MIT 14.662 Spring 2026: Lecture slides 8 – Skills, Tasks, and Technologies (Part 2)

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February 25, 2026 (rev 2026/03/01)

Agenda

1. **Tasks, Automation, and the Rise in U.S. Wage Inequality: Acemoglu-Restrepo '22**
2. **New Frontiers: The Origins and Content of New Work, 1940–2018 (ACSS '24)**
   - What is the occupational content of new work?
   - Where does new work come from?
   - What does new work do?
3. **Conclusions and next steps**
4. **[Optional self-study] Skill Complementarity of Broadband Internet: Akerman, Gaarder, Mogstad '15**

Labor share decline: Observed and predicted

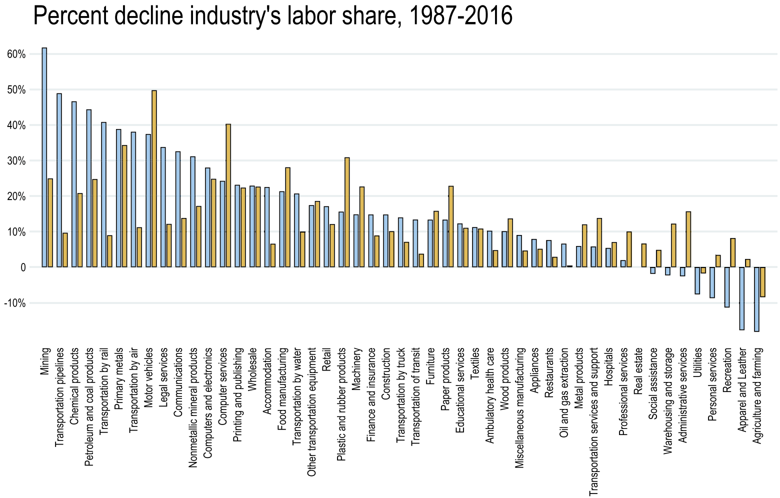


FIGURE 3.—Percent decline in industry labor shares (in light gray/blue) and automation-driven labor share declines (in dark gray/orange), 1987–2016. See text for variable definitions.

Predictors of labor share decline

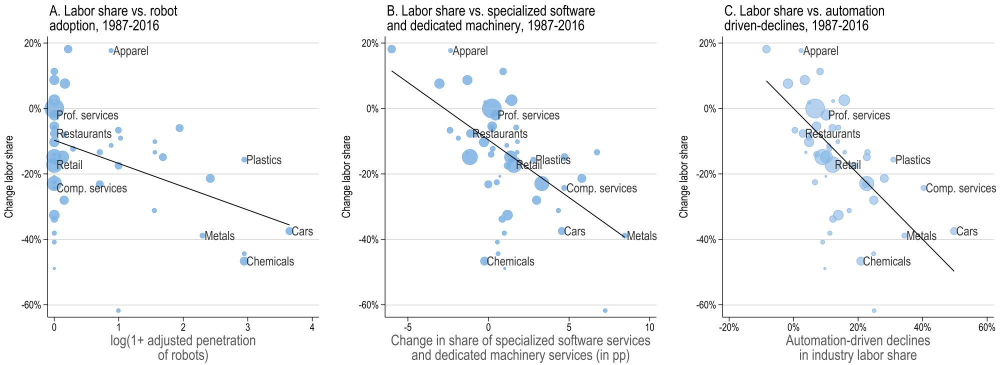


FIGURE 4.—Relationship between automation technologies and changes in industry labor shares. See text for variable definitions. The five industries with the highest and the five industries with the lowest changes in their labor shares are identified in the figures.

Acemoglu-Restrepo '22

Setup: The familiar task model

Aggregate production function

$$Y = \left(\frac{1}{M} \int_{\tau} \left(M \cdot y\left(x\right)\right)^{\frac{\lambda-1}{\lambda}} \right)^{\frac{\lambda}{\lambda-1}}$$

- Equivalent to setup we've been using so far
- Only diff is that elasticity of substitution is $\lambda > 0$. If $\lambda = 1$, back in Cobb-Douglas case

Task level production function

$$y\left(x\right) = A_k \psi_k\left(x\right) \cdot k\left(s\right) + \Sigma_{g \in \mathcal{G}} A_g \cdot \psi_g\left(x\right) l_g\left(x\right)$$

- Also equivalent to familiar setup
- One type of capital
- $\mathcal{G}$ types of labor, each inelastically supplied l_g
- $\psi_k\left(x\right)$ and $\left\{\psi_g\right\}_{g \in \mathcal{G}}$ determine comparative advantage
- Task-specific productivity is zero for factors that cannot perform a task

Capital production function ("roundabout")

$$c = y - \int_{\mathcal{T}} \left(k\left(x\right) / q\left(x\right)\right) \cdot dx$$

- Hence, all factors are ultimately labor (kind of a paradox)

Equilibrium conditions

- Labor endowments $\mathcal{L} = \left(l_1, l_2, ..., l_G\right)$
- Wages $\mathbf{w} = \left(w_1, w, ..., w_G\right)$
- Labor allocations $l_g(x)$, capital allocation $k(x)$
    1. Allocation of tasks to factors minimizes cost
    2. Capital production decisions maximize net output
    3. Markets for labor and capital clear

Group specific exposure to routine task displacement

A-R direct task displacement measure

$$\text{Task displacement}_g^{\text{direct}} = \sum_{i \in \mathcal{I}} \omega_g^i \cdot \frac{\omega_{gi}^R}{\omega_i^R} \cdot \left(-d \ln s_i^{L,\text{Auto}} \right)$$

- **Assumption**: Only routine tasks can be automated and, within an industry, different groups of workers are displaced from their routine tasks at a common rate
- ω_g^i is the share of group g workers' wages earned in industry i (relative to their total earnings). Captures group $g's$ exposure to industry i
- Second term, $\frac{\omega_{gi}^R}{\omega_i^R}$ parameterizes the specialization of group g in routine jobs within industry i
  - ω_{gi}^R is the share of wages earned in routine jobs in industry i by workers in group g relative to their total earnings in that industry
  - ω_i^R is the share of wages earned in routine jobs by all workers in industry i relative to the total wage bill of the industry
- Third term, $-d \ln s_i^{L,\text{Auto}}$, is % fall in industry $i's$ labor share (estimated to be) due to automation

How are routine tasks measured?

