Automation, New Work, and Human Expertise

ABFER 11th Annual Conference Master Class

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MIT Shaping the Future of Work Initiative

23 May 2024

Agenda

1. **Expertise – A unifying conceptual notion**
2. **The task model – What is it, and why is it?**
3. **Recent evidence on new work**
4. **Some concluding thoughts**

What makes labor economically valuable?

In industrialized countries, labor's value arguably comes from expertise

- *Def'n* **Expertise**: Domain-specific knowledge or competency thatâs needed to accomplish a particular goal

Not all expertise is valuable — two conditions needed for specific expertise to have market value

1. Enables a valuable objective
   - Data sciences, not (most) card tricks
2. Is scarce
   - Diamond water paradox
   - The ‘Syndrome paradox’


WHEN EVERYONE IS SPECIAL
NO ONE IS.
memegenerator.net

Stranded expertise: London black cab drivers

London's Cabbies Say 'The Knowledge' Is Better Than Uber And A GPS

OCTOBER 21, 2015 · 1:15 PM ET

HEARD ON ALL THINGS CONSIDERED

Leila Fadel

3-Minute Listen + PLAYLIST

Taxis wait in London in June 2014. By law, the drivers of London's black cabs must memorize all of the city's streets, a process that takes years of study. The taxi drivers are opposed to Uber and drivers using a GPS, but the High Court ruled in favor of Uber last week.

Why was computerization labor-displacing for admin assistants but not for economists?

From expertise perspective, what makes an innovation 'good' or 'bad' for labor?

Expertise-complementary innovations

1. **Automate non-expert tasks**
   - Tasks that are not specialized but nevertheless complementary become cheaper, less labor-intensive
   - Remaining labor-demanding tasks become scarcer, hence more valuable
   - Relies on the idea that new expert labor is not elastically supplied

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2. **Instantiate new demands for expertise**
   - Novel human capital required that is not already abundant or very readily acquired
   - Knowledge of new tool – AI radiology
   - Provision of new good or service – Flight, indoor plumbing, pickleball instruction

Expertise-displacing innovations

1. 'Strand' previously valuable expertise – making it economically irrelevant (e.g., Waze + London taxi drivers)
2. Crowd workers into elastically supplied, non-expert tasks (*Snow Crash* scenario)
3. Make expertise 'too' abundant – the Syndrome paradox

Many of these questions involve some notion of task bundling within jobs

See papers by

- Dessain and Santos, "Adaptive organizations," *JPE* 2006
- Oren Danieli, "Revisiting US wage inequality at the bottom 50%" *ReStud* forthcoming

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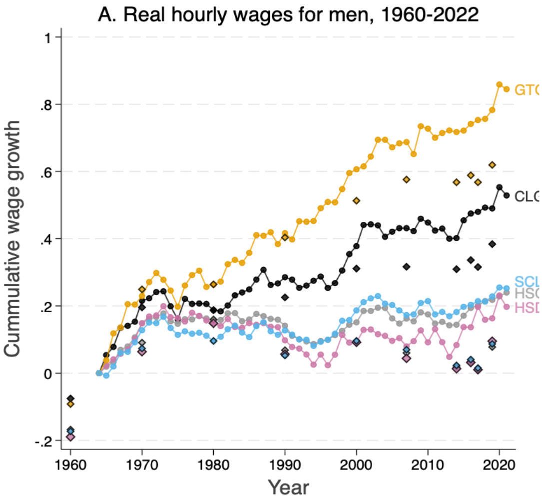
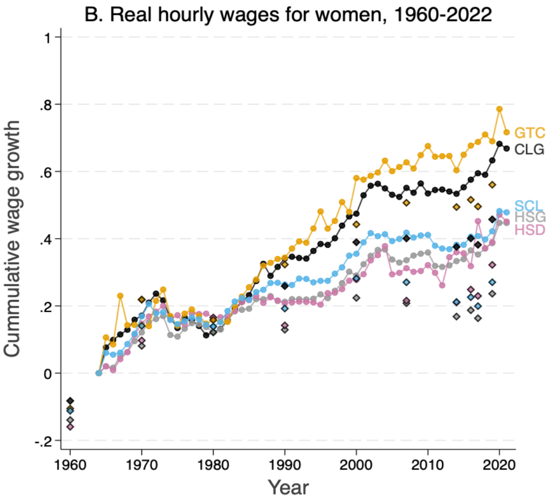
Why a ‘Task Model’?

Linking Expertise, Tasks, and Technologies

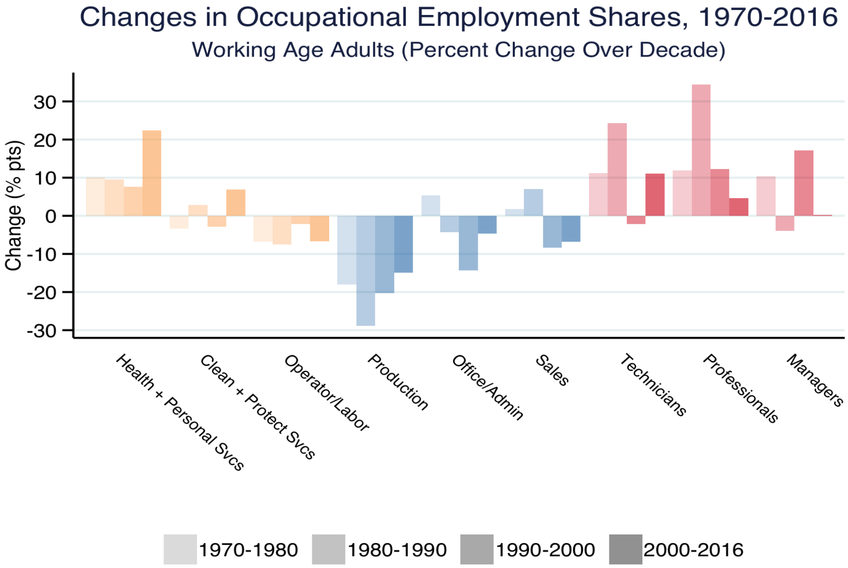
Declining real wages among non-college workers after 1980 – Despite falling relative supply





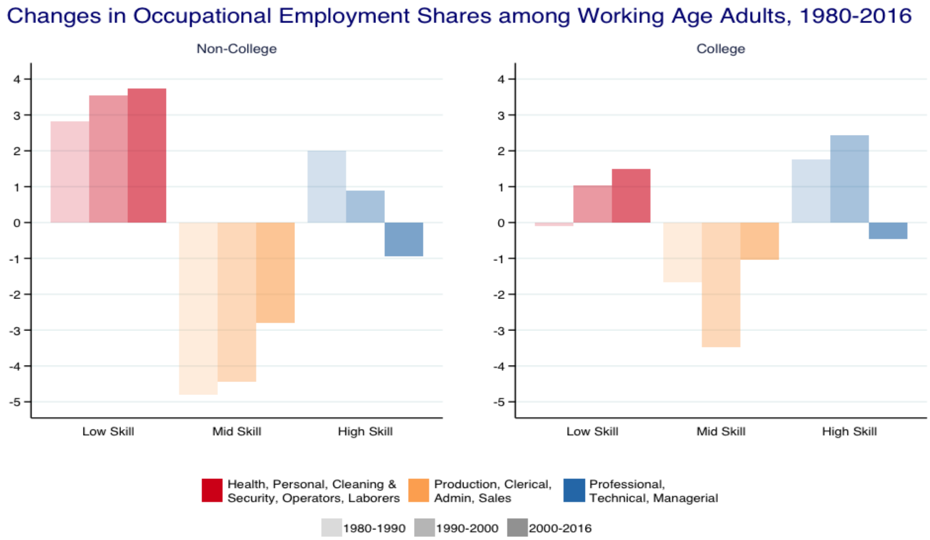
Autor 2019, Acemoglu/Restrepo 2022, 2023

Occupational polarization, 1970 – 2016: % change in employment by occupational category



Autor 2019

Changes in employment shares 1970-2016 by broad category: Non-college v. college workers

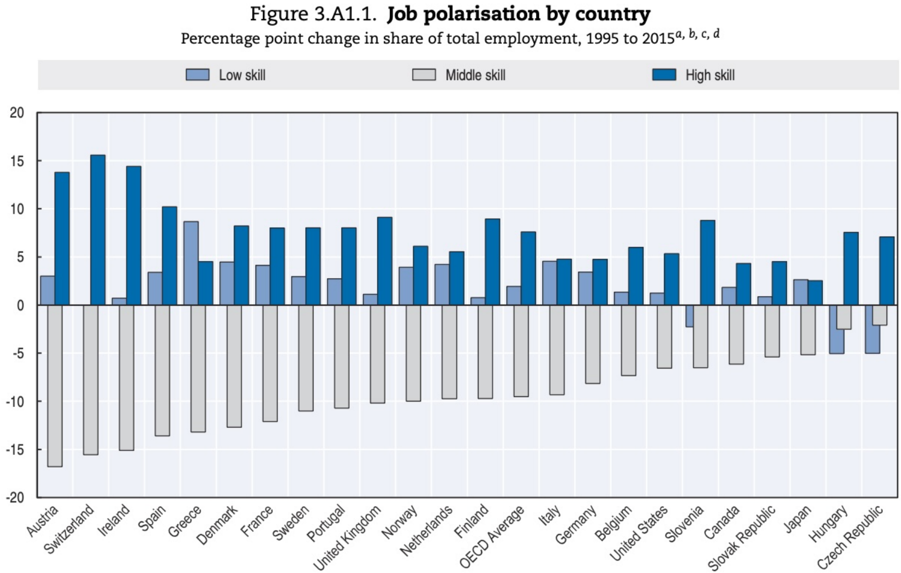


Autor 2019

Occupational polarization in sixteen EU countries, 1993-2010

Goos, Manning and Salomons 2014

Occupational polarization in 23 OECD countries, 1995-2015



OECD 2017

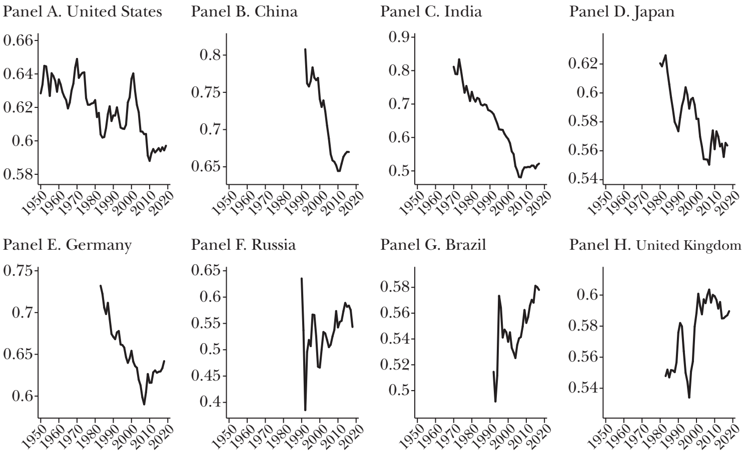
Occupational polarization in 23 OECD countries: Table notes

Note: High-skill occupations include jobs classified under the ISCO-88 major groups 1, 2, and 3. That is, legislators, senior officials, and managers (group 1), professionals (group 2), and technicians and associate professionals (group 3). Middle-skill occupations include jobs classified under the ISCO-88 major groups 4, 7, and 8. That is, clerks (group 4), craft and related trades workers (group 7), and plant and machine operators and assemblers (group 8). Low-skill occupations include jobs classified under the ISCO-88 major groups 5 and 9. That is, service workers and shop and market sales workers (group 5), and elementary occupations (group 9). As agricultural, fishery and mining industries were not included in the analysis, those occupations within ISCO-88 group 6 (skill agricultural and fisheries workers) were likewise excluded. The above chart includes 15 of the 18 listed industries. The excluded industries are the following: Agriculture, hunting, forestry and fishing (1), Mining and quarrying (2), and Community, social and personal services (18). As a result of unavailable data for 1995, a different starting year was used for some countries. Norway, Slovenia, and Hungary used 1996; Finland, Sweden and the Czech Republic used 1997, while the Slovak Republic used 1998. The OECD average is a simple unweighted average of the selected OECD countries. Data for Japan over the period examined is reported under four different industry classifications and highly aggregate occupation groups.

