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

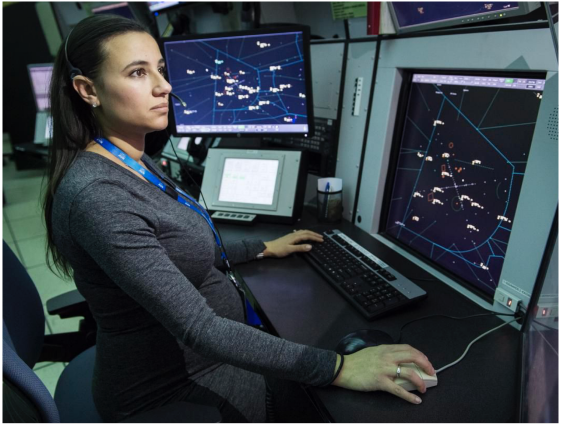
David Autor, MIT Department of Economics and NBER
Neil Thompson, MIT CSAIL and MIT FutureTech

IAB Nürnberg — January 15, 2025

What's the difference between these two occupations?

Crossing Guard

Median annual earnings $36,370



Air Traffic Controller

Median annual earnings $137,380

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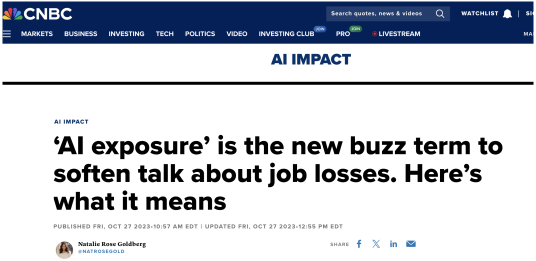
IMF report: 40 percent of jobs exposed to AI



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AI IMPACT

AI IMPACT

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

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Natalie Rose Goldberg
@NATROSEGOLD

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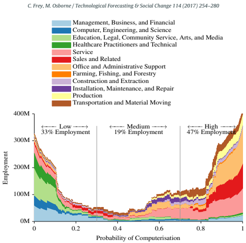
Economists also equate 'exposure' with job loss



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

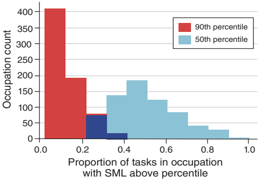
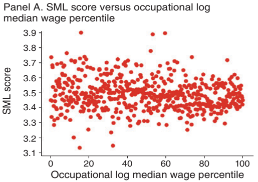


FIGURE 1. FREQUENCY COUNTS OF OCCUPATIONAL TASK PROPORTIONS ABOVE NINETIETH, SEVENTY-FIFTH, AND FIFTIETH PERCENTILES



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

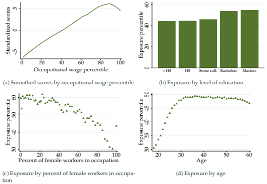
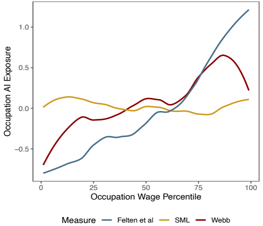
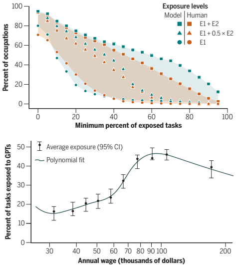


Figure 7: Exposure to AI by demographic group

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



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



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

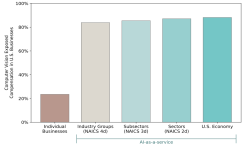


Figure 8 Fraction of vision task compensation economically-attractive to automate if single systems are deployed at this scope.

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

When does ‘exposure’ replace experts? When does it augment expertise?

- Does automation or AI ‘exposure’ $\rightarrow$ Occupation, job, wages at risk?

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  3. Depending on **which tasks** are automated, automation could diminish or amplify the demand for human **expertise**

Defining expertise

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

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

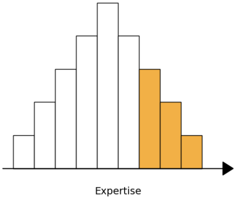
1. The goal it enables must itself have market value
2. The expertise must be scarce


WHEN EVERYONE IS ~~SPECIAL~~
Expert
NO ONE IS.
memegenerator.net

When does automation exposure replace experts vs. complement expertise?