- A consistent mapping of the 49 industries in the BEA data to Census industry classifications
- For each industry, compute the share of wages earned in routine jobs by a demographic group
- 500 demographic groups:
    - 5 education groups
    - 2 sexes
    - 5×10-year age bins $\{16-25, 26-35, 36-45, 46-55, 56-65\}$
    - 5 race groups: White, Black, Hispanic, Asian, Other
    - 2 nativities: US-born and foreign-born
- Definition of routine occupations from Acemoglu-Autor '11 (actually from Autor-Dorn '13), where employment-weighted third of occupations in 1980 are classified as *routine task-intensive*

(a) Very successful prediction; (b) monotone in education

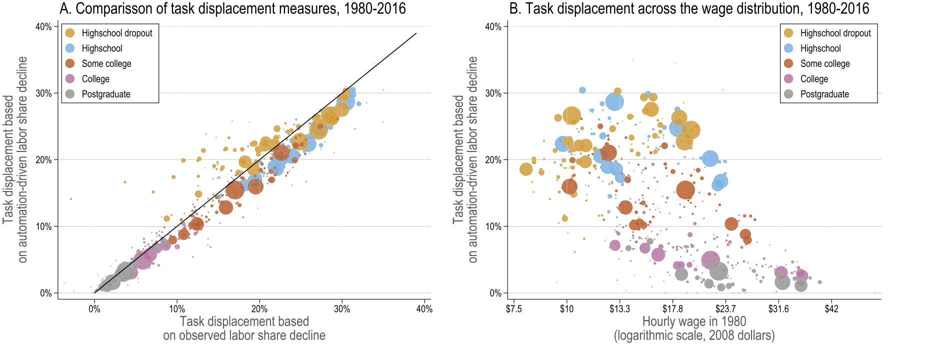
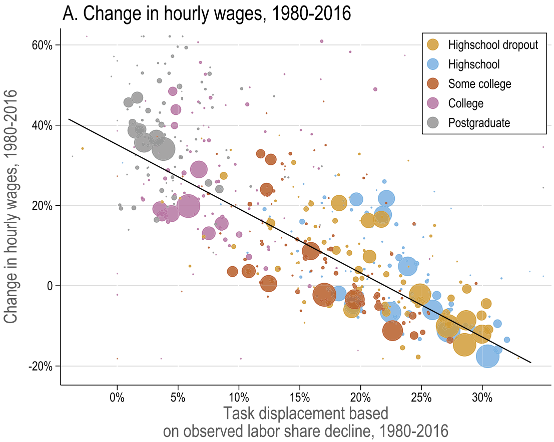
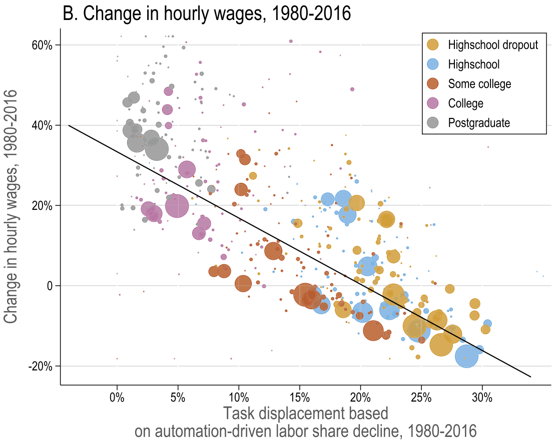


FIGURE 5.—Direct task displacement measures for the 500 demographic groups in our sample. The left panel shows a scatter plot between our two task displacement measures. The first, computed from observed labor share declines, is on the horizontal axis, while the second, computed from automation-driven labor share declines, is on the vertical axis. The 45° degree line is shown in black. The right panel plots our measure of task displacement computed from automation-driven labor share declines against the baseline hourly wages of groups in 1980. Marker sizes indicate the share of hours worked by each group and shades of gray (different colors) indicate education levels. See text for variable definitions.

Acemoglu-Restrepo '22

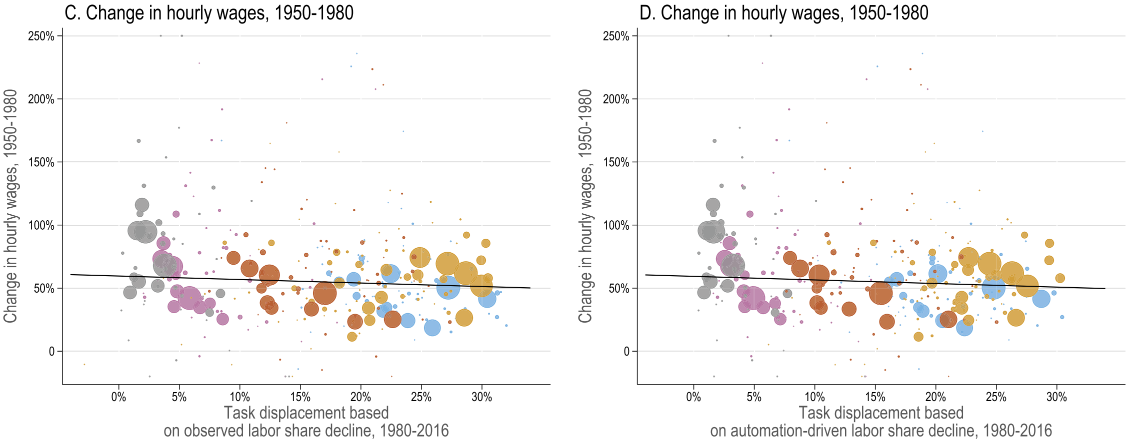
Wage relationships: 1980–2016





Acemoglu-Restrepo '22

Wage relationships, falsification test: 1950–1980

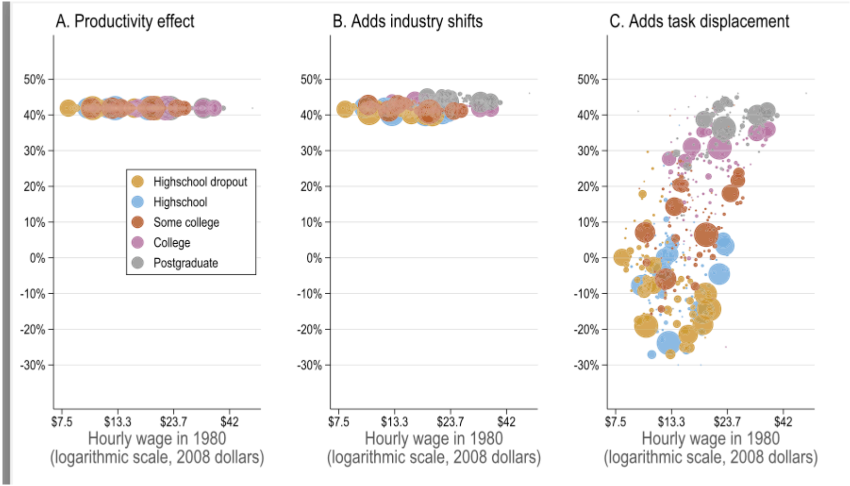


Acemoglu-Restrepo '22

Margins of adjustment to technical change

1. Common productivity effect increases wages (this is the Solow residual or TFP)
2. In the presence of multiple sectors, wages additionally depend on changes in industry composition that take place in response to technological shifts. Workers' exposure depends on their industry affiliations
3. Each group $g's$ wage depends on its direct task displacement—the automation-induced displacement it experiences, now summed across all industries

Decomposition of wage change components



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4. **'Ripple' effects determine propagation of displacement effects**

Automation, Capital Deepening, and Ripple Effects

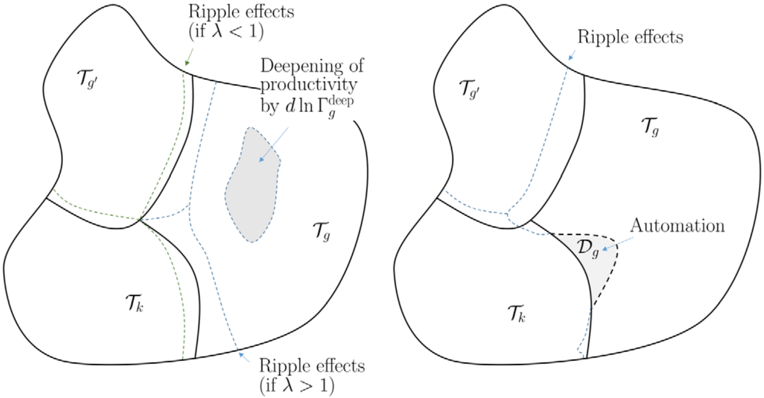

FIGURE 2.—The direct effects of technology and ripple effects. The left panel shows the effects of an increase of $d \ln \Gamma_g^{\text{deep}}$ in the productivity of group g in tasks in $\mathcal{T}_g$. The right panel depicts the effects of automation technologies that reduce the task share of worker g by $d \ln \Gamma_g^{\text{auto}}$.