OECD 2017

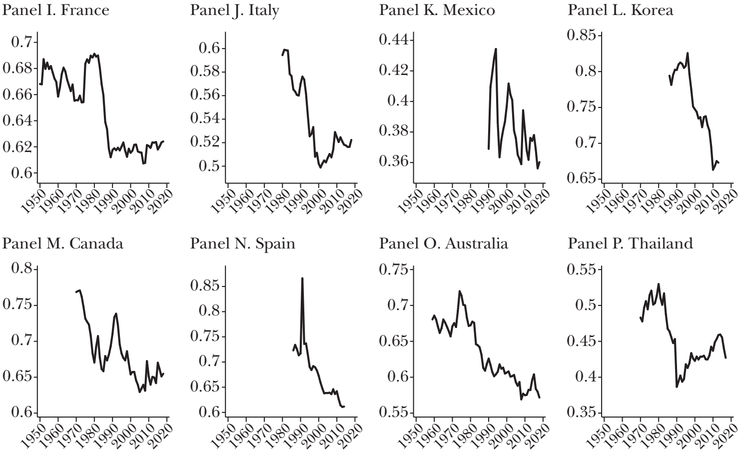
Labor's falling share of national income

Figure 2
Labor Share around the World



Karabarbounis, 2024

Labor's falling share of national income



Source: Author's calculations based on Penn World Tables (Feenstra, Inklaar, and Timmer 2015, PWT version 10.01). Details in Karabarbounis (2024).

Karabarbounis, 2024

The Task Model — Key Ingredients

Task model – A model of skills, tasks and technologies

1. **Explicit distinction between skills and tasks**
   - Tasks—Unit of work activity that produces output
   - Skill—Worker's *expertise* in performing various tasks

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3. **Allow for multiple sources of competing task 'supplies'**
   - Workers of different skill levels
   - Automation: Tasks subsumed by machines, AKA extensive margin technological Δ
   - Capital deepening: Intensive margin technological Δ
   - Trade in tasks also feasible (though won't develop that here)

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4. **Fluid interplay between skills, tasks and technologies**
   - Technological advances can: displace workers from tasks; increase productivity; augment or reduce labor demand; affect labor's share of output

Task model – Origins

Framework builds on

- Dornbusch, Fischer, Samuelson (1977)
- Kremer (1993)
- Acemoglu and Zilibotti (2001)
- Autor, Levy, Murnane (2003)
- Grossman, Rossi-Hansberg (2008)
- Acemoglu and Autor (2011)
- Acemoglu and Restrepo (2016, 2017, 2018 – 2024)
- Autor, Chin, Salomons, Seegmiller (forthcoming)

Task model: The key concepts

- **Multiple forms of technological change – with distinct effects**

  1. Capital deepening (traditional)
  2. Automation
  3. New task creation
  4. 'Leveling up' (augmentation)

- **Multiple forms of technological change – with distinct effects**
    1. Capital deepening (traditional)
    2. Automation
    3. New task creation
    4. 'Leveling up' (augmentation)
- **Key empirical manifestations**
    1. Wages
    2. Labor share
    3. Labor tasks made obsolete (automation)
    4. Labor tasks newly created (new work)

The Aggregate Production Function —
Tasks into Output

Tasks are complements

1. **Production requires the completion of a range of tasks**
2. **Need not assume that task space is fixed/static**
   - Creation of new tasks will ultimately be important
3. **Tasks are complements**
   - Automating a subset does not make the remainder redundant
   - Extreme example: O-Ring Production Function (Kremer '93)

Aggregate production function

Aggregate output Y

- Produced by combining the services, $y(x)$, of a unit measure of tasks $x \in [N-1, N]$:

$$\ln Y = \int_{N-1}^{N} \ln y(x) dx,$$

- Tasks run between $N-1$ and N allows for changes in *range* of tasks
- Notice that this is a Cobb-Douglas structure with identical factor shares for services of each task

The production of individual tasks

Tasks produced by human labor, $\ell(x)$, or by machines, $m(x)$

- Tasks above I are **not technologically automated** and must be produced by labor:

$$y(x) = \begin{cases} \gamma_L(x)\ell(x) + \gamma_M(x)m(x) & \text{if } x \in [N-1, I] \\ \gamma_L(x)\ell(x) & \text{if } x \in (I, N]. \end{cases}$$

- $\gamma_L(x) =$productivity of labor in task x, increasing in x
- $\gamma_M(x) =$productivity of machines in automated tasks
- **Comparative advantage**: $\gamma_L(x)/\gamma_M(x)$ is increasing in x
- L workers and K units of capital (machines) supplied inelastically

Restrictions on comparative advantage of labor versus capital

Simplifying assumption

$$\frac{\gamma_L(N)}{\gamma_M(N-1)} > \frac{W}{R} > \frac{\gamma_L(I)}{\gamma_M(I)} \tag{1}$$

- where R is the capital rental rate
- Implies that tasks below I are produced with machines/offshoring

Assumption says that new tasks (rising N) raise output

- Wage ratio not so high that new task creation lowers output
- Not so low so that technologically automated tasks are still performed by labor

Aggregate output and total factor productivity

Aggregate output takes the form

$$Y = \Theta \left(\frac{K}{I - N + 1} \right)^{I-N+1} \left(\frac{L}{N - I} \right)^{N-I},$$
$$\Theta = \exp \left(\int_{N-1}^{I} \ln \gamma_M(x) dx + \int_{I}^{N} \ln \gamma_L(x) dx \right)$$

- Notice that this production function is **pure Cobb-Douglas with non-constant shares**
- Θ = Solow residual: *All* technological Δ generates Hicks-neutral TFP gains, raising Θ

The demand for labor is given by

$$W = (N - I)\frac{Y}{L}$$

- This expression is equal to labor share of total output, $(N - I)$, times output Y divided by number of workers L
- The share of labor in national income is given by

$$s_L = \frac{WL}{Y} = N - I$$

Capital and Labor Augmenting Technical Change – The Traditional Mechanisms

Capital augmenting technological Δ: A canonical mechanism

Machines get better at what they do

- Consider an increase in the productivity of machines by $d \ln \gamma_M(x) = d \ln \gamma_M > 0$ for $x < I$, with no change in the extensive margin of automation, I
- Wage impact is

$$d \ln W = d \ln Y/L = (I - N + 1) d \ln \gamma_M > 0$$

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This is a pure capital-labor complementarity

- Electric lighting increased operating hours, work precision, and safety w/o changing task allocation
- Improvements in tractors make farm workers more efficient (without changing task allocation?)
- Better auto-assembly robots improve quality of welds (robots have been doing the welding for years)

Labor augmenting technological Δ: A canonical mechanism

An increase in labor productivity, $d \ln \gamma_L(x) > 0$, with no Δ in extensive automation margin, I

- Wage impact is

$$d \ln W = d \ln Y/L = (N + 1 - I) d \ln \gamma_L > 0$$

- This is a a pure factor-augmenting technological change, as in the Katz-Murphy/Tinbergen model
- This could come from rising education or better management practices

Automation — Labor-Displacing Technical Change

A Non-Traditional Mechanism

Automation – Labor-displacing technical change

Automation or trade/offshoring (an increase in I) generates a displacement effect

- From prior equation

$$\frac{d \ln W}{dI} = \underbrace{\frac{d \ln(N - I)}{dI}}_{\substack{\text{Displacement} \\ \text{effect} < 0}} + \underbrace{\frac{d \ln(Y/L)}{dI}}_{\substack{\text{Productivity} \\ \text{effect} > 0}}$$

- The displacement effect implies that **wages—marginal product of labor—can decline**, despite the fact that output per worker rises
- **Wages necessarily grow by less than output per worker** $\rightarrow$ labor share falls

$$\frac{ds_L}{dI} = -1 < 0$$

Displacement also has a productivity effect

By reducing cost of producing a subset of tasks, automation raises productivity in remaining tasks

- Formally

$$\frac{d\ln(Y/L)}{dI} = \ln\left(\frac{W}{\gamma_L(I)}\right) - \ln\left(\frac{R}{\gamma_M(I)}\right) > 0$$

- Note that $\ln\left[w/\gamma_L\left(I\right)\right] - \ln\left[R/\gamma_M\left(I\right)\right]$ is the cost difference btwn labor and capital/offshoring in the marginal task I

Displacement also has a productivity effect

The overall impact on labor demand can be written as

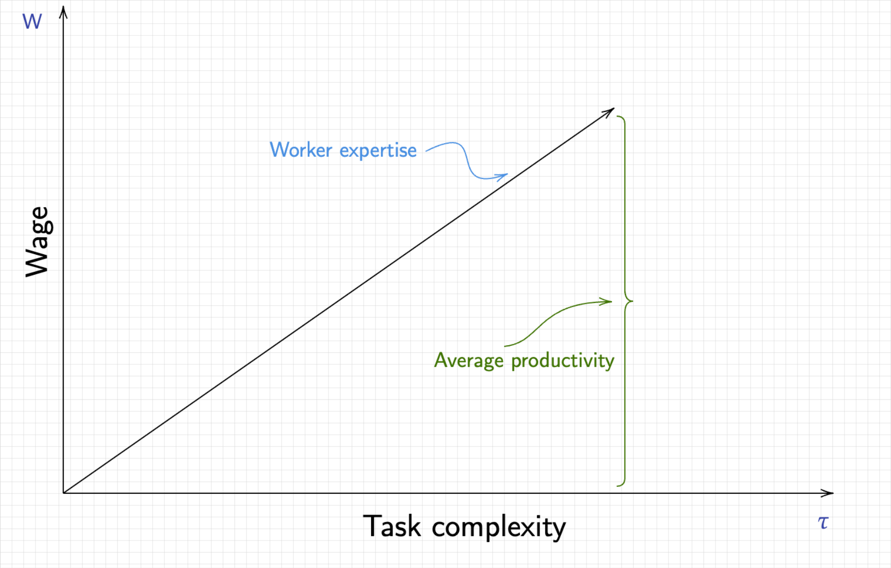
$$\frac{d \ln W}{dI} = \underbrace{-\frac{1}{N-I}}_{\substack{\text{Displacement} \\ \text{effect} < 0}} + \underbrace{\ln\left(\frac{W}{\gamma_L(I)}\right) - \ln\left(\frac{R}{\gamma_M(I)}\right)}_{\substack{\text{Productivity} \\ \text{effect} > 0}}$$