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

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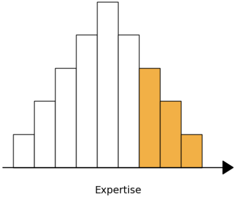

Expert tasks automated

	Labor productivity
	Average expertise
	Employment
	Wages

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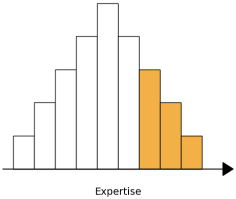

Expert tasks automated

$\uparrow$	**Labor productivity**
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$\rightarrow$ **or** $\downarrow$	**Wages**

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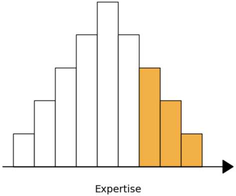

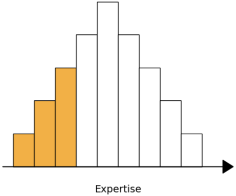

Expert tasks automated		Inexpert tasks automated
$\uparrow$	Labor productivity	
$\downarrow$	Average expertise	
$\uparrow$	Employment	
$\rightarrow$ or $\downarrow$	Wages	

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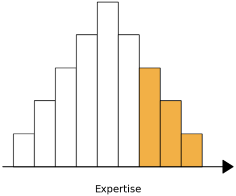
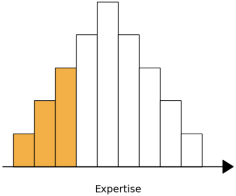
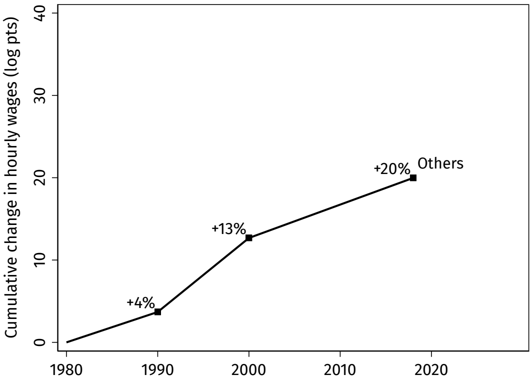


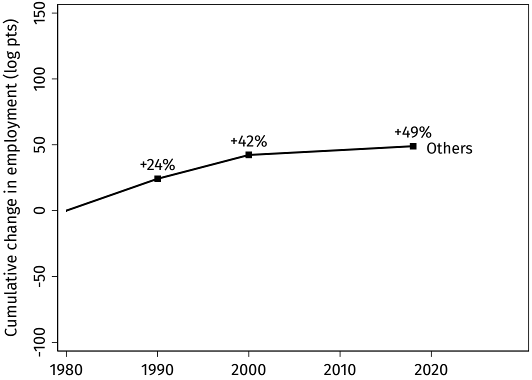


Expert tasks automated		Inexpert tasks automated
↑	Labor productivity	↑
↓	Average expertise	↑
↑	Employment	→ or ↓
→ or ↓	Wages	↑