Acemoglu-Restrepo '22

Decomposition of wage change components: Adding ripple effects
Q: Why do ripple effects make the slope shallower?

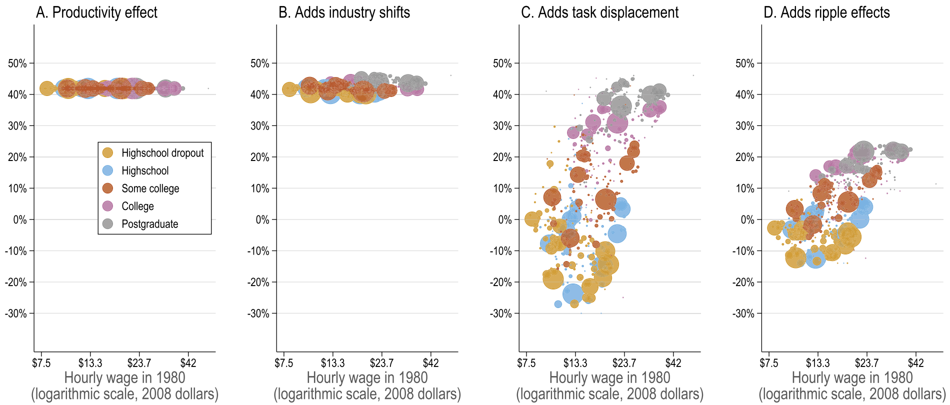

FIGURE 7.—Contribution of productivity effects, industry shifts, direct displacement effects, and ripple effects to the predicted change in hourly wages, 1980–2016. Marker sizes indicate the share of hours worked by each group and shades of gray (different colors) indicate education levels. See text for variable definitions.

Acemoglu-Restrepo '22

Actual versus predicted wage changes

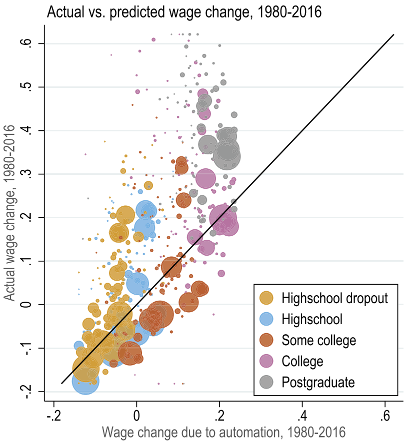

FIGURE 8.—Observed wage changes (vertical axis) versus predicted wage changes in general equilibrium due to automation (horizontal axis). the 45° line is shown in black. Marker sizes indicate the share of hours worked by each group and shades of gray (different colors) indicate education levels. See text for variable definitions.

Acemoglu-Restrepo '22

Some follow-up questions

1. Results imply very strong comparative advantage diffs across narrow demographic groups – plausible?
2. Many of the demo groups that fared badly are much less numerous than they used to be
3. Do results differ by gender – and if so, how and why?
4. Does this work too well?

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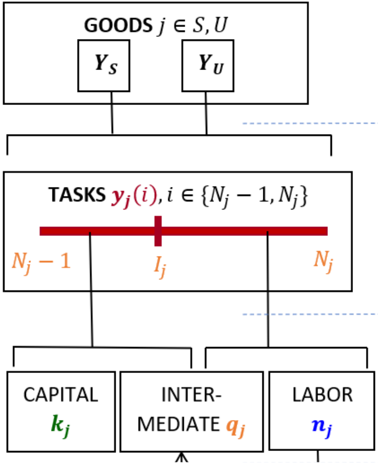
Objectives: Analyzing new work

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

Conceptual model



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

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

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

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

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

Inelastic supply of k

l and h mobile between sectors

Summary of conceptual model

A two-sector task model of labor demand, with two types of technical change

- **Two types of labor, H and L, inelastically supplied**
  - Labor flows freely across sectors (law of one price for skills)
- **Two types of capital, K_S and K_U, inelastically supplied**
  - Capital is sector-specific, does not flow across sectors
- **Two sectors: H and L intensive, producing Y_S and Y_U**
  - Each sector produces a distinct good, using a CES production function
  - Uses high skill labor, low skill labor, and capital.
  - The S sector is more skill-intensive than the U sector
  - A unit mass of tasks in each sector, with different skill intensities
  - Outputs of both sectors combined Cobb-Douglas to form a unique final good, Y

Summary of conceptual model continued

A two-sector task model of labor demand, with two types of technical change

- **Endogenous technological responses in each sector**
  - Automation & new task creation can occur in each sector, w/different effects on labor demand
  - Demand shift favoring either sector spurs new task creation in that sector
  - Capital scarcity in each sector spurs automation in that sector
  - Positive sectoral demand shocks cause more new task creation than automation b/c labor flows across sectors, capital does not
  - Sectoral demand shocks raise price of capital relative to labor, induces labor-using new task creation

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
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

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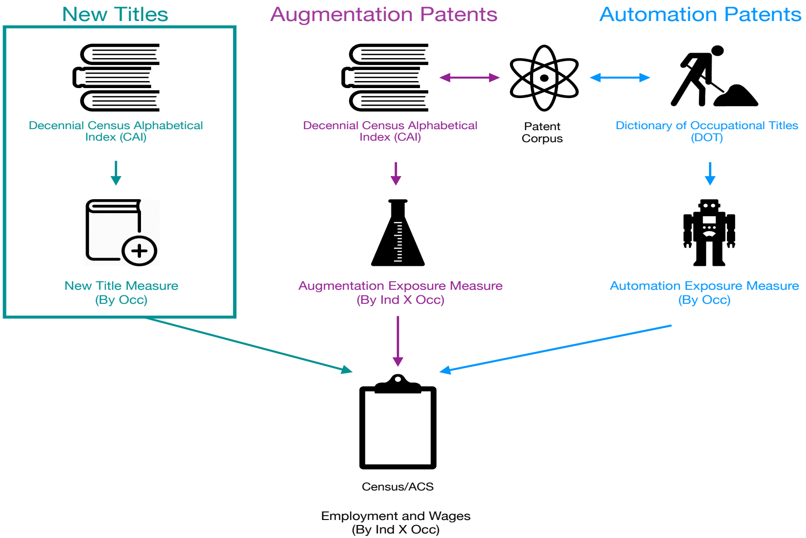
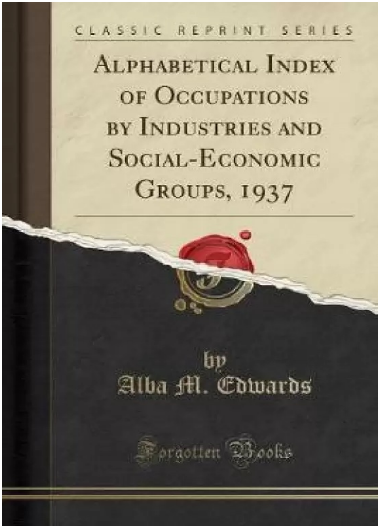
Identify new titles using Census coding volumes, 1940–2018



