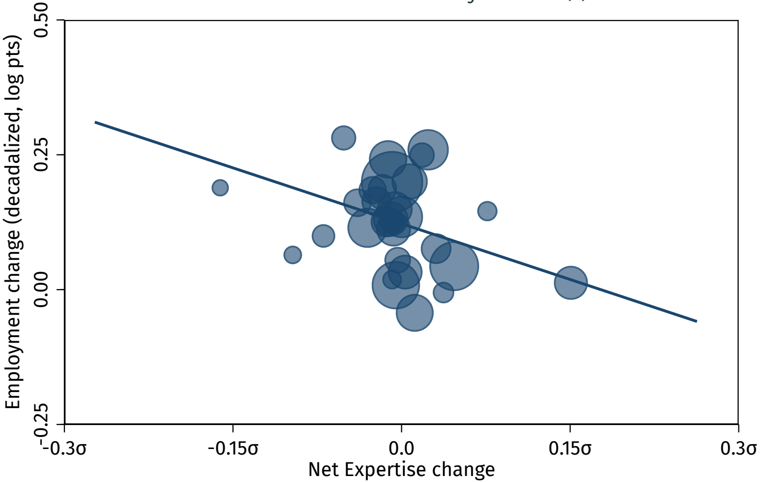
Δ Expertise: Task Addition

Evidence II of IV —

Does $+\Delta$Expertise predict $-\Delta$Employment?

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

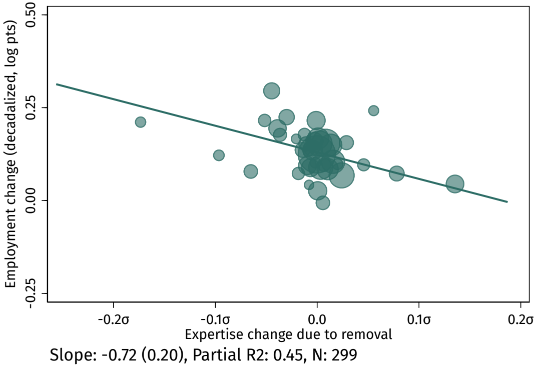
$$\Delta \ln \text{EMP}_j = \alpha + \beta \Delta \text{XPT}_j^{net} + \gamma_{J(j)} + \epsilon_j$$

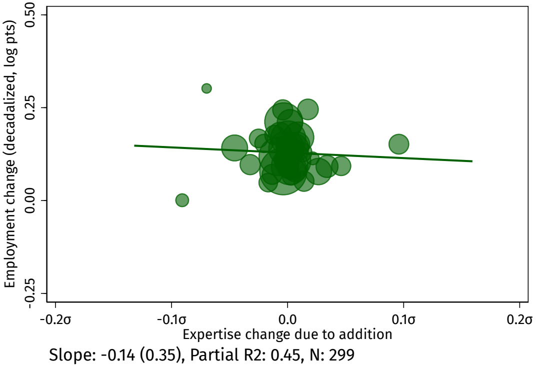


Slope: -0.69 (0.24), Partial R2: 0.02, N: 303

Removing inexpert tasks and adding expert tasks: $\downarrow$ employment

$$\Delta \ln \mathrm{EMP}_j = \alpha + \beta_1 \Delta \mathrm{XPT}_j^{sub} + \beta_2 \Delta \mathrm{XPT}_j^{add} + \gamma_{J(j)} + \epsilon_j$$