Wage and employment change across all occupations

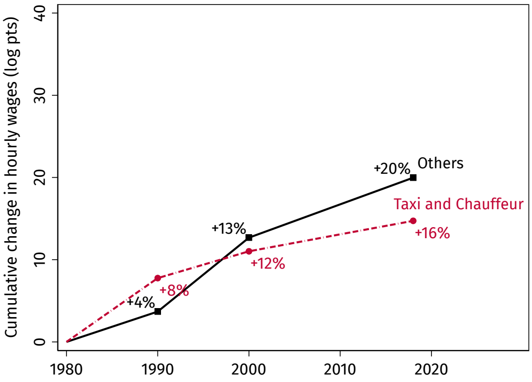


Cumulative Wage Change

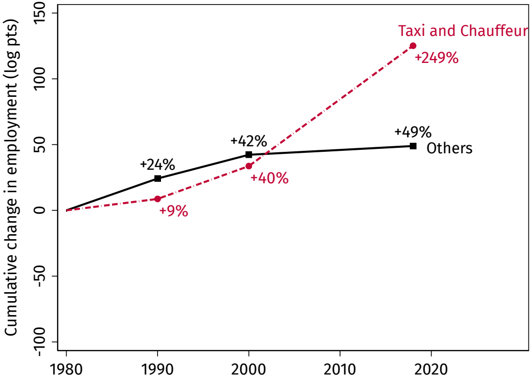


Cumulative Employment Change

Taxi drivers: Expertise, wages fell, employment rose

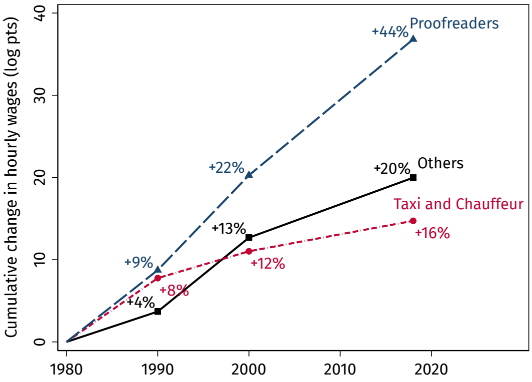


Cumulative Wage Change

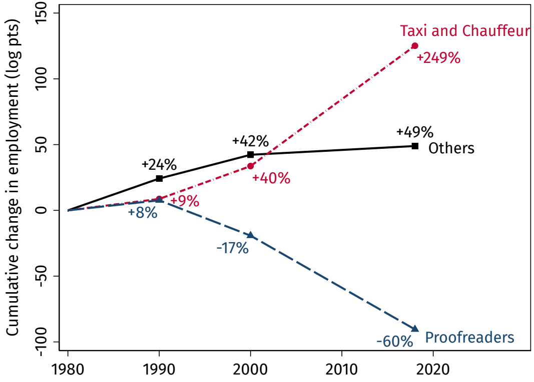


Cumulative Employment Change

Proofreaders: Expertise upgraded, wages rose, employment fell



Cumulative Wage Change



Cumulative Employment Change

When expert tasks are eliminated — Free entry and angry incumbents

THE TASK BEFORE US

When does automation exposure replace experts vs complement expertise?

Model—

Conceptual foundations

Expertise and automation: Foundations

1. The tasks comprising an occupation are **indivisible** → All must be performed
   - Automating one set of tasks does not eliminate the need for the others (Acemoglu-Autor '11)

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4. All occupations also have some **generic tasks**
   - Can be done by all workers but are not subject to automation
   - Generic tasks may require physical dexterity, multi-sensory interactions, common sense

Model—

The math

Model — Workers and expertise supply

Workers

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

Expertise is like... Russian stacking dolls

Model — Occupations and expertise demands

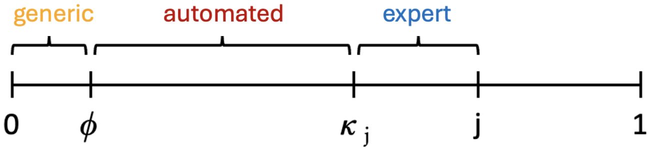
Occupations

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

Model — Generic tasks, expert tasks, and automation

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

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



Model — Worker-level production function is Cobb-Douglas

Output of worker i supplying ℓ_i to occ j:

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

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

Model – Aggregate production and the price index

Occupational outputs are combined into aggregate good

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

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

  where $\sigma > 1$ is the elasticity of substitution

- Price index for Y is

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

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

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

Workers arbitrage wage diffs, constrained by own expertise endowments

- Expertise replacement
  - More expert workers j can *always* flow into less expert occupations $j' < j$
  - If all expert tasks in an occ are automated, occ becomes generic $\rightarrow$ open to any worker
  - As occs go from expert to generic, their wages cannot exceed that in any expert occ, $j > \kappa$
  - *Cause — Inexpert labor is elastically supplied*

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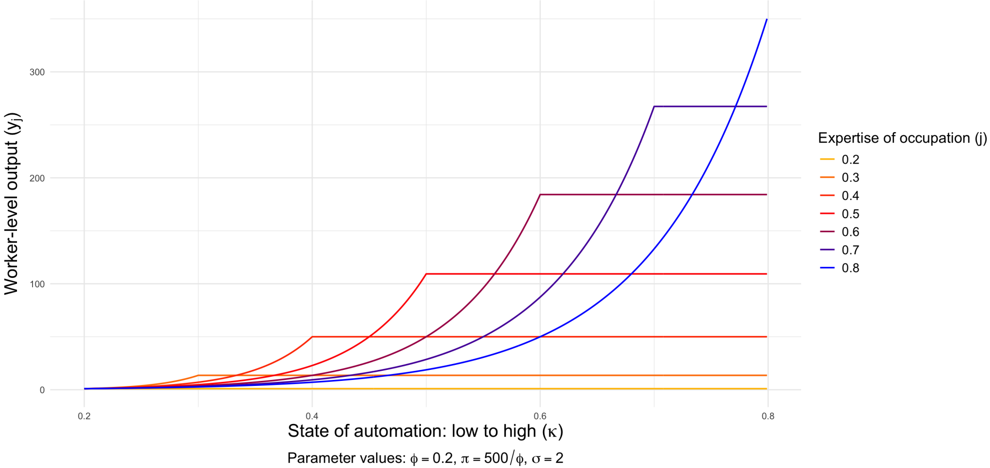
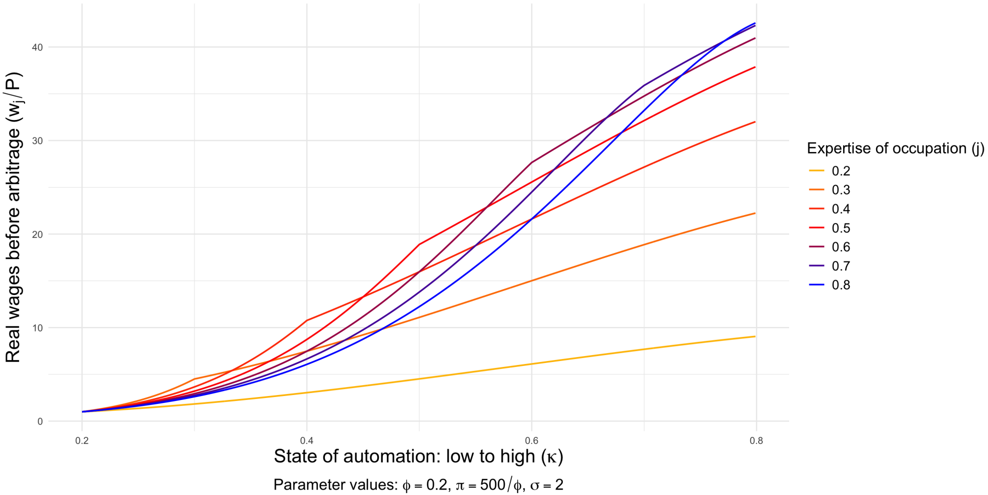
  - *Cause — Inexpert labor is elastically supplied*
- Expertise augmentation
  - Less expert workers j' can *never* flow into more expert, non-automated tasks where $j' > j$
  - As κ rises, real value of more expert occs rises
  - Relative and real wages of remaining experts rise
  - *Cause — Expert labor supply is inelastically supplied*