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

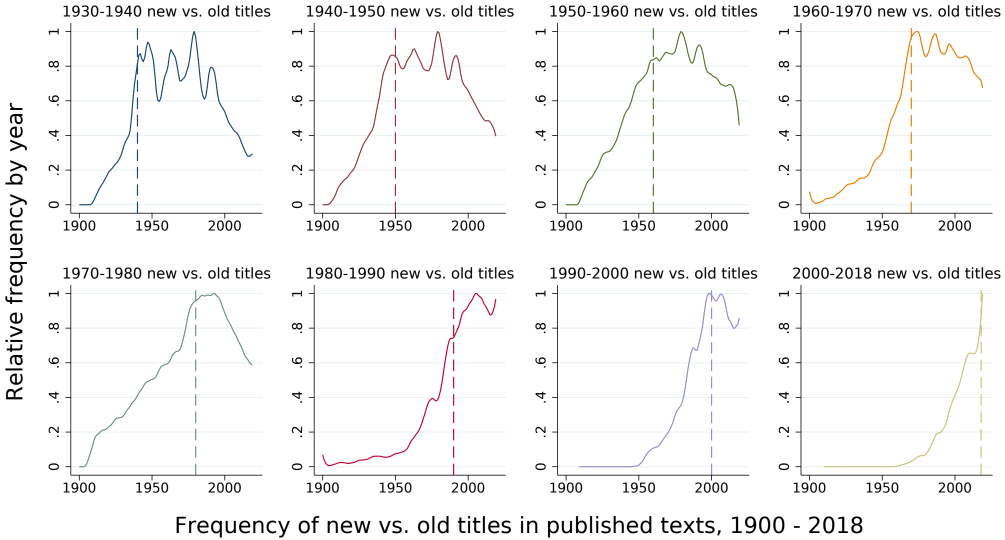
Each title is classified to a Census occupation

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

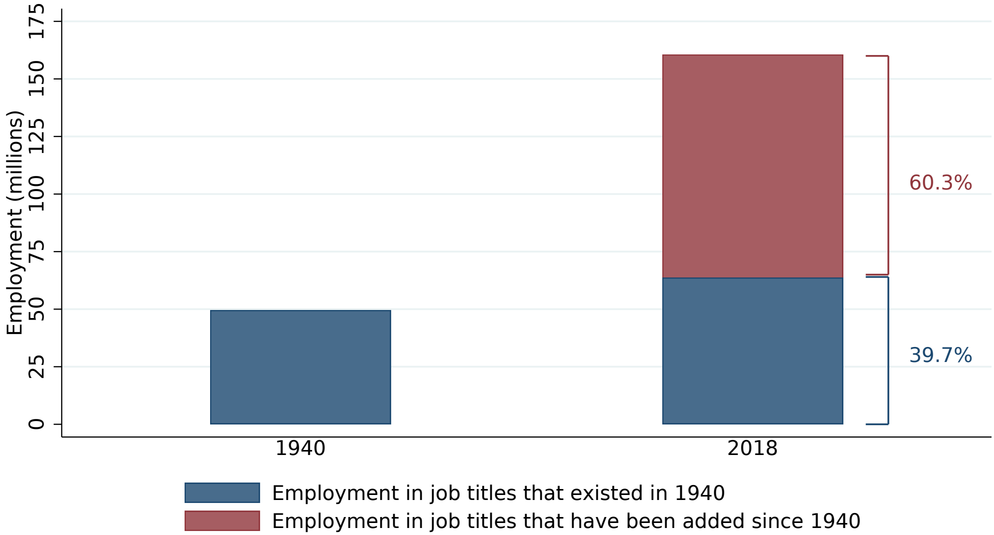


Quantifying new work

- **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

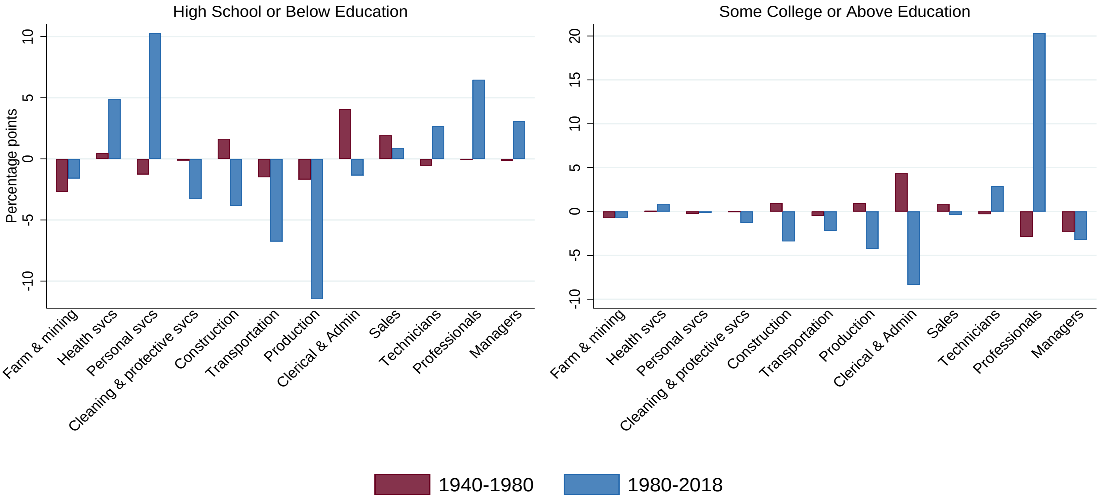
- **Do not use cardinal properties of measure in primary analysis**
  - Studying predictors of new title *flows* by occupation $\times$ decade
  - When analyzing employment/wage outcomes, treat new titles as an intermediating variable, not a cause