Net effect on labor demand (seen in the wage) is <u>**ambiguous**</u>

1. **Case 1: Productivity effect dominates displacement effect**: $\gamma_M(I)/R >> \gamma_L(I)/W$.
   <u>Productivity jump big enough</u> to overcome displacement effect

2. **Case 1: Displacement effect dominates productivity effect**: $\gamma_M(I)/R \approx \gamma_L(I)/W$.
   New technologies/trade are <u>so-so</u>

Automation visualized in the task model



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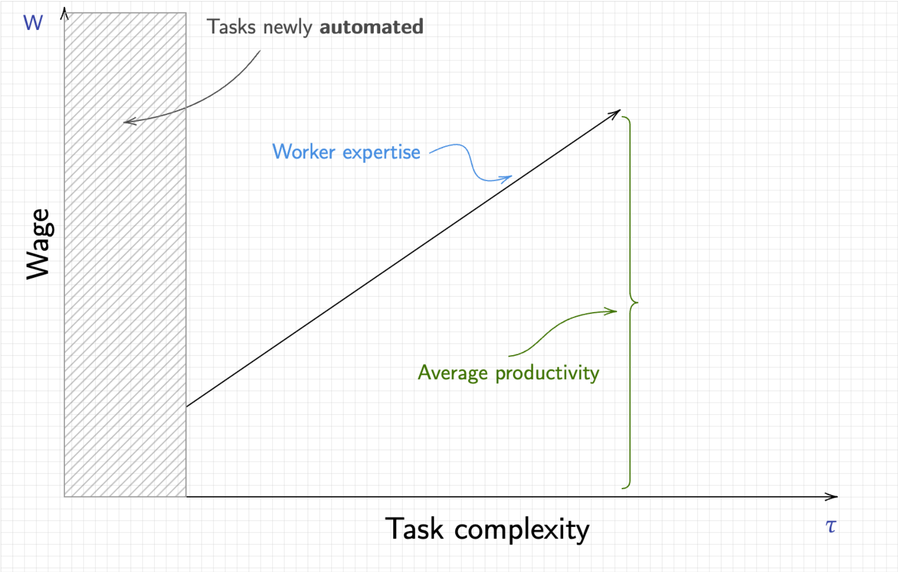

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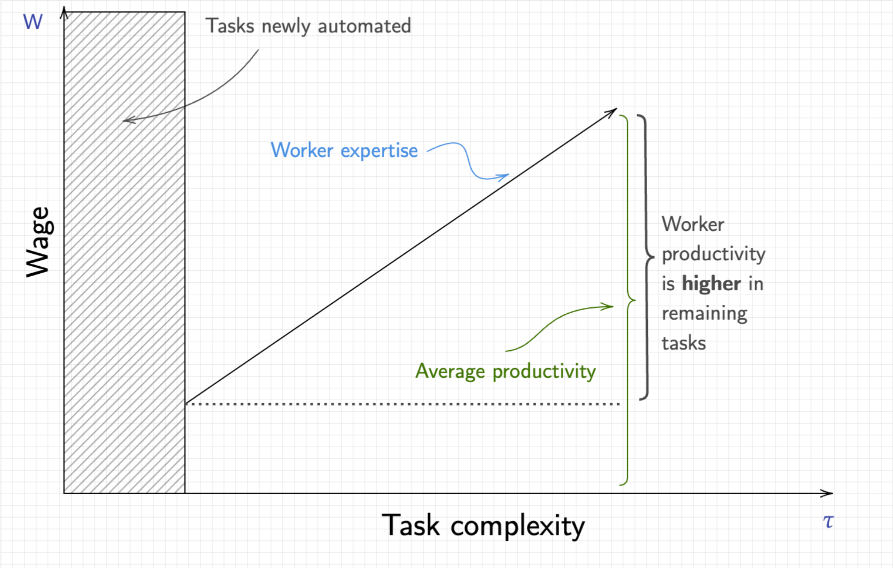

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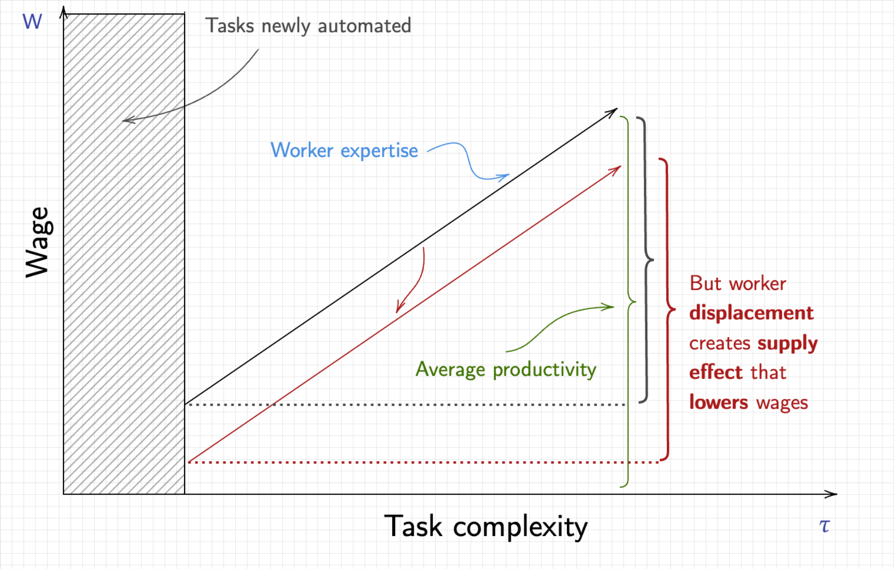


Labor-Reinstating Technical Change: New Task Creation

A Non-Traditional Mechanism

Creation of new, labor-using tasks may be counterbalancing force

1. In 19th-century Britain, rapid expansion of new industries and jobs—engineers, machinists, repairmen, and managers (Landes, 1969, Chandler, 1977, and Mokyr, 1990)
2. In early 20th-century America, agricultural mechanization coincided with a large increase in employment in new industry and factory jobs (Olmstead and Rhode, 2001, Rasmussen, 1982)
3. From 1940 to 2018, new tasks and job titles explain large fraction of all employment growth (Autor, Chin, Salomons, Seegmiller, 2022)
4. In general, new tasks have in the last four decades tended to be more skill-intensive—which is both good and bad news, but this was not always so

New tasks and the demand for labor

- **An increase in N—the creation of new tasks—raises productivity**

$$\frac{d \ln Y/L}{dN} = \ln\left(\frac{R}{\gamma_M(N-1)}\right) - \ln\left(\frac{W}{\gamma_L(N)}\right) > 0$$

which is positive from Assumption 1

- Besides its effect on productivity, new tasks also increase labor demand and equilibrium wages by creating a *reinstatement effect*:

$$\frac{d \ln W}{dN} = \underbrace{\ln\left(\frac{R}{\gamma_M(N-1)}\right) - \ln\left(\frac{W}{\gamma_L(N)}\right)}_{\substack{\text{Productivity} \\ \text{effect} > 0}} + \underbrace{\frac{1}{N-I}}_{\substack{\text{Reinstatement} \\ \text{effect} > 0}}$$

Creation of new tasks generates additional labor demand, raise share of labor in national income

- Total wage effect equals

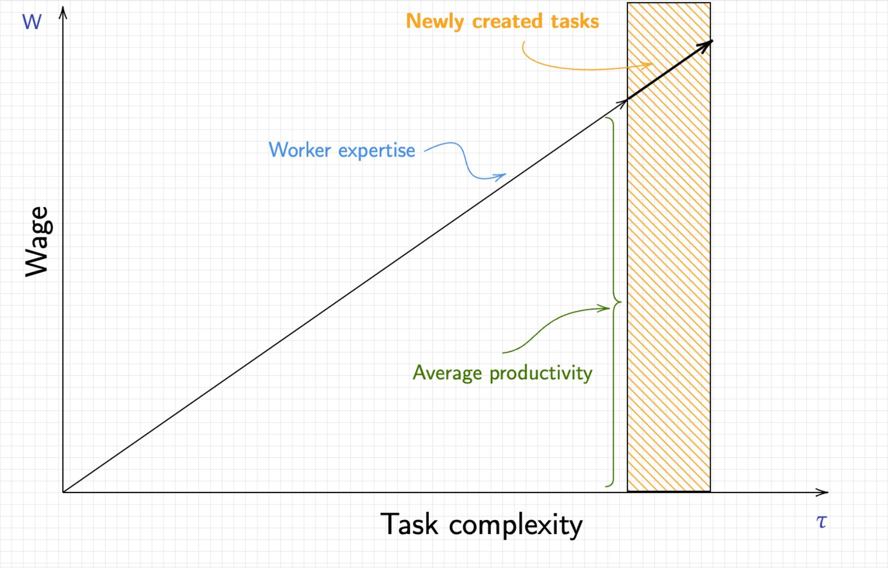
$$d \ln W = \left[\ln \left(\frac{R}{\gamma_M(N-1)} \right) - \ln \left(\frac{W}{\gamma_L(N)} \right) \right] dN + \left[\ln \left(\frac{W}{\gamma_L(I)} \right) - \ln \left(\frac{R}{\gamma_M(I)} \right) \right] dI + \frac{1}{N-I}(dN - dI),$$

and also for the labor share, we get

$$ds_L = dN - dI.$$

- Labor share stable and wages increase 1:1 w/productivity **iff** new tasks, N, introduced at same rate as automation, I

New task creation visualized in the task model



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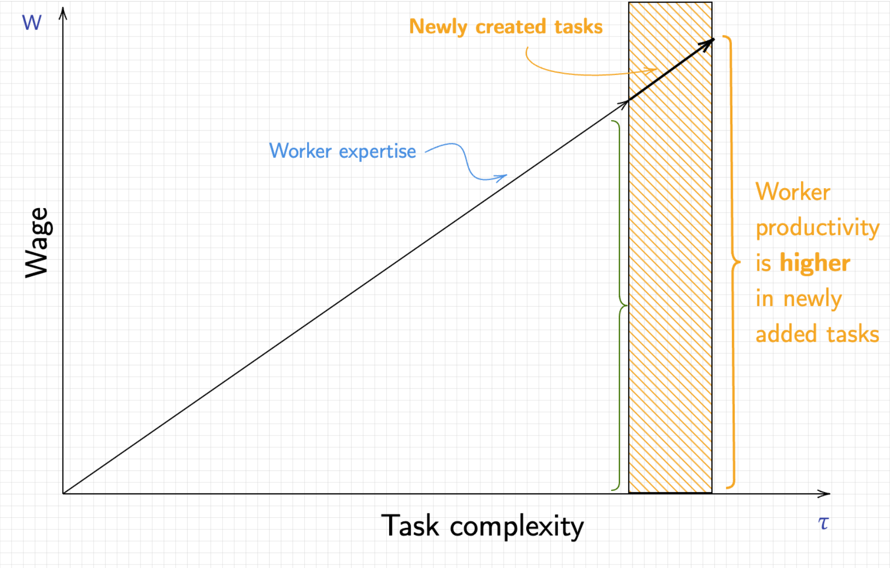