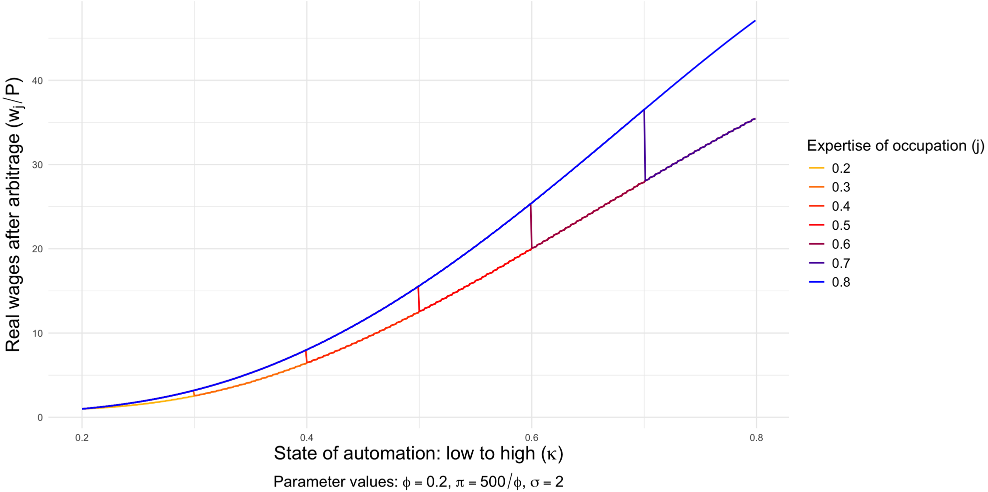
Automation first raises productivity in low-expertise occs, but ultimately raises it by more in high-expertise occs



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



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



Model—
Implications

Primary implications taken to the data

1. Expert work commands higher wages than generic work
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   - Adding tasks may lower expertise demands — *if added tasks are inexpert*
   - Removing tasks may raise expertise — *if removed tasks are inexpert*
3. Change in occ's expertise demands will have opposing effects on wages, employment
   - Increase in expertise demand will raise wages, reduce employment (relative)
   - Fall in expertise demand will reduce wages, raise employment (relative)
   - Labor arbitrage is key: *Inexpert labor supply is elastic; Expert labor supply is inelastic*

What matters: Not only *quantity* of tasks added/removed but *expertise* of those tasks

Empirics—

What we must/will measure

Empirical approach

What we will measure

1. How much expertise a job requires

Empirical approach

What we will measure

1. How much expertise a job requires
2. Which tasks have been removed from and added to an occupation

Empirical approach

What we will measure

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

Measuring the expertise requirements of job tasks

Measuring expertise by harnessing Zipf's Law of Abbrevation

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

- Linguistic regularity: frequently used words tend to be shorter than rare words
  - Known in neuroscience as the Efficient Coding Hypothesis (Barlow 1961)
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  - *Specialized words—such as those used by experts—will be longer, less-frequent than words* denoting generic, common tasks
- Relevance to measuring expertise demands of job tasks
  - **Familiar terms are short and simple** → Non-expert
  - **Job tasks characterized by rare, complex words** → (More) Expert