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

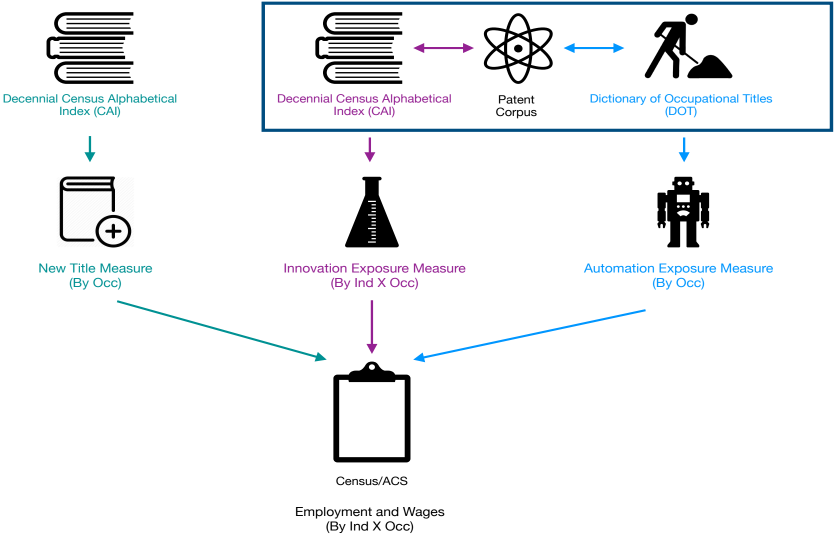


New work polarizes relative to pre-existing work between 1980 and 2018

Occupational locus of new vs. pre-existing work by education and era



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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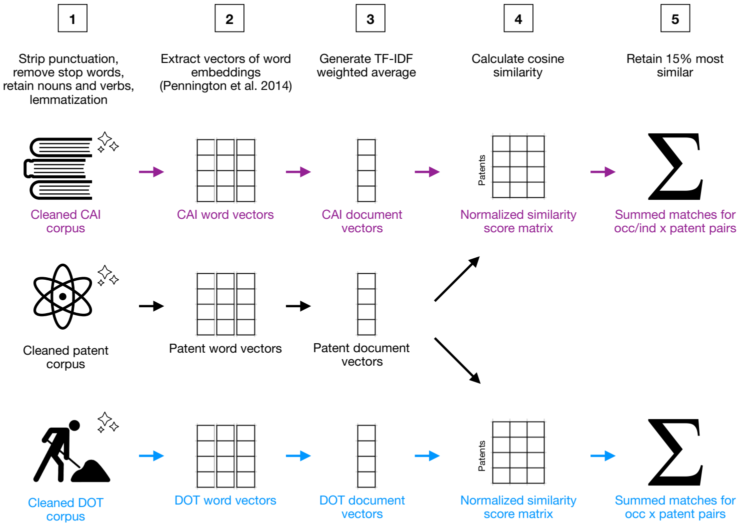
Dictionary of Occupational Titles, 1939, '77

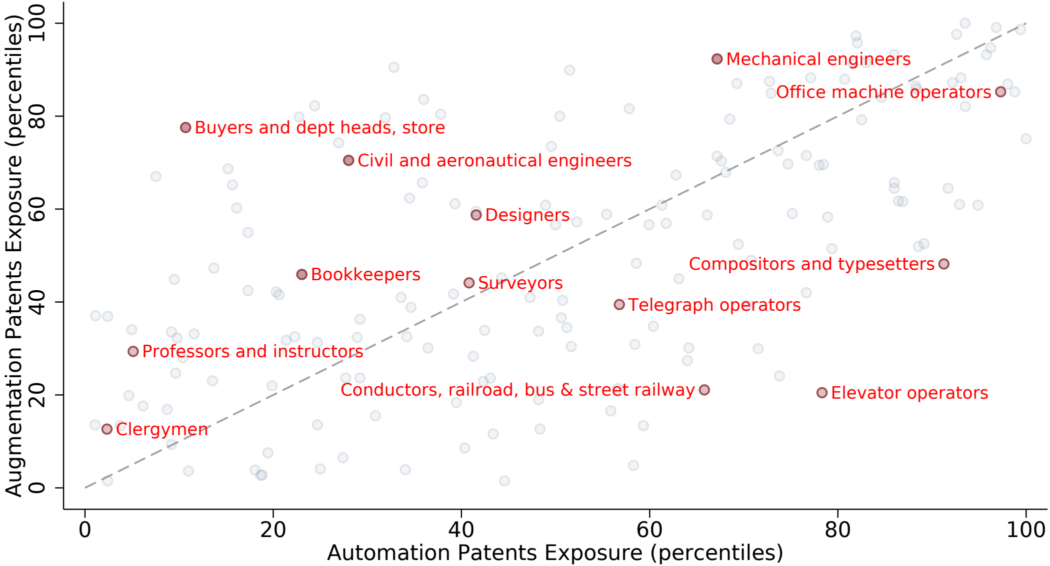
MEDICAL TECHNICIAN; hospital technician; laboratory assistant, medical; laboratory technician, medical (medical ser.) 0-50.01. Performs medical duties in a hospital or medical laboratory making laboratory tests of urine, blood, animal parasites, infections, and animal inoculations; makes blood counts 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.

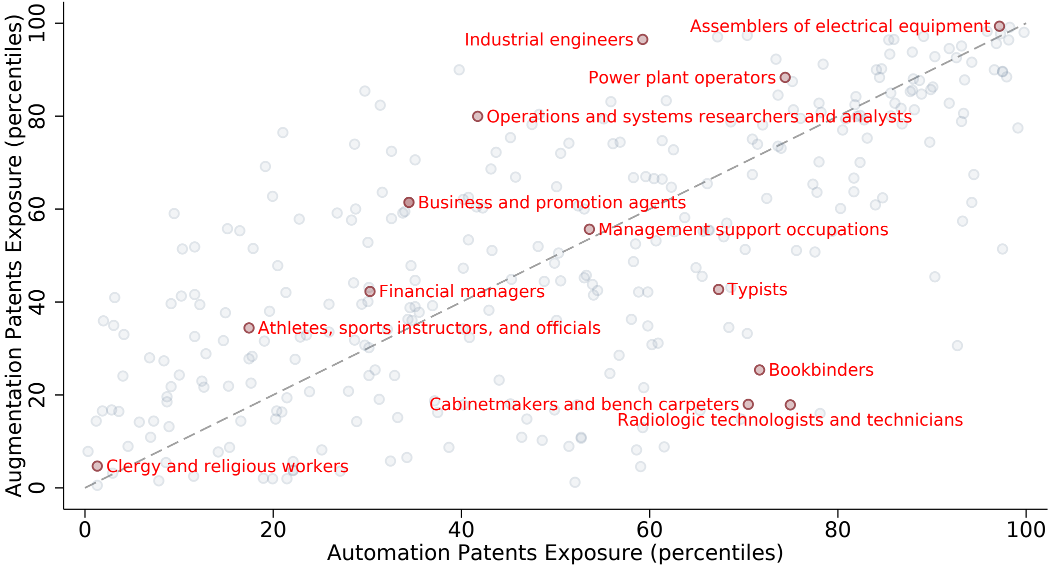
Linking Augmentation & Automation technologies to occupations



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



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



Agenda

1. **Tasks, Automation, and the Rise in U.S. Wage Inequality: Acemoglu-Restrepo ’22**

2. **New Frontiers: The Origins and Content of New Work, 1940–2018 (ACSS ’24)**
   - What is the occupational content of new work?
   - Where does new work come from?
   - What does new work do?