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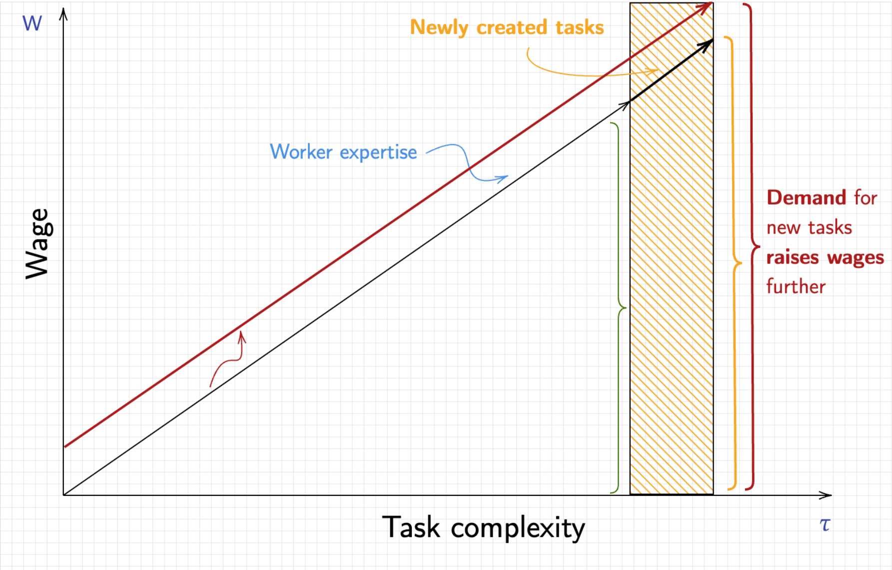
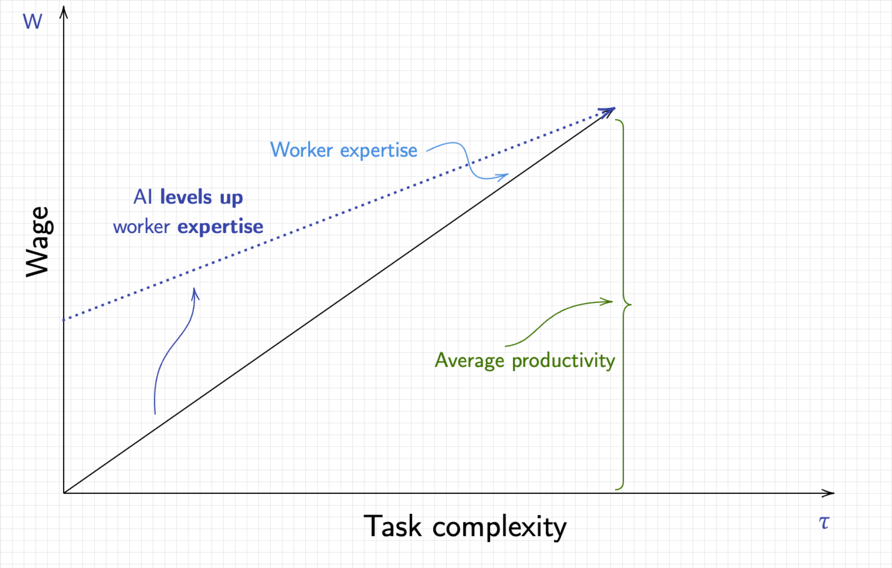


Compressing Productivity Differentials (‘Leveling Up’) —
A Non-Traditional Mechanism

Leveling up

- Many tools are a lever for the application of expertise
- Instead of machines replacing labor tasks, they may enable workers to accomplish new tasks, or more accomplish them more effectively
- But tools require their own expertise

‘Leveling up’ visualized in the task model



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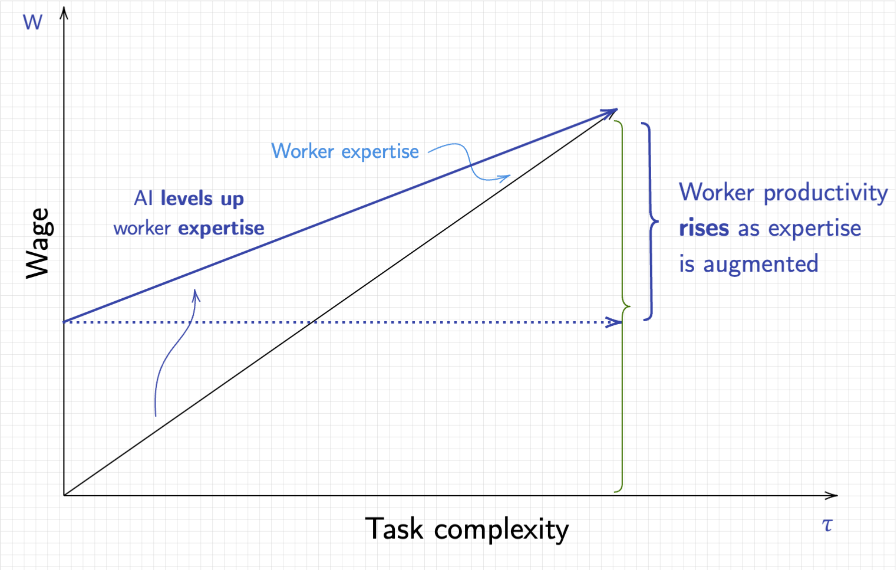

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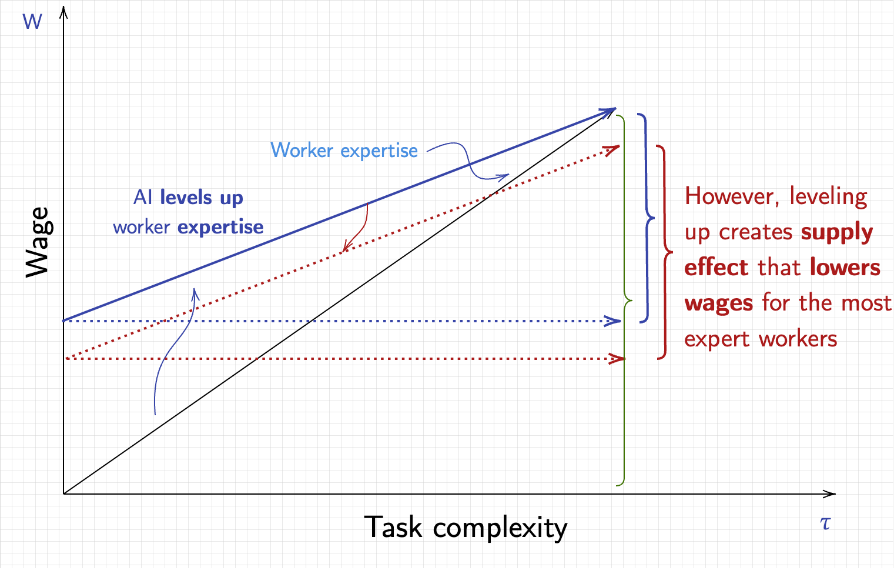

Task Model – Summing Up

Task model – What is it good for?

1. **A simple model for understanding different mechanisms of technical change**
   - Capital-labor complementarity
   - Automation: capital-labor substitution, expertise elimination
   - New task creation: new expertise requirements/opportunities

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2. **A framework for analyzing how GPTs and specific technologies shape expertise demands**
   - The Industrial Revolution, the Information Age, the AI Era

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   - Evolution of wages and productivity
   - Shifts in labor's share of output

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   - Reallocation of labor/skills across tasks
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   - Shifts in labor's share of output
4. **Of course, much is missing...**
   - Task bundling and within-job complementarities
   - Organizational design
   - Role for human agency

Agenda

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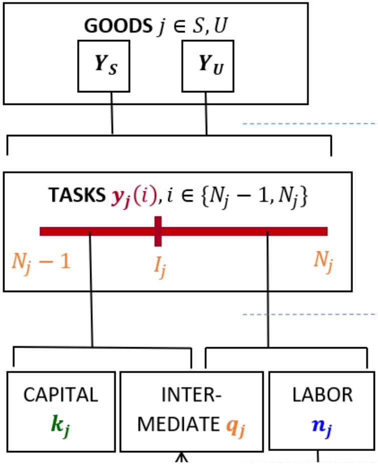
Some Recent Work on New Work –
Autor, Chin, Salomons, Seegmiller '24

Objectives: Analyzing new work

1. **What is the content of new work? Measure over eight decades, 1940–2018**

2. **Where does new work come from? Explore its technological and economic origins**

3. **What does new work do? Analyze its relationship to labor demand**



$$u(Y_U, Y_S) = Y_U^{\beta} Y_S^{1-\beta} \quad with\ \beta \in (0,1)$$

$$Y_j = A_j \left(\int_{N_j-1}^{N_j} \boldsymbol{y_j}(i)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}$$

$$\boldsymbol{y_j}(i) = \begin{cases} B_j \boldsymbol{q_j}(i)^{\eta_j} \left(\boldsymbol{k_j}(i) + \gamma_j(i) \boldsymbol{n_j}(i) \right)^{1-\eta_j} & \text{if } i \leq I_j \\ B_j \boldsymbol{q_j}(i)^{\eta_j} \left(\gamma_j(i) \boldsymbol{n_j}(i) \right)^{1-\eta_j} & \text{if } i > I_j \end{cases}$$

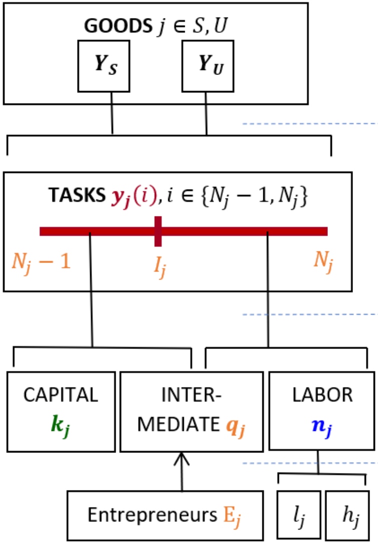
$$with\ \eta_j \in (0,1)$$

$$\boldsymbol{n_j}(i) = l_j(i)^{\alpha_j} h(i)^{1-\alpha_j} \quad with\ 1 > \alpha_U > \alpha_S > 0$$