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

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

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

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

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

Ingredients for measuring Dale-Chall task scores

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

Measuring expertise – Examples

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

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

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

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

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

Source for employment and earnings data

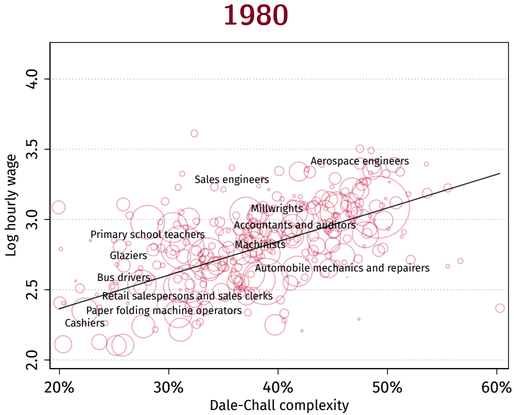
- Harmonized US Census employment and earnings data for 1980, 2000, 2018 from Autor Chin Salomons Seegmiller '24
- 306 consistent, comprehensive occupations (`occ1990dd18`)
- We also use the ACSS '24 measure of the *addition of new titles to occupations* ("new work"), which builds on (Lin '11), to validate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

Evidence—

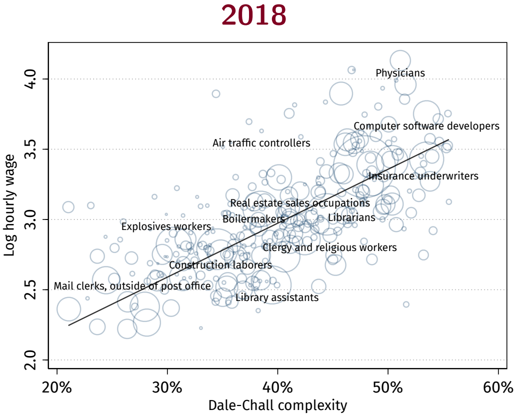
Expertise requirements predict wage levels

Expertise and log wages by occupation, 1980 and 2018

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



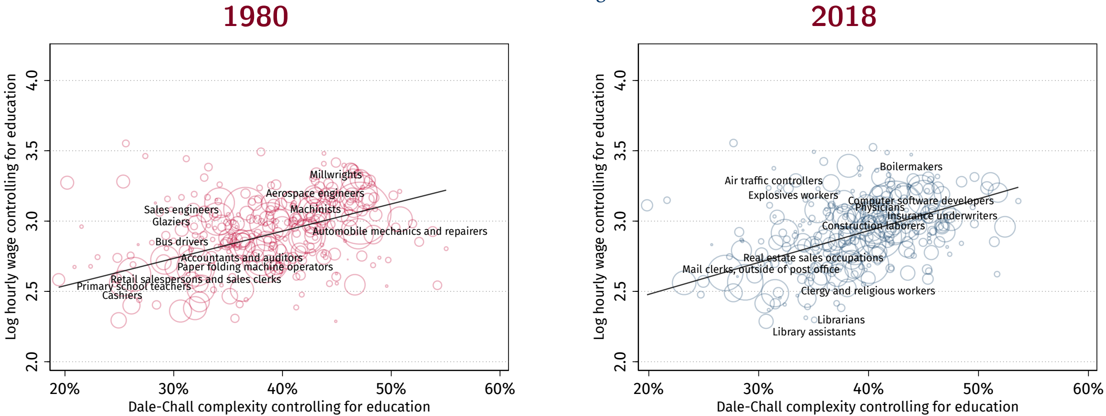
Slope: 2.39 (0.17), R2: 0.39, N: 306



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

Expertise and log wages by occupation, conditional on education

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



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

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

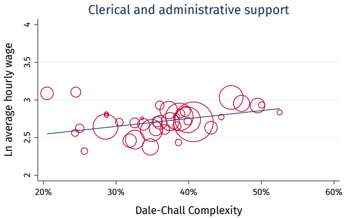
High and low expertise occupations by broad category

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

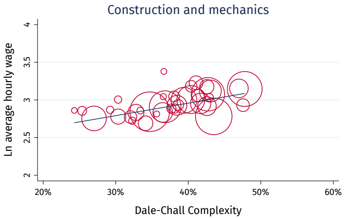
High and low expertise occupations by broad category—A few examples

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

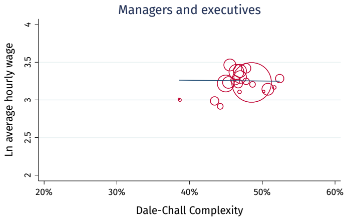
Expertise/wage scatterplots by broad occupation