3. **Conclusions and next steps**

4. **[Optional self-study] Skill Complementarity of Broadband Internet: Akerman, Gaarder, Mogstad ’15**

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

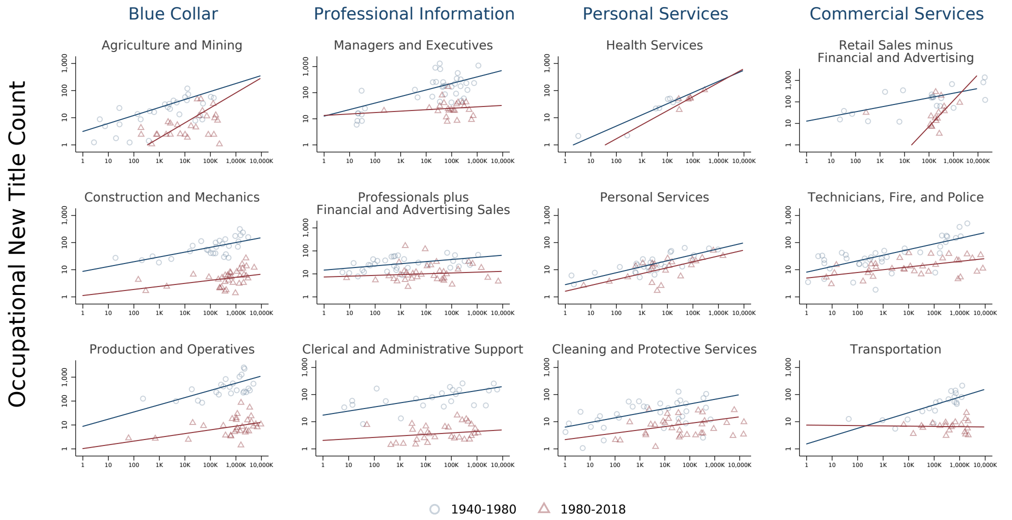
New titles emerge in augmentation-exposed occupations

	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

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



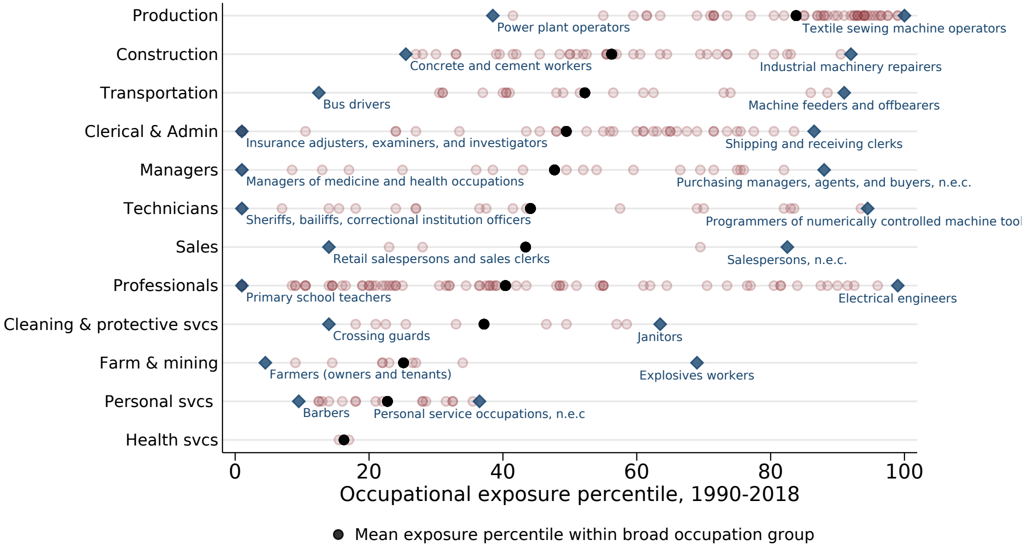
Do occupational demand shifts spur/retard new job type creation?

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



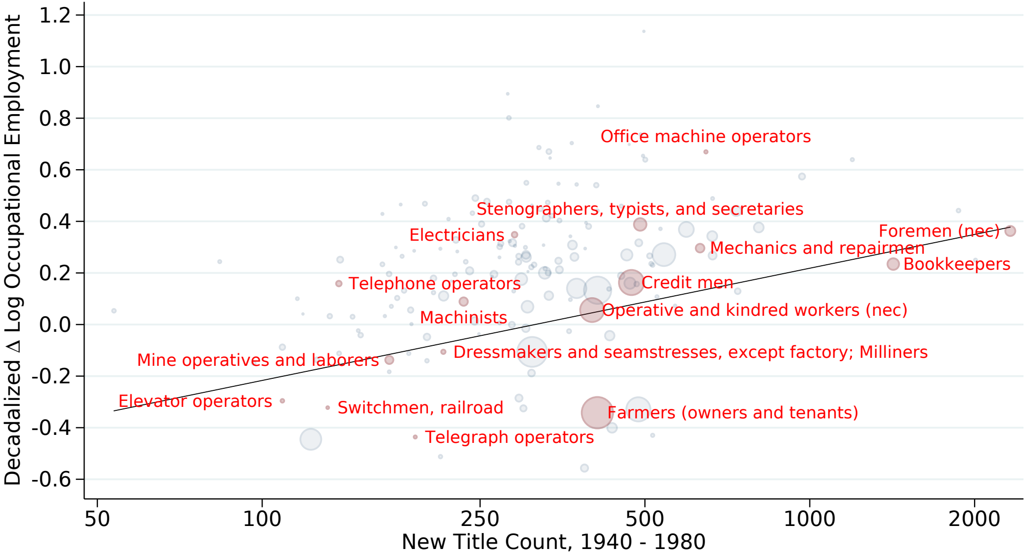
Less new title creation in occupations exposed to import competition

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

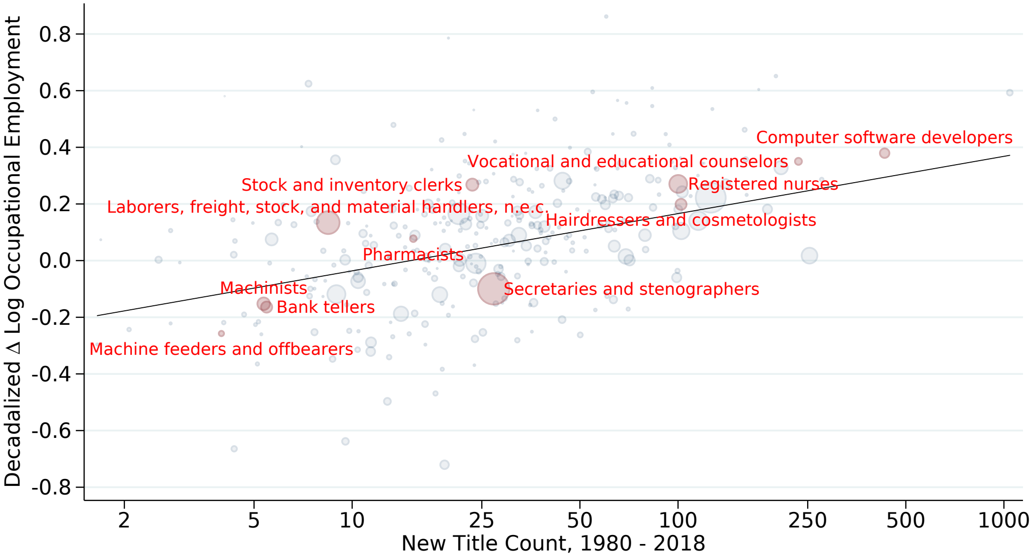
Negative binomial models, coefficients multiplied by 100. Standard errors clustered by occupation in parentheses. Observations weighted by start-of-period occupational employment shares. Augmentation and automation exposure measures correspond to the log of the weighted counts of matched patents. $^{+}p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