Inelastic supply of k

l and h mobile between sectors

Conceptual model



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$$\boldsymbol{y_j(i)} = \begin{cases} B_j \boldsymbol{q_j(i)}^{\eta_j} \left(\boldsymbol{k_j(i)} + \gamma_j(i) \boldsymbol{n_j(i)} \right)^{1-\eta_j} & \text{if } i \le I_j \\ B_j \boldsymbol{q_j(i)}^{\eta_j} \left(\gamma_j(i) \boldsymbol{n_j(i)} \right)^{1-\eta_j} & \text{if } i > I_j \end{cases}$$

$$with\ \eta_j \in (0,1)$$

$$\boldsymbol{n_j(i)} = l_j(i)^{\alpha_j} h(i)^{1-\alpha_j} \quad with\ 1 > \alpha_U > \alpha_S > 0$$

Inelastic supply of k

l and h mobile between sectors

Elastic supply of E; mobile between sectors

E produce intermediates which raise $\mathrm{I_j}$ or $\mathrm{N_j}$

Main testable hypotheses (informally)

1. **Augmentation creates new tasks; Automation does not**
   - Augmentation *complements* labor's outputs, demands specialization, new expertise
   - Conversely, automation *substitutes* labor's inputs, doesn't generate labor-using tasks

Main testable hypotheses (informally)

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   - Conversely, automation *substitutes* labor's inputs, doesn't generate labor-using tasks
2. **New task creation responds elastically to demand shocks**
   - Outward shifts in occupational demand *accelerate* emergence of new tasks
   - Inward shifts in occupational demand *slow* emergence of new tasks

Main testable hypotheses (informally)

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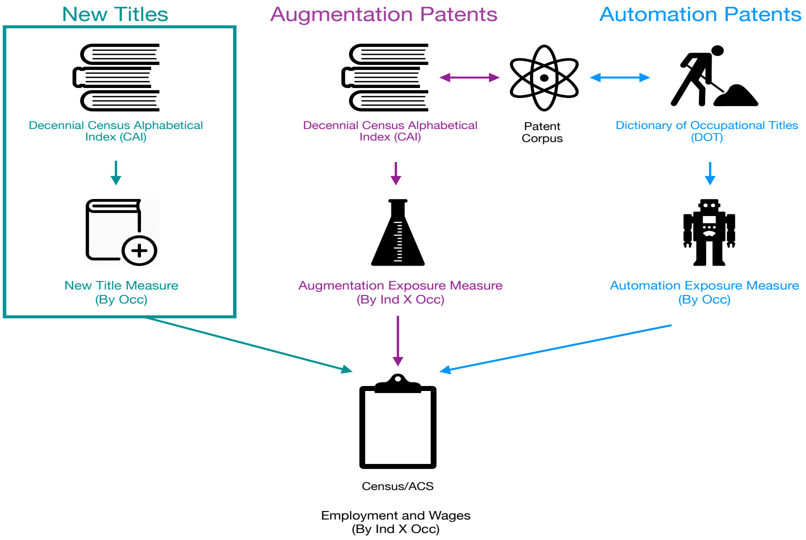
   - Conversely, automation *substitutes* labor's inputs, doesn't generate labor-using tasks
2. **New task creation responds elastically to demand shocks**
   - Outward shifts in occupational demand *accelerate* emergence of new tasks
   - Inward shifts in occupational demand *slow* emergence of new tasks
3. **Augmentation & automation occur in same occs—with opposing employment effects**
   - New task creation $\rightarrow$ Increases employment and wagebill
   - Task automation $\rightarrow$ Decreases employment and wagebill

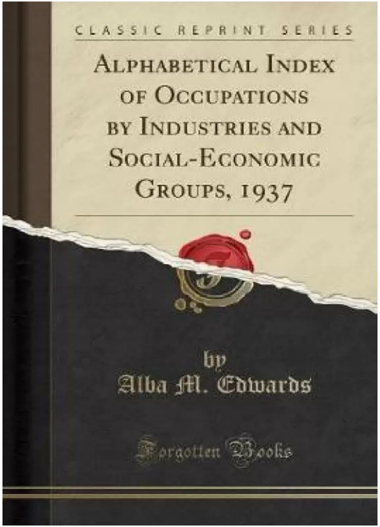
Measuring New Work

Identify new titles using Census coding volumes, 1940–2018



Census Alphabetical Index (CAIO) of Occupations and Industries 1940–2018

- Detailed lists of occupation titles (15K–30K) and industry titles (10K–20K) in each decade
- Each title classified to a Census occupation or Census industry
- Intended as coding aide for occupation and industry write-ins
    - *Comprehensive list of specific industries and occupations [...] continuously updated through review of census and survey questionnaires'*
- We use CAIO volumes 1940, 1950, 1960, 1970, 1980, 1990, 2000, 2010, 2018



Example of Index of Occupation (CAIO) entries, 1990

208 HEALTH TECHNOLOGISTS AND TECHNICIANS, N.E.C.

Ambulance driver, para-medic
Animal technician
Artificial-limb fitter—(372)

Assistant
  Anesthesiologist
  Anesthetic
  Laboratory, n. s.—Medical school 850
  Medical—(812)
  Occupational therapy

  Ophthalmic
  Optometric
  Orthopedic
  Orthotics
  Pharmacist's

  Physical therapist
  Physical therapy
  Podiatrist's—830
  Prosthetics
  Public health
  Speech correction
  Speech therapy

Audiometrist
Biochemistry technician
Biological technician, health
Brace maker—372,831,840
Brain-wave technician—(840)
C.M.T. (certified medical technician)

Cardiograph operator—(840)
Cardiographer—(840)
Cardiopulmonary technician
Cardiovascular technologist
Certified medical technician

Child-health associate—831,832,840
Closed circuit screen watcher—831
Dialysis technician
E.e.g. technician—(840)
E.e.g. technologist

E.k.g. technician—(840)
E.m.t.
Electrocardiograph operator—(840)
Electrocardiograph technician—(840)
Electroencephalograph technician— (840)

Emergency medical technician
Encephalographer—(831)
Environmental health sanitarian
Environmental-health technician
Environmental-health technologist

Extracorporeal-circulation specialist
Food-service technician—831,832,840
Health sanitarian
Hospital technician—831
Industrial hygienist

Inspector
  Sanitarian—840

Laboratory technician, veterinary
Laboratory technician, n. s.—030,812
Laboratory technician, n. s.— Medical school 850
Laboratory tester—030,812
Laboratory tester—Medical school 850
Laboratory worker, n. s.—030,812
Laboratory worker, n. s.—Medical school 850

Mechanic
  Orthopedic

Medical-emergency technician
Medical research (less than bachelor's degree)
Medical service technician
Medtronics technician
O.B. technician—831
Occupational therapy technician

Ocular-care technician
Ocular-care technologist
Operating-room technician—831
Ophthalmic technician
Ophthalmic technologist

Optometric technologist
Orthopedic-brace maker
Orthopedic technician

Orthoptic technician
Orthoptist

Orthotist
Otometric technician
Oxygen-equipment technician
Oxygen-therapy technician
Para-medic, emergency treatment

Para-medic, n. s.—401,910
Pediatric associate—831,832,840
Perfusionist
Pharmacy laboratory technician—812- 840
Pharmacy technician

Physician's aide—831,832,840
Prosthetist
Public-health technician
Public-health technologist
Radiological-health specialist

Radiological-health technician
Rehabilitation technician—831
Respiratory therapy technician
Restoration officer—831
Restoration technician—831,832,840
Sanitarian—470,471,831,840
Scrub technician—831

Supervisor
  Central supply—831
  Central supply technician—831
  Laboratory—Medical school 850

Surgical-brace maker
Surgical technician
Surgical technologist

Teachers, exc. elementary & secondary
  Prosthetic aides—831,832,840

Technician, health type n. s.
Technician, n. s.—Medical school 850
Watch-closed-circuit screen—831
Water-pollution specialist

Examples of job titles

- Artificial-limb fitter
- Brain-wave technician
- Extracorporeal-circulation specialist
- Ocular-care technician
- Surgical-brace maker

∼30,000 titles per edition

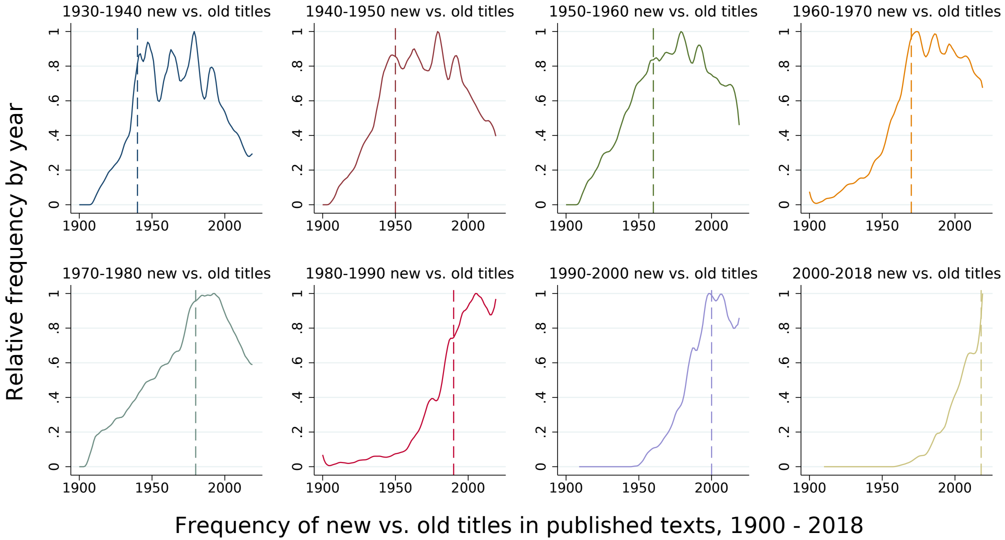
Each title is classified to a Census occupation

Identify new titles by comparing successive CAIO editions

What is new work? Example job titles captured by U.S. Census, 1940–2018

New job titles added to Census Index of Occupations		
1940	Automatic welding machine operator	Acrobatic dancer
1950	Airplane designer	Tattooer
1960	Textile chemist	Pageants director
1970	Engineer computer application	Mental-health counselor
1980	Controller, remotely-piloted vehicle	Hypnotherapist
1990	Circuit layout designer	Conference planner
2000	Artificial intelligence specialist	Amusement park worker
2010	Technician, wind turbine	Sommelier
2018	Cybersecurity analyst	Drama therapist