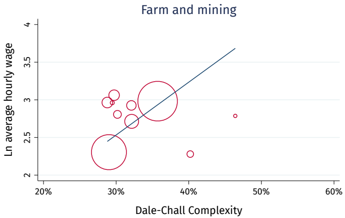
Slope: 1.05 (0.41), adj-R2: 0.13, N: 39



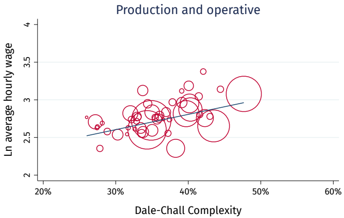
Slope: 1.66 (0.33), adj-R2: 0.40, N: 37



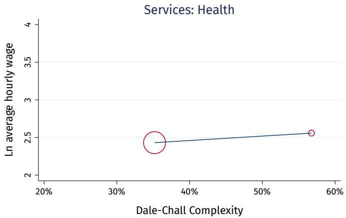
Slope: -0.10 (1.17), adj-R2: -0.05, N: 21



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

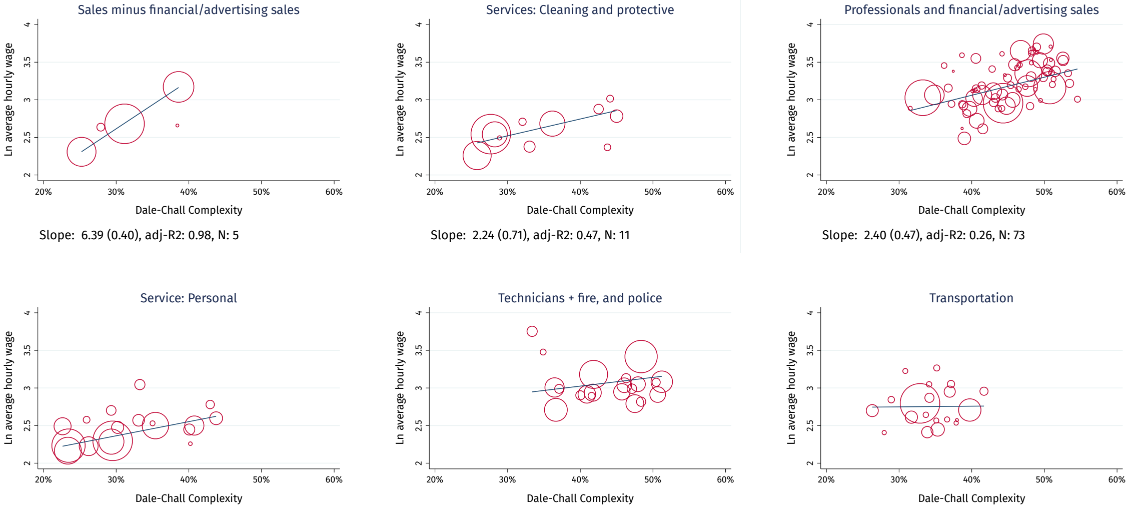


Slope: 2.03 (0.43), adj-R2: 0.30, N: 49



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

Expertise/wage scatterplots by broad occupation



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

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

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

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

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

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

Measuring changes in expertise requirements

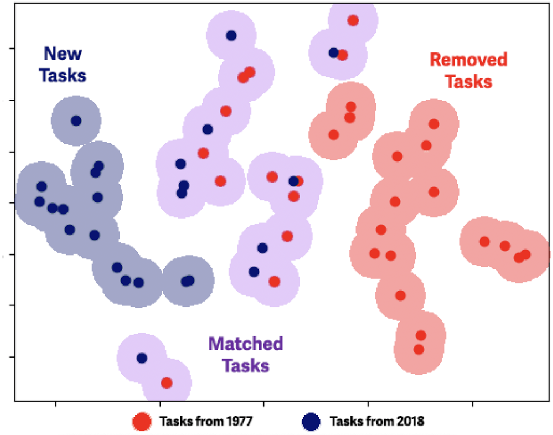
How we measure tasks removed and added

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

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

❸ **Identify unmatched tasks**:

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



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

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

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

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

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

How we calculate changes in expertise

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

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

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

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

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

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

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

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

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

Expertise downgrading

Tasks Removed

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

Consider tasks removed and retained by Typists, 1977 – 2018

Expertise downgrading

Tasks Removed

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

Tasks Retained

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

Consider tasks removed and retained by Statistical Clerks, 1977 – 2018

Expertise upgrading

Tasks Removed

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

Consider tasks removed and retained by Statistical Clerks, 1977 – 2018

Expertise upgrading

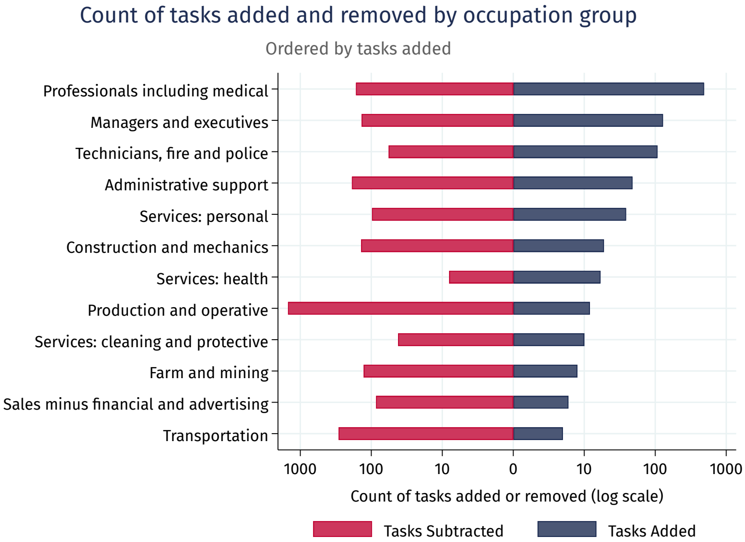
Tasks Removed

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

Tasks Retained

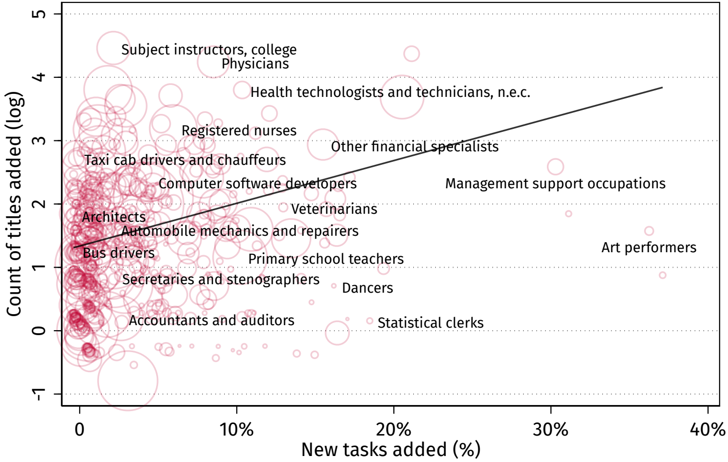
- Applies standardized mathematical formulas, principles, and methodology to technological problems... in relation to specific industrial and research objectives
- Confers with professional, scientific, and engineering personnel to plan projects
- Analyzes processed data to detect errors

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



New titles added and new tasks added

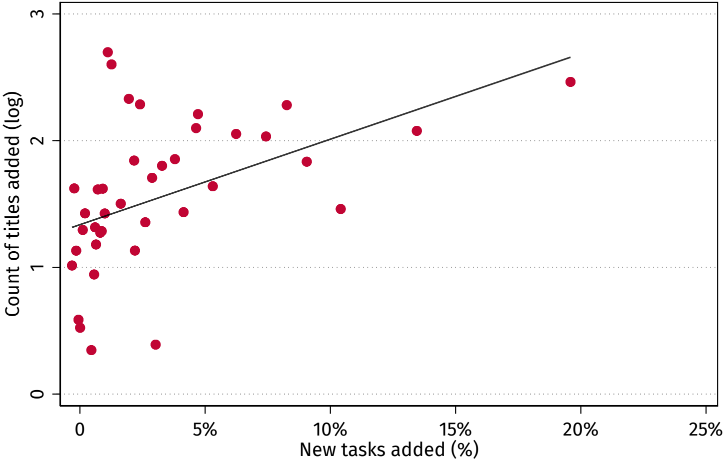
$$\ln(\text{New Titles})_{jt} = \alpha + \beta \Delta_{\text{add},jt} + \epsilon_{tj}$$



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

New titles added and new tasks added

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



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

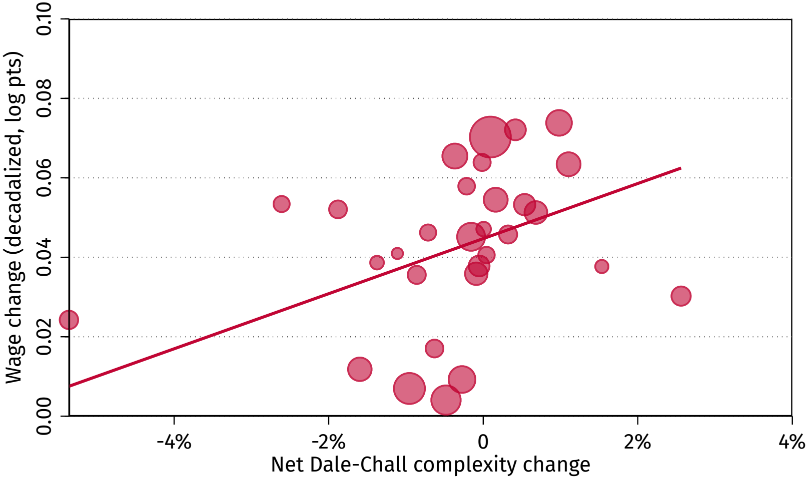
Evidence—

Δ Wages vs Δ Expertise

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

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

▸ table



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

Do Δ wages reflect Δ wage premiums or Δ expertise demands?