Agenda

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



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



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

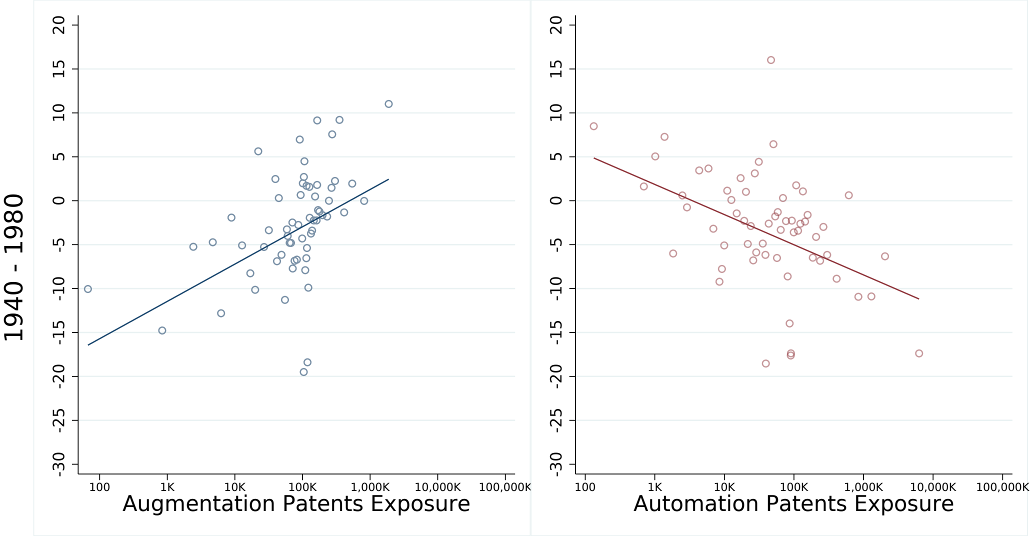
Dependent Variable: Decadalized Log Employment Change in Occ-Ind Cells, Stacked Long-Difference

	(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

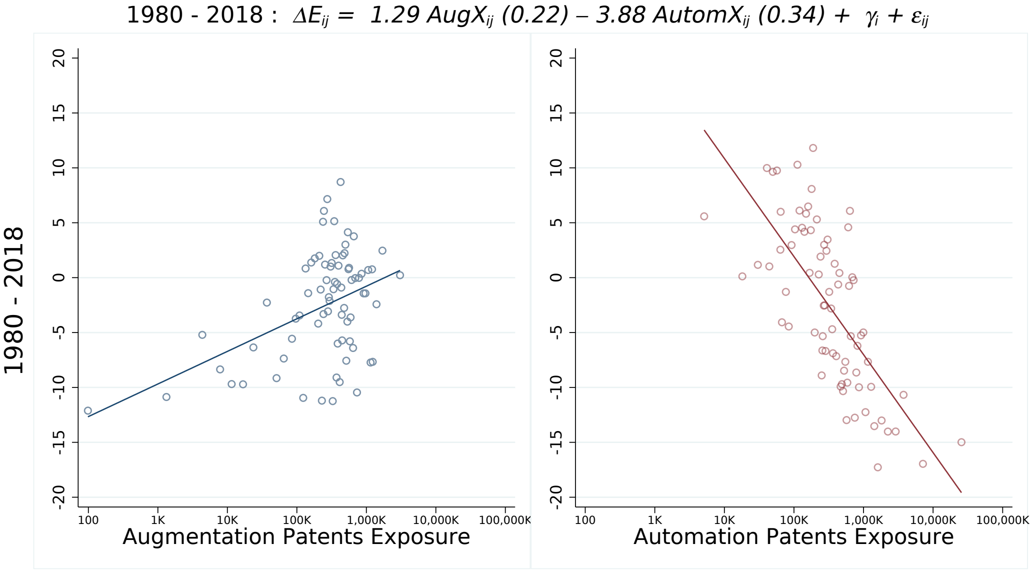
N = 33,900 changes in employment and wagebill in consistently defined Census occupations over 1940–1980 and 1980–2018. Dependent variable is decadalized and multiplied by 100 so that growth rates are expressed in per-decade percentage points. $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p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

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



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
4. **What's needed next on this agenda?**

Agenda

Conclusions and next steps

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

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

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4. **[Optional self-study] Skill Complementarity of Broadband Internet: Akerman, Gaarder, Mogstad '15**

The skill complementarity of broadband Internet:
Rollout of broadband Internet in Norway, 2001 – 2005

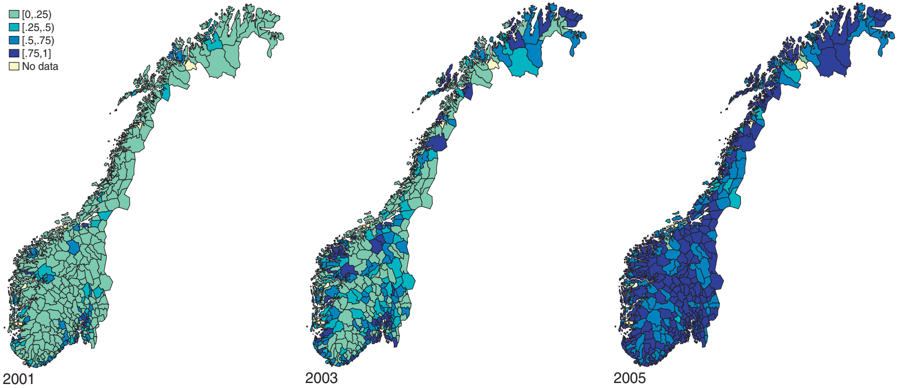


FIGURE I

Geographical Distribution of Broadband Availability Rates

The graphs show the geographical distribution of broadband availability rates of households in 2001, 2003, and 2005.

Akerman, Gaarder, Mogstad 2015

Estimated effect of broadband availability on wages and employment by skill level

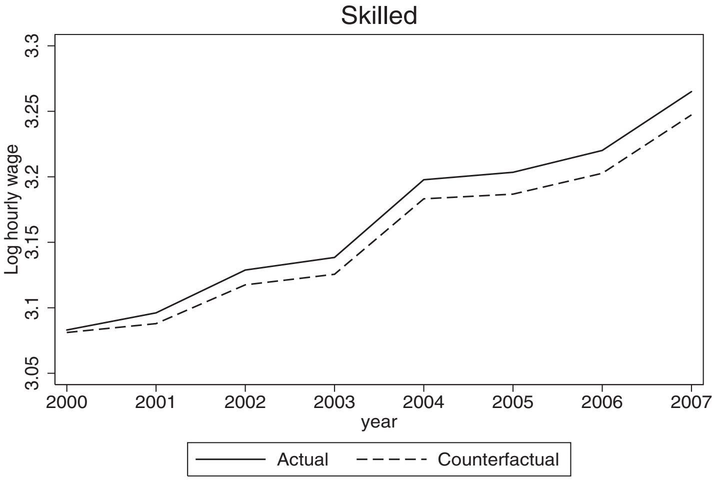
Intention-to-Treat Effects on Wages and Employment