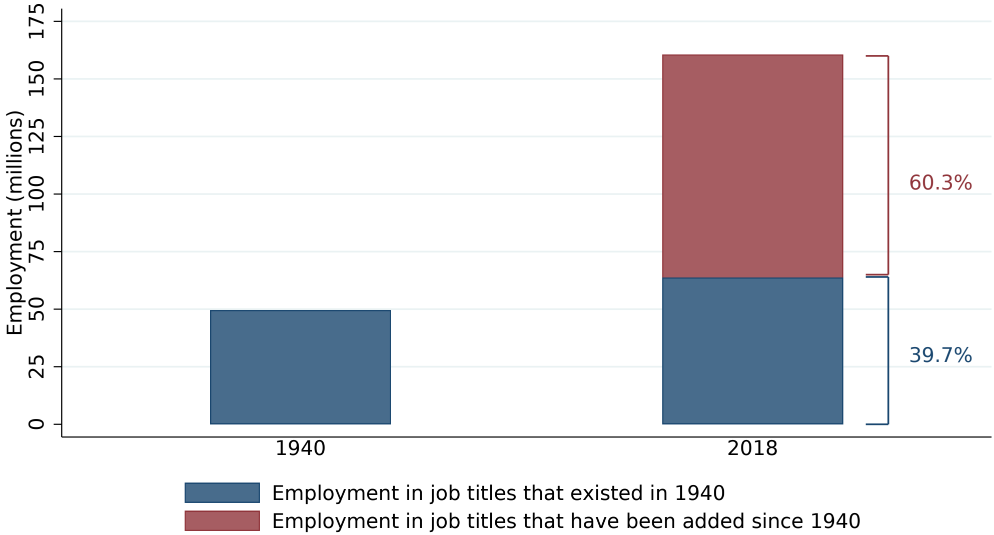
Google Ngram Viewer data: Census captures new titles as they popularize



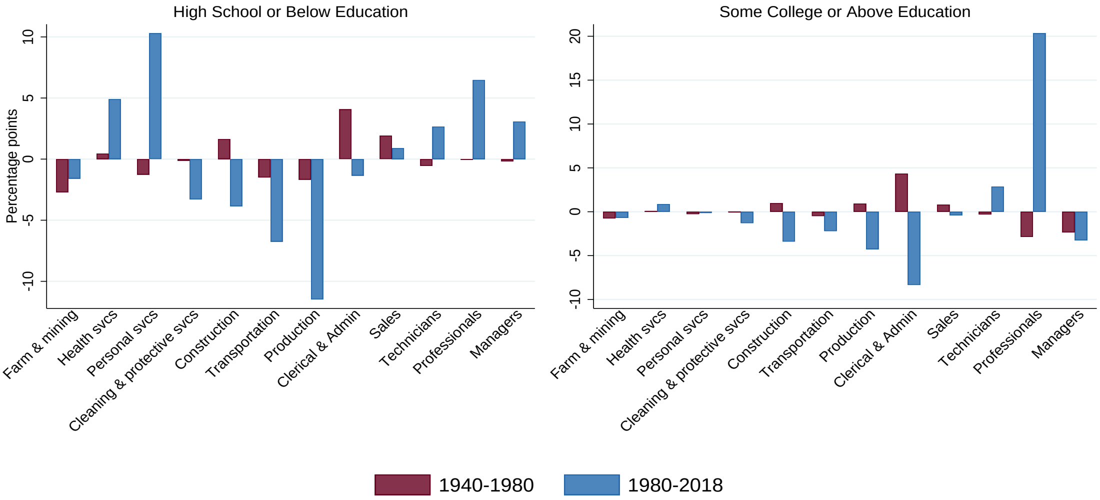
Quantifying new work

- **Quantifying the flow of new titles ('new work')**
  1. Flow of *$newtitles_{jt}$* by Census occupation during a decade (e.g., 1940 – 1950)
  2. *or* new title share $\frac{newtitles_{jt}}{alltitles_{jt}}$, equals the flow of new titles over stock of titles within Census occupation during a decade
- **We do not use cardinal properties of measure in primary analysis**
  - Studying predictors of new title *flows* by occupation $\times$ decade
  - When analyzing employment/wage outcomes, treat new titles as an intermediating variable, not a cause

Majority of jobs done in 2018 not yet 'invented' as of 1940

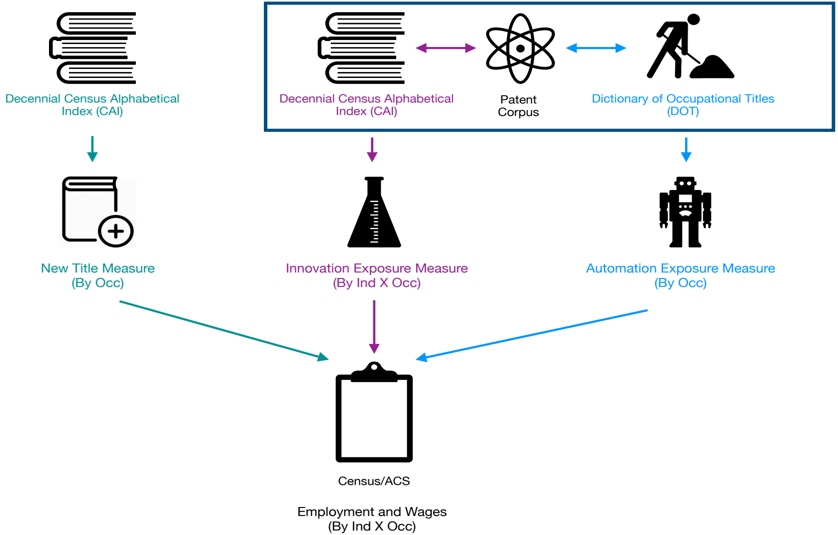


New work polarizes relative to pre-existing work between 1980 and 2018
Occupational locus of new vs. pre-existing work by education and era



Measuring Occupations' Exposure to Automation and Augmentation Innovations

Using patent texts to measure augmenting and automating innovations



Health Technologists & Technicians: Outputs vs. Inputs (automation)

Census Index of Occupations, 1990

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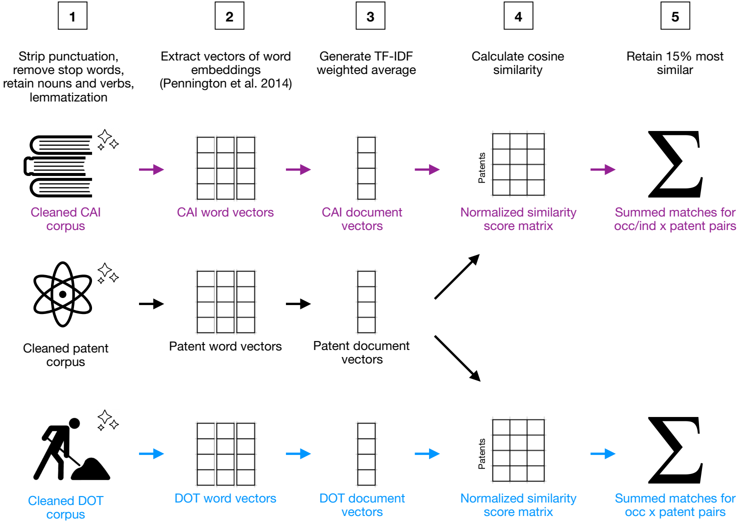
Dictionary of Occupational Titles, 1939, '77

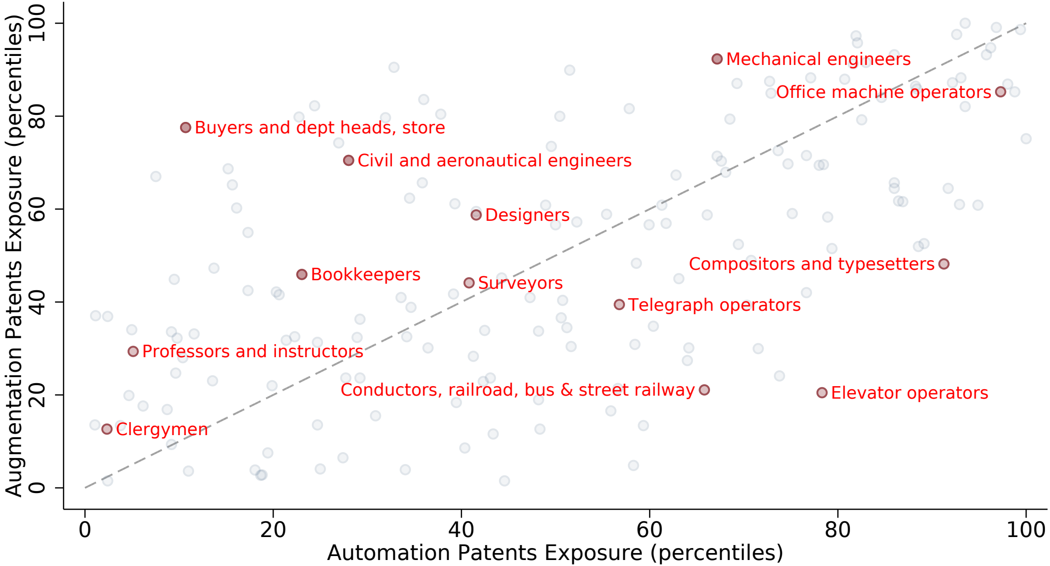
MEDICAL TECHNICIAN; hospital technician; laboratory assistant, medical; laboratory technician, medical (medical ser.) **0-50.01.** Performs medical duties in a hospital or medical laboratory making laboratory tests of urine, blood, animal parasites, infections, and animal inoculations; makes blood counts and smears; gives biological skin tests; prepares vaccines; types blood for transfusions. May engage in research.

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.

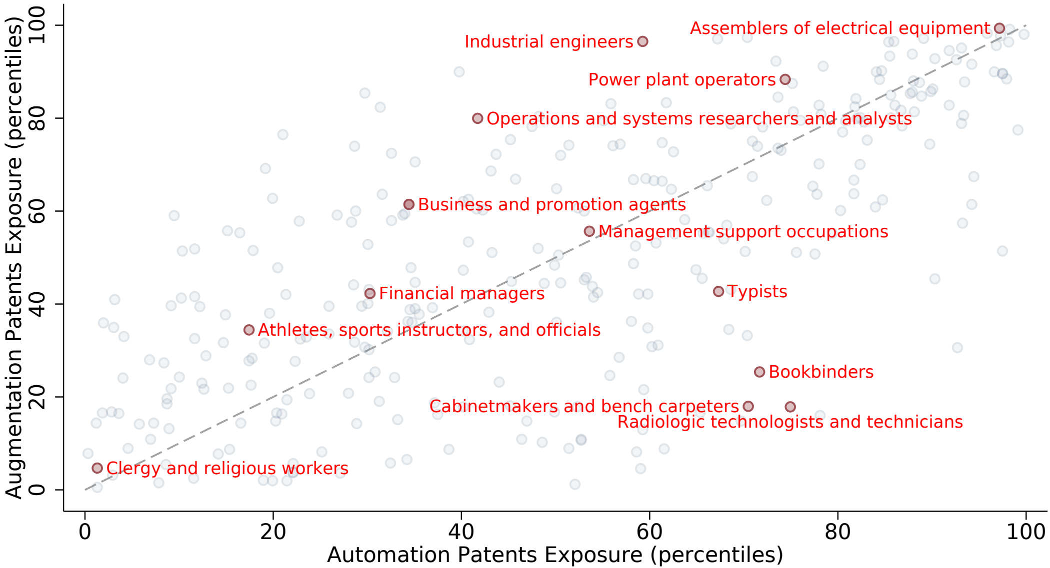
Linking Augmentation & Automation technologies to occupations



Automation and augmentation co-occur in many occupations, 1940–1980



Automation and augmentation co-occur in many occupations, 1980–2018



Where Does New Work Come From?