Δ Expertise: Task Removal

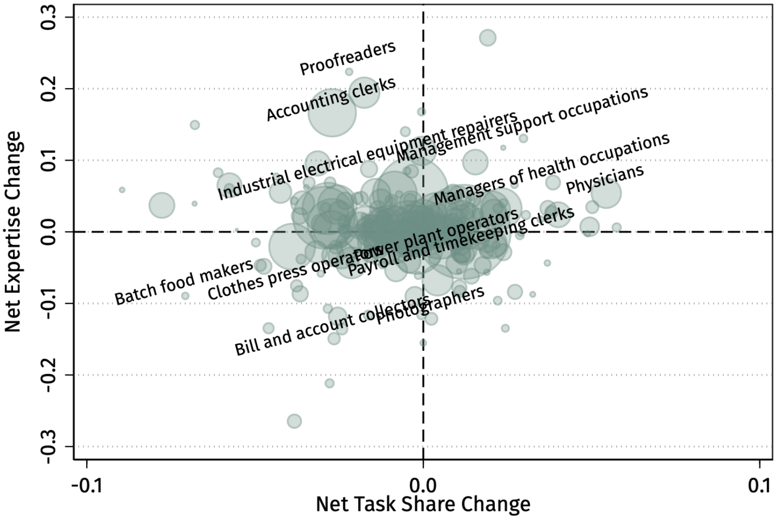
Δ Expertise: Task Addition

Evidence III of IV —

Distinguishing ΔExpertise vs ΔTasks

Key distinction: ΔExpertise reduces labor supply
ΔTasks raises labor demand

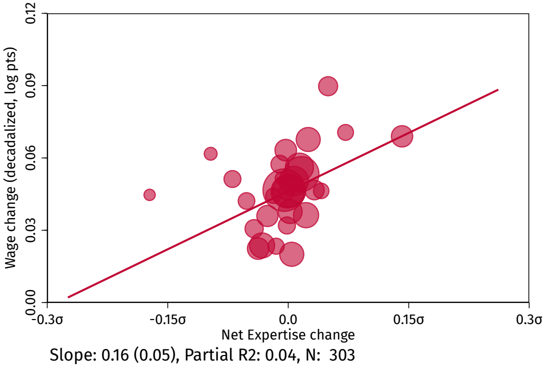
Occupation-level $\Delta's$ in task %, task expertise, 1980–2018 → Uncorrelated

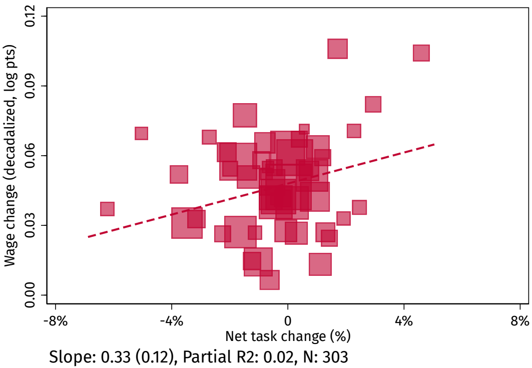


Slope: -0.19 (0.14), adj-R2: 0.00, N: 303

How many tasks vs which tasks: Wage regressions

$$\Delta \ln w_j = \alpha + \beta_1 \Delta \mathrm{XPT}_j^{net} + \beta_2 \Delta \mathrm{TASK}_j^{net} + \gamma_{J(j)} + \epsilon_j,$$

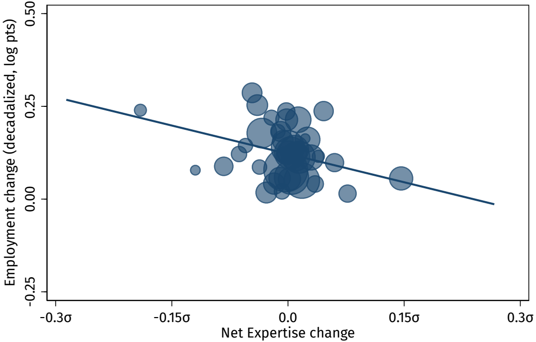




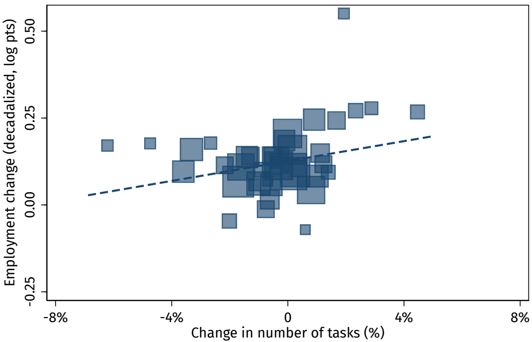
Change in Expertise (σ) **Change in Tasks (%)**

How many tasks vs which tasks: Employment regressions

$$\Delta \ln \text{EMP}_j = \alpha + \beta_1 \Delta \text{XPT}_j^{net} + \beta_2 \Delta \text{TASK}_j^{net} + \gamma_{J(j)} + \epsilon_j$$



Slope: -0.51 (0.20), Partial R2: 0.43, N: 303



Slope: 1.43 (0.52), Partial R2: 0.43, N: 303

Change in Expertise (σ)

Change in Tasks (%)

Evidence IV of IV —

Routine task removal and expertise polarization

Paradox: Sharp employment polarization but modest wage polarization

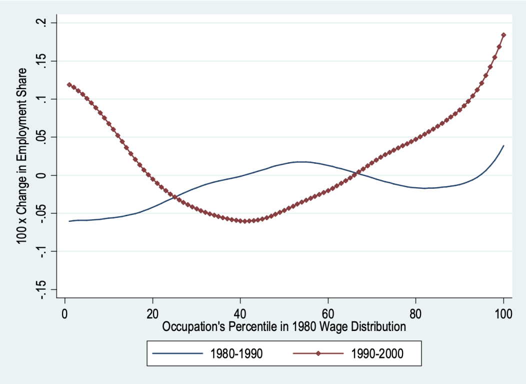


Figure 3. Smoothed Changes in Occupational Employment Shares 1980 - 2000, with occupations ranked by their 1980 Median Wage. Source: Census Integrated Public Use Microsamples, 1980, 1990 and 2000.