Dependent variable	(1) Log hourly wage	(2)	(3) Employment	(4)
	2 skills	3 skills	2 skills	3 skills
Unskilled	2.939***		0.691***	
	(0.00455)		(0.00262)	
Low skilled		2.905***		0.664***
		(0.00431)		(0.00231)
Medium skilled		2.977***		0.731***
		(0.00454)		(0.00288)
Skilled	3.169***	3.171***	0.734***	0.737***
	(0.00420)	(0.00407)	(0.00480)	(0.00477)
Availability ×				
Unskilled	−0.00622		0.000794	
	(0.00455)		(0.00252)	
Low skilled		−0.0108***		−0.00392
		(0.00325)		(0.00244)
Medium skilled		−0.00793		0.00388
		(0.00600)		(0.00281)
Skilled	0.0178**	0.0202***	0.0208**	0.0225**
	(0.00720)	(0.00692)	(0.00920)	(0.00892)
Worker-year observations	8,759,388	8,759,388	20,327,515	20,327,515
		p-values		
Test for no skill bias	.000	.000	.012	.001

Akerman, Gaarder, Mogstad 2015

Estimated effect of broadband availability on evolution of high-skill wages

(a) Log hourly wages



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Estimated effect of broadband availability on evolution of low-skill wages

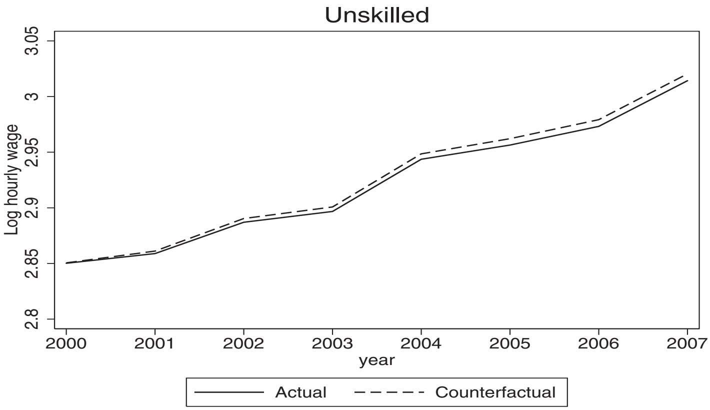


FIGURE III

Actual and Counterfactual Trends in Labor Market Outcomes

Akerman, Gaarder, Mogstad 2015

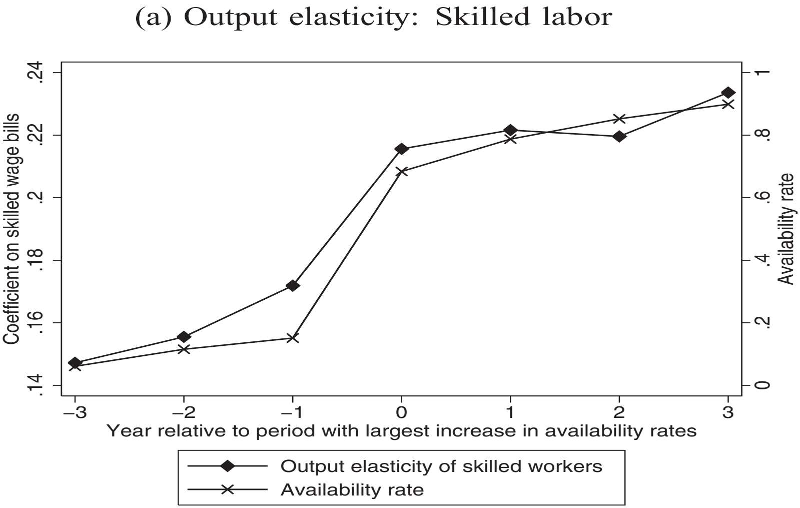
Estimated effect of broadband availability on log value-added by skill group

Intention-to-Treat Effects on Output Elasticities

Dependent variable	(1)	(2)
	Log value added	
	2 skills	3 skills
Intercept	3.880***	4.537***
	(0.0965)	(0.0791)
Log capital	0.100***	0.0981***
	(0.00495)	(0.00490)
Log unskilled	0.576***	
	(0.0116)	
Log low skilled		0.298***
		(0.00804)
Log medium skilled		0.265***
		(0.00684)
Log skilled	0.136***	0.134***
	(0.00678)	(0.00636)
Availability ×		
Intercept	−0.500***	−0.561***
	(0.111)	(0.0976)
Log capital	−0.00169	0.000188
	(0.00750)	(0.00661)
Log unskilled	−0.0226	
	(0.0234)	
Log low skilled		−0.0274***
		(0.00934)
Log medium skilled		0.0179*
		(0.00967)
Log skilled	0.0755***	0.0645***
	(0.0166)	(0.0137)
Firm-year observations	149,676	137,498
	p-values	
Test for no skill bias	.012	.000

Akerman, Gaarder, Mogstad 2015

Estimated effect of broadband on output elasticity of high-skill labor



Akerman, Gaarder, Mogstad 2015

Estimated effect of broadband on output elasticity of low-skill labor

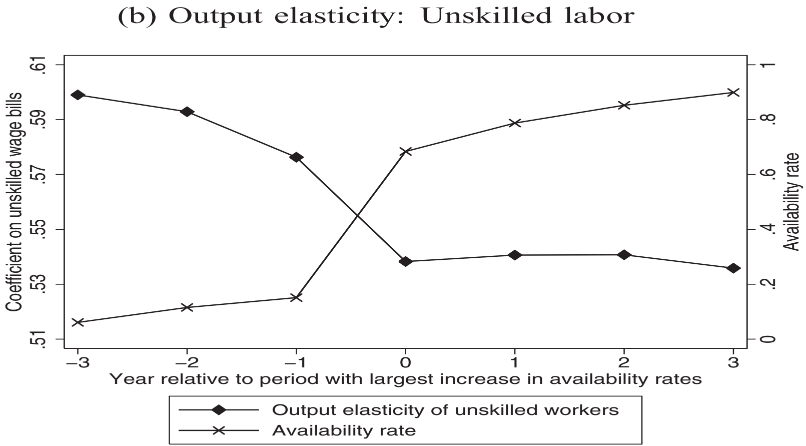


FIGURE II

Output Elasticities and Skill Premiums, Before and After the Largest Increase in Availability Rates (Period 0)

Akerman, Gaarder, Mogstad 2015

Estimated effect of broadband availability on task-wage premiums

Wage Regressions with Interactions between Tasks and Broadband Availability

	(1)	(2)	(3)
Dependent variable	Log hourly wage		
		Skill categories	
		2 skill levels	3 skill levels
Abstract	0.371***	0.283***	0.272***
	(0.0142)	(0.0139)	(0.0140)
Routine	−0.0641***	−0.0664***	−0.0700***
	(0.00653)	(0.00573)	(0.00577)
Manual	0.0248***	0.0156**	0.0138*
	(0.00791)	(0.00769)	(0.00740)
Availability × Abstract	0.173***	0.157***	0.157***
	(0.0320)	(0.0298)	(0.0297)
Availability × Routine	−0.0357***	−0.0344***	−0.0338***
	(0.00798)	(0.00766)	(0.00791)
Availability × Manual	0.00200	0.00145	0.00273
	(0.0115)	(0.0107)	(0.0104)
Worker-year observations	4,586,333	4,586,333	4,586,333
Controlling for educational attainment:			
Skill levels	No	Yes	Yes
Availability × Skill levels	No	Yes	Yes
Tests for no task bias:		*p*-values	
Equality of abstract and routine	.000	.000	.000
Equality of abstract and manual	.000	.000	.000
Equality of manual and routine	.041	.040	.036

Akerman, Gaarder, Mogstad 2015