Do augmentation and automation have distinct relationships with new titles?

The hypothesis

- **New titles emerge in augmentation-exposed occupations**
- **New titles do not (differentially) emerge in automation-exposed occupations**

Testing the hypothesis

- **Outcome variable**: Emergence rate of new titles in an occupation in each decade, 1940 – 2018
- **Explanatory variables**: Flows of *augmentation & automation patents* linked to that occupation in each decade, 1940 – 2018

Prediction

- **The flow of augmentation patents predicts new title emergence in each decade**
- **the flow of automation patents does not**

Do augmentation and automation have distinct relationships with new titles?

Relating augmentation and automation to new occupation titles, 1940–2018

$$\ln\left(E\left[\text{newtitles}_{jt}\right]\right) = \beta_1 \text{AugX}_{jt} + \beta_2 \text{AutX}_{jt} + \beta_3 \frac{E_{j,t-1}}{\sum_j E_{j,t-1}} + D_t \left(+D_{Jt}\right)$$

- **newtitles**$_{jt}$: Occupational new title count
- **AugX**$_{jt}$: Occupational exposure to augmentation, log patent count
- **AutX**$_{jt}$: Occupational exposure to automation, log patent count
- **Controls**: Occupational employment shares, and fixed effects, where J indexes 12 broad occupation groups

New titles emerge in augmentation-exposed occupations

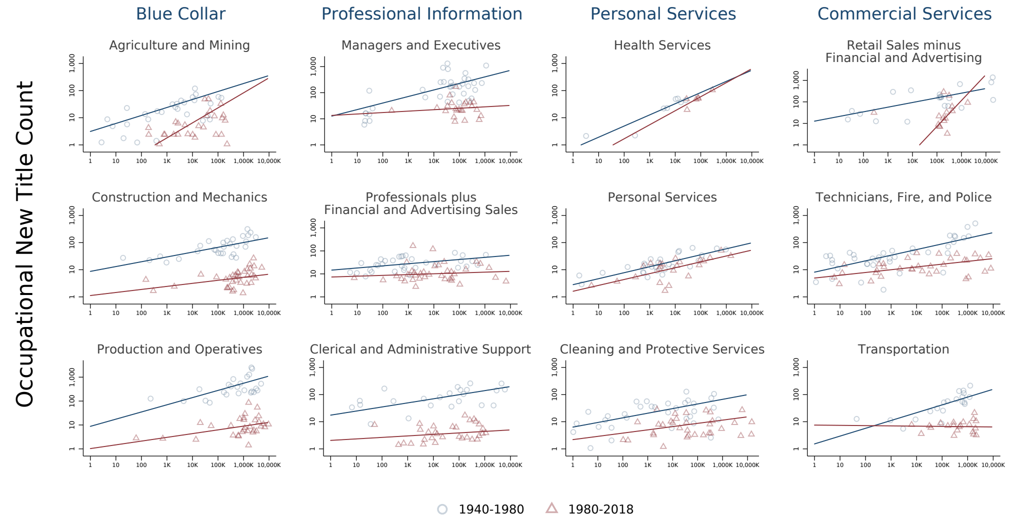
Dependent Variable: **Occupational New Title Count**, 1940–2018

	(1)	(2)	(3)	(4)	(5)
Augmentation Exposure	17.81***	21.46***		16.85***	21.02***
	(3.52)	(3.74)		(3.96)	(3.54)
Automation Exposure			12.75**	1.89	2.35
			(3.93)	(4.52)	(4.07)
N	1,535	1,535	1,535	1,535	1,535
Occ Emp Shares	X	X	X	X	X
Time FE	X		X	X	
Broad Occ × Time FE		X			X

Negative binomial models, coefficients multiplied by 100. Twelve broad occupations are defined consistently across all decades. Standard errors clustered by occupation × 40-year period in parentheses. Observations weighted by start-of-period occupational employment shares. Augmentation and automation exposure measures correspond to the log of the weighted counts of matched patents. $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

New job titles emerge in occupations experiencing technological augmentation

$$\textbf{Newtitles}_{jt} = \beta_1 \textbf{AugX}_{jt} + \beta_2 \left(E_{jt} / \Sigma_j E_{jt}\right) + D_t + \varepsilon_{jt}$$



It's Not Only About Technology—

Demand shifts, *More* work, and *New* work

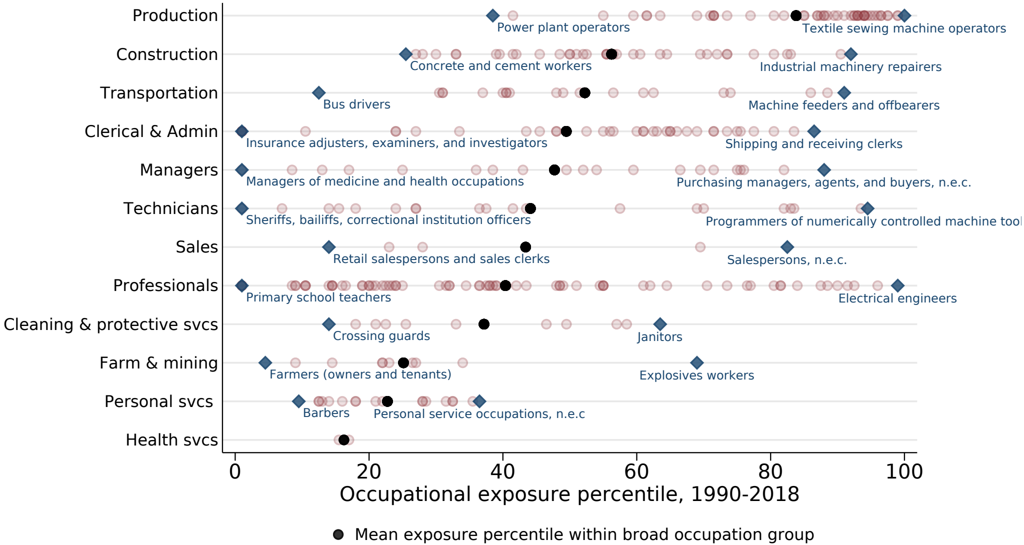
Do occupational demand shifts spur/retard new job type creation?

Relating new title emergence in consistent occupation cells to occupational exposure to changes in industry demands, 1980/90–2018

$$\ln E\left[\text{newtitles}_{jt}\right]) = \beta_1 \text{DemandX}^k_{jt} + D_t + \gamma Z_{jt}$$

- $\textbf{newtitles}_{jt}$: Occupational new title count
- $\textbf{DemandX}^k_{jt} = \sum_i \frac{E_{ij,t-1}}{E_{j,t-1}} \times \boldsymbol{\Delta}\textbf{demand}^k_{it}$
  - $\frac{E_{ij,t-1}}{E_{j,t-1}}$: share of occupation j's employment in industry i at start of decade $(t-1)$
  - $\Delta\text{demand}^k_{it}$: industry i's predicted change in demand due to:
    - Δ industry imports from China to developed countries other than the US; *or*
    - Δ pop age structure $\times$ age-specific commodity demands
- Z_{jt}: Controls, including occupational employment shares, manufacturing employment shares, and exposure to augmentation.

Occupational exposure to China-U.S. trade shock: It's not just production occs



Less new title creation in occupations exposed to import competition

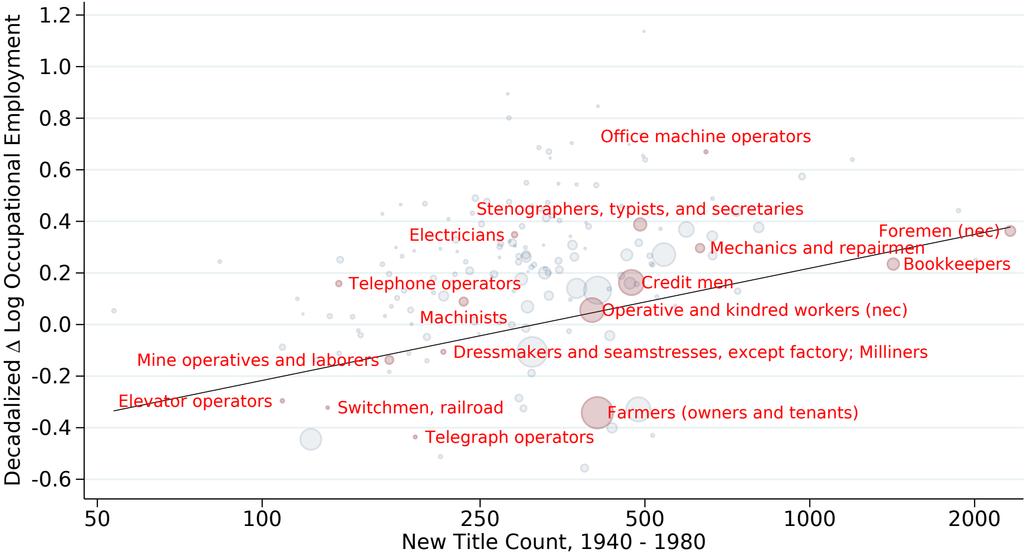
Dependent Variable: **Occupational New Title Count**

	Years 2000 & 2018				Years 1980 & 1990 (Placebo Test)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Import Exposure	−15.44**	−12.13*	−17.49***	−17.73***	3.95	11.77	−2.99	−1.76
	(5.23)	(5.53)	(5.13)	(5.17)	(20.40)	(20.47)	(13.24)	(12.53)
Augmentation Exposure		7.94+	9.38**	8.32**		19.57***	20.00***	20.60***
		(4.60)	(3.00)	(2.91)		(3.15)	(1.77)	(1.92)
N	610	610	610	610	588	588	588	588
Time FE	X	X	X	X	X	X	X	X
Occ Emp Shares	X	X	X	X	X	X	X	X
Ind Exposure Control	X	X	X	X	X	X	X	X
Broad Occ FE	X		X	X	X		X	X
Δ Occ Emp Shares				X				X

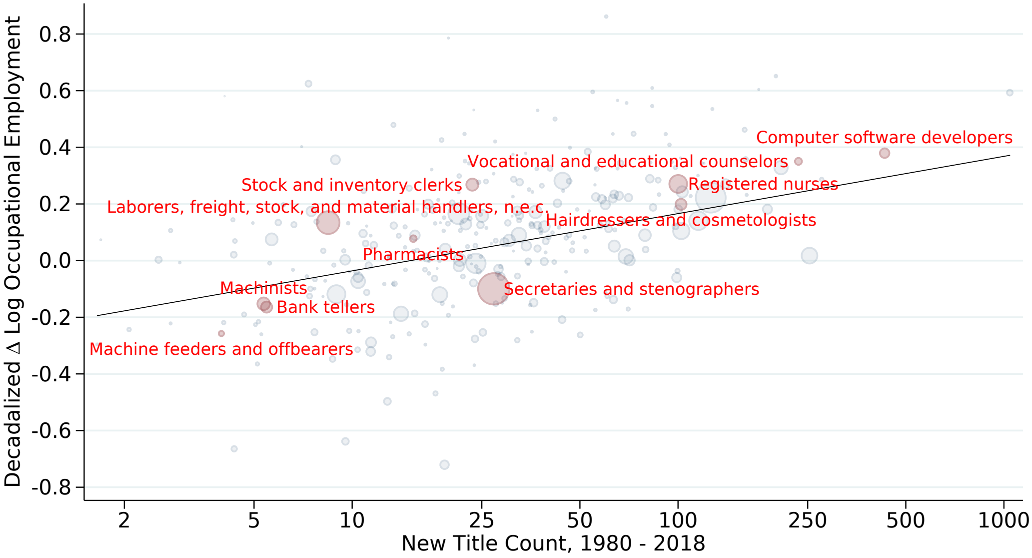
Negative binomial models, coefficients multiplied by 100. Standard errors clustered by occupation in parentheses. Observations weighted by start-of-period occupational employment shares. Augmentation and automation exposure measures correspond to the log of the weighted counts of matched patents. $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

What Does New Work Do?