Employment

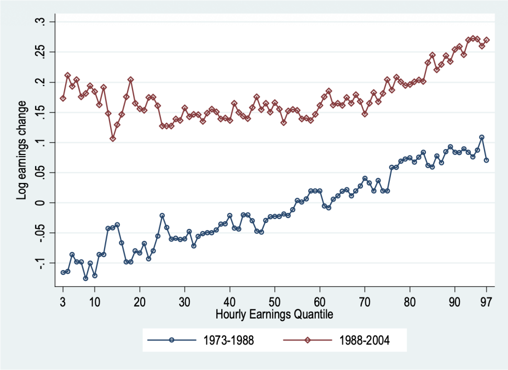
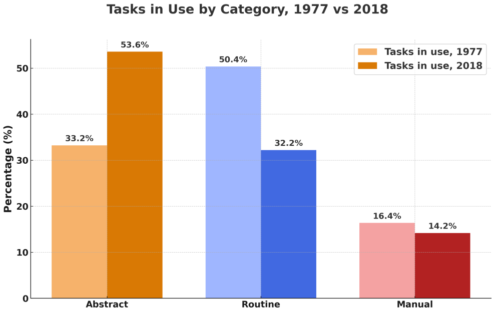


Figure 2. Changes in Male and Female Log Real Hourly Earnings by Percentile 1973 - 1988 and 1988 - 2004. Source: see Figure 1.

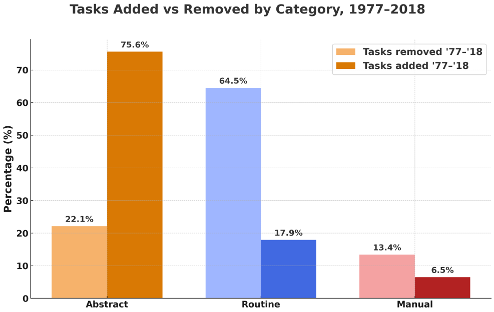
Wages

Tasks in-use, added, and removed, 1977-2018: Abstract, Routine, Manual

Routine share of tasks in use
fell from 50% to 32%



65% of tasks removed were Routine
76% of *tasks added were Abstract*



Calculating routine task exposure: ΔExpertise and ΔTasks

- Calculate $\Delta\text{Expertise}_j$, ΔTasks_j if all 1980 routine tasks were removed from j

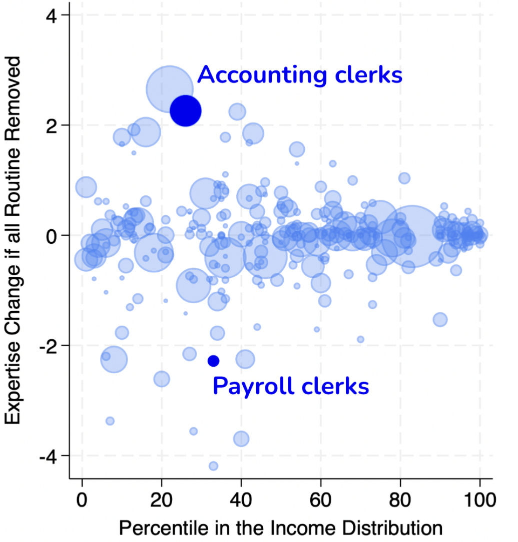
Predicted change in expertise: $\Delta\widetilde{\mathrm{XPT}}_j \equiv \mathrm{XPT}^{\mathrm{nr}}_{j,1977} - \mathrm{XPT}_{j,1977}$

Predicted change in tasks: $\Delta\widetilde{\mathrm{TASK}}_j \equiv 1 - \dfrac{N^{1977}_{j\in\mathrm{nr}}}{N^{1977}_j}$

- Regress changes in Δexpertise, Δwages, and Δemployment on these variables

$$\Delta Y_j = \alpha + \beta_1 \Delta\widetilde{\mathrm{XPT}}_j + \beta_2 \Delta\widetilde{\mathrm{TASK}}_j + \gamma \mu_{0j} + \varepsilon_j.$$

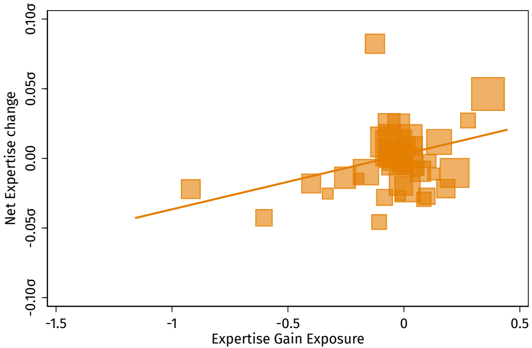
How routine task removal predictor works



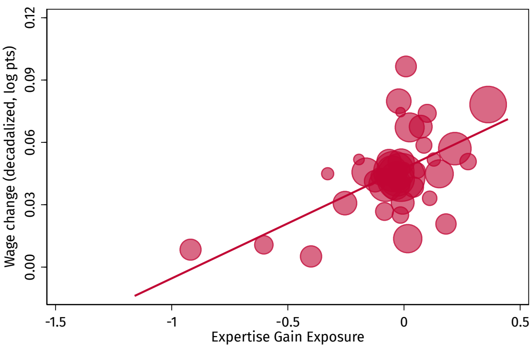
- Accounting Clerks were at the 28^{th} wage pctile in 1980
- Payroll Clerks were at the 33^{rd} pctile in 1980
- If all routine tasks removed from Accounting Clerk expertise rises: $\Delta\widetilde{\mathrm{XPT}}_j \approx +2\sigma$
- If all routine tasks removed from Payroll Clerk expertise falls: $\Delta\widetilde{\mathrm{XPT}}_j \approx -2\sigma$

Routine task removal predicts expertise and wage changes

$$\Delta Y_j = \alpha + \beta_1 \Delta \widetilde{XPT}_j + \beta_2 \Delta \widetilde{TASK}_j + \gamma_{J(j)} + \epsilon_j$$



Slope: 0.04 (0.01), Partial R2: 0.14, N: 300



Slope: 0.05 (0.01), Partial R2: 0.48, N: 300

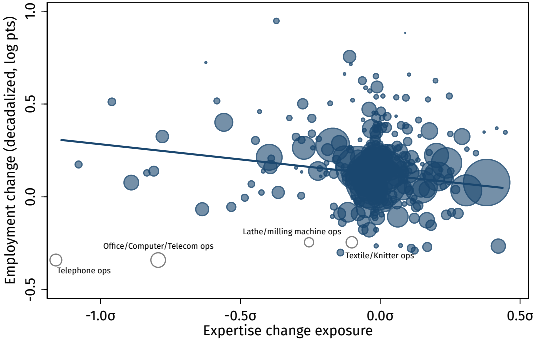
Predicted expertise change
vs. actual expertise change

Predicted expertise change
vs. actual wage change

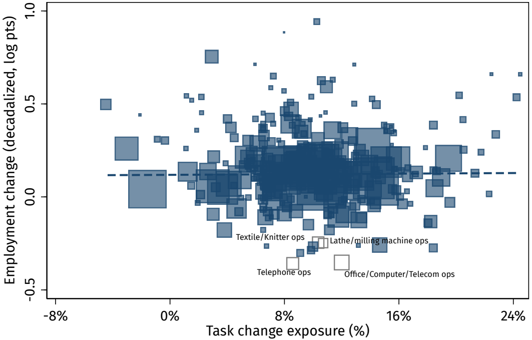
Many routine-task intensive occs contract as they become more expert

Change in employment vs. predicted change in expertise and tasks

$$\Delta \ln \text{EMP}_j = \alpha + \beta_1 \Delta\widetilde{\text{XPT}}_j + \beta_2 \Delta\widetilde{\text{TASK}}_j + \gamma_{J(j)} + \epsilon_j$$



Slope: -0.16 (0.04), Partial R2: 0.05, N: 296



Slope: 0.04 (0.17), Partial R2: -0.00, N: 296

$\Delta \text{Emp}_j | \Delta\widetilde{\text{XPT}}_j$

$\Delta \text{Emp}_j | \Delta\widetilde{\text{Tasks}}_j$

Conclusions

- Automation both replaces experts and augments expertise
  - Relevant questions is not exclusively *how many tasks* but also *which tasks*
- Focusing only on technology *exposure* assumes replacement, ignores augmentation
  - Consider checkout clerks (high exposure) vs. data scientists (high exposure)
  - Or air traffic controllers (high exposure) vs. crossing guards (low exposure)
- Consider both quantity and expertise—AKA, content—of job tasks
  - Current paper 'predicts the past'
  - Extending from *backcasting* to *forecasting*
  - **Forecasting:** See Hosseini and Lichtenger, "Generative AI, Expertise, and Inequality: A Race Between Productivity and Scarcity" (2026)