Correlation: Where new titles emerge 1940–1980, employment grows



Correlation equally strong in 1980–2018, driven by different occupations ¿0



Does augmentation expand employment—and does automation erode it?

The hypothesis

- **Occupations exposed to augmentation technologies see rising employment**
- **Occupations exposed to automation technologies see falling employment**

Testing the hypothesis

- **Outcome variable**: Growth in occupation's *employment*, 1940–1980 & 1980–2018
- **Explanatory variable 1**: Flow of *augmentation patents* linked to occupation
- **Explanatory variable 2**: Flow of *automation patents* linked to occupation

Prediction

- **Occupations that are augmented grow; those that are automated contract**
- A strenuous test: Most occupations are exposed to *both* simultaneously

Augmentation vs. automation: Opposite impacts on employment growth?

Predict employment growth within 3-digit ind-occ cells, 1940–1980 & 1980–2018

$$\Delta \mathrm{E}_{ij} = \beta_1 \mathrm{AugX}_{ij} + \beta_2 \mathrm{AutX}_j + D_i \, (+D_J) + \varepsilon_{ij}$$

- $\mathbf{\Delta E}_{ij}$: Log employment change by consistent Census occupation j and industry i, long differences over 1940–1980 and 1980–2018
- $\mathbf{AugX}_{ij}$: Augmentation exposure
- $\mathbf{AutX}_j$: Automation exposure
- **Controls**: Fixed effects, where J indexes 12 broad occupation groups.

Builds on Kogan et al '19, Webb '20, **but with key addition:** Augmentation

1940-2018 (OLS & IV): Emp grows with augmentation, shrinks with automation

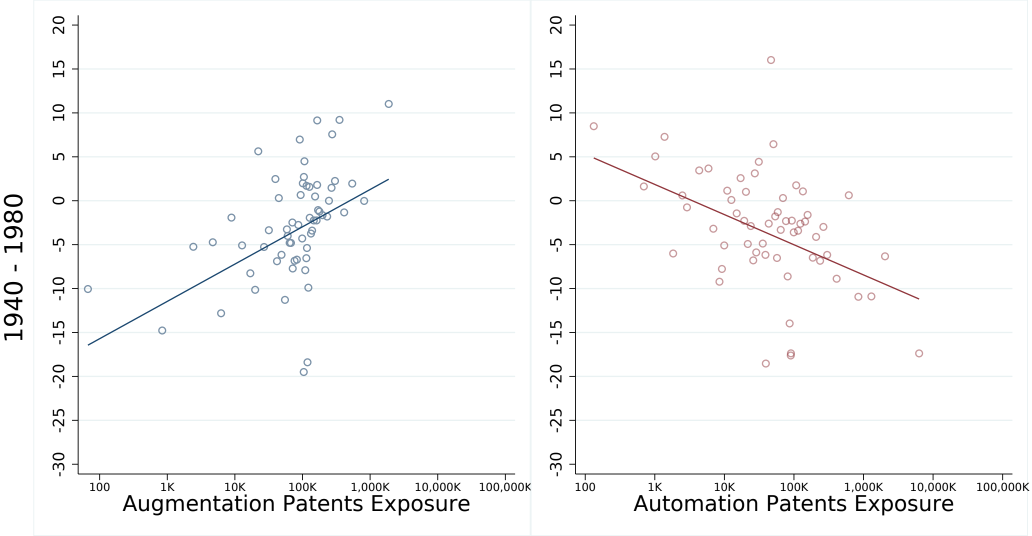
Dependent Variable: Decadalized Log **Employment Change** in Occ-Ind Cells, Stacked Long-Difference

	(1)	(2)	(3)	(4)	(5)	(6)
			OLS			
Augmentation Exposure	0.82***	1.18***			1.51***	1.36***
	(0.21)	(0.21)			(0.21)	(0.22)
Automation Exposure			−1.82***	−0.61	−2.27***	−1.00*
			(0.27)	(0.40)	(0.27)	(0.40)
R^2	0.52	0.57	0.53	0.56	0.53	0.57
			2SLS			
Augmentation Exposure	2.73**	2.78**			4.34***	3.60***
	(0.92)	(0.94)			(0.93)	(0.96)
Automation Exposure			−3.24***	−3.94***	−4.02***	−4.21***
			(0.63)	(0.91)	(0.62)	(0.93)
F-stat (Aug)	259.30	262.57			127.90	150.59
F-stat (Aut)			327.80	292.63	202.73	145.03
Ind × Time FE	X	X	X	X	X	X
Broad Occ × Time FE		X		X		X

N = 33,900 changes in employment and wagebill in consistently defined Census occupations over 1940–1980 and 1980–2018. Dependent variable is decadalized and multiplied by 100 so that growth rates are expressed in per-decade percentage points. $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

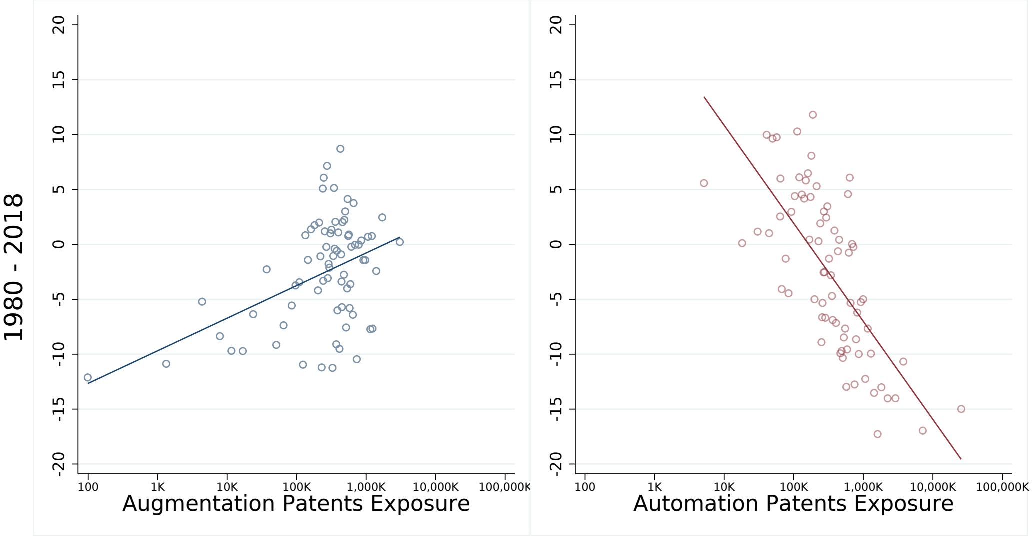
Employment growth in industry-occupation cells, 1940–1980

1940 - 1980 : $\Delta E_{ij} = 1.85\ AugX_{ij}\ (0.39) - 1.49\ AutomX_{ij}\ (0.40) + \gamma_i + \varepsilon_{ij}$



Employment growth in industry-occupation cells, 1980–2018

$$1980 - 2018: \Delta E_{ij} = 1.29\ AugX_{ij}\ (0.22) - 3.88\ AutomX_{ij}\ (0.34) + \gamma_i + \varepsilon_{ij}$$



1940-2018 (OLS & IV): Impacts both inside & outside of manufacturing

	100 × Decadalized ΔLn(Employment)		100 × Decadalized ΔLn(Adjusted Wagebill)	
	Non-Manuf	**Manuf**	**Non-Manuf**	**Manuf**
	(1)	(2)	(3)	(4)
		OLS		
Augmentation Exposure	1.58***	1.16***	1.74***	1.11***
	(0.25)	(0.32)	(0.29)	(0.32)
Automation Exposure	−2.65***	−1.01**	−2.64***	−1.32***
	(0.33)	(0.37)	(0.35)	(0.37)
R^2	0.52	0.55	0.51	0.52
		2SLS		
Augmentation Exposure	4.04***	4.57**	4.90***	4.77**
	(1.10)	(1.77)	(1.21)	(1.76)
Automation Exposure	−3.68***	−6.10***	−3.30***	−6.46***
	(0.70)	(1.10)	(0.74)	(1.11)
F-stat (Aug)	90.41	79.05	90.41	79.05
F-stat (Aut)	155.31	58.28	155.31	58.28
Ind × Time FE	X	X	X	X
N	21,795	12,105	21,795	12,105

Changes in employment and wagebill in consistently defined Census occupations over 1940–1980 and 1980–2018. Standard errors clustered by industry-occupation cell in parentheses. $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Recap

1. **The content of new work**
   - **More than 60% of 2018 employment in job titles that didn't exist in 1940**
   - **Locus of new job title creation polarized after 1980**
     - **1940-80** – Flow of new work largely reflects stock of pre-existing work
     - **1980-18** – *Non-college* low-paid personal svc occs, *College* prof and mgmt occs
2. **Where new work comes from**
   - **Augmentation and demand shocks both shape where new work emerges**
     - Augmentation patents generate 'new work' (new titles) but automation patents do not
     - New title flows respond elastically to inward/outward demand shocks
3. **What new work does**
   - **Task displacement and new task creation occur simultaneously, yet...**
     - Augmentation expands occupational employment and wagebills
     - Automation erodes occupational employment and wagebills
     - Labor displacement from automation appears to have accelerated since 1980

Agenda

1. Expertise – A unifying conceptual notion
2. The task model – What is it, and why is it?
3. Recent evidence on new work
4. **Some concluding thoughts**

Some concluding thoughts

Robert Solow '57 (1924-2023) established the central role of tech Δ in economic growth

- But economists over-learned Solow's lesson (though Solow did not)
- Growth is good, but consequences are potentially nuanced, not necessarily Pareto-improving
- This was long understood re international trade, only recently widely recognized re tech Δ

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Some fairly urgent questions

1. Do we have too much or too little automation?
2. Do we have enough 'new tasks'–and are these even needed?
3. What shapes labor and skill complementarity/substitution attributes of new work?
4. Has automation accelerated relative to augmentation/reinstatement? And if so, why?
5. How will AI change these answers?

These questions did not seem as urgent a decade ago as they do now

Thank You