Calculate Δ expertise demands as changes in composition-adjusted wages

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

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

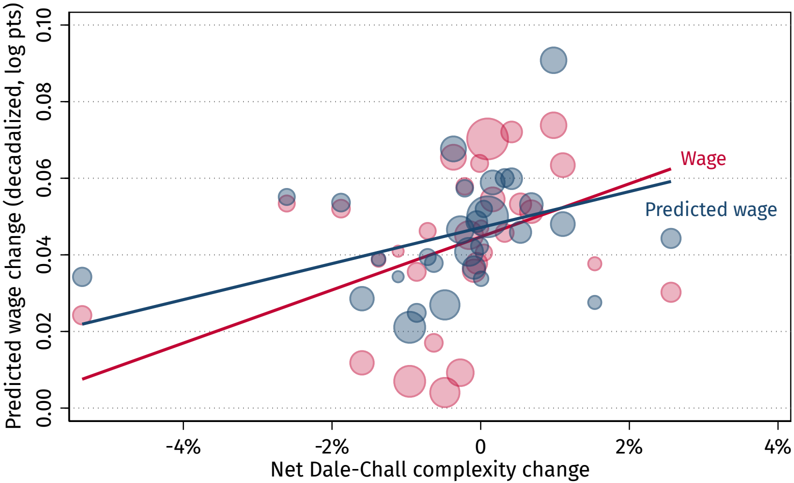
- Calculate predicted log wage $\hat{w}_{ijt} = E\left[w_{ijt}|X_{ij}, t\right]$ for each worker
- Collapse to occupation-year cells $\bar{\hat{w}}_{jt}$
- Wage components are
  - $\Delta\bar{\hat{w}}_{jt}$ is the change in mean log wages in occupation j attributable to changes in education, experience,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

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

Δ occ expertise (and raw wages) vs. ΔDCC (expertise), 1980–2018

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

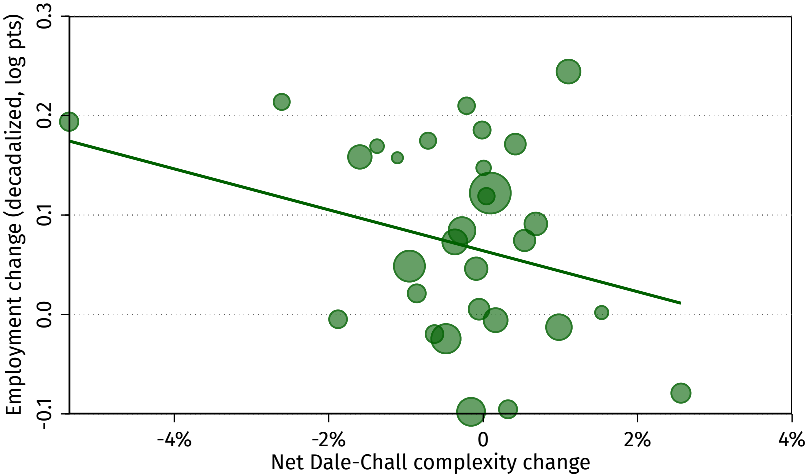
▸ table



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

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

▸ table

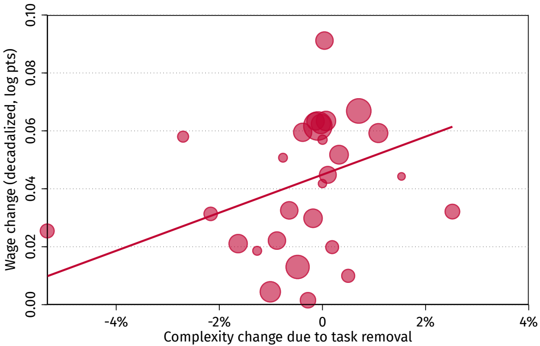


Slope: -1.88 (0.86), Partial R2: 0.01, N: 305

Removing inexpert tasks and adding expert tasks: Both ↑ wages

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

▸ table



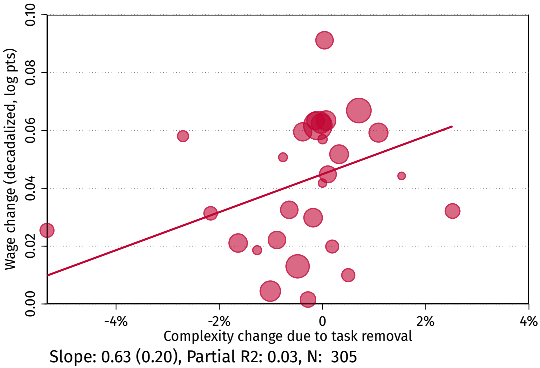
Slope: 0.63 (0.20), Partial R2: 0.03, N: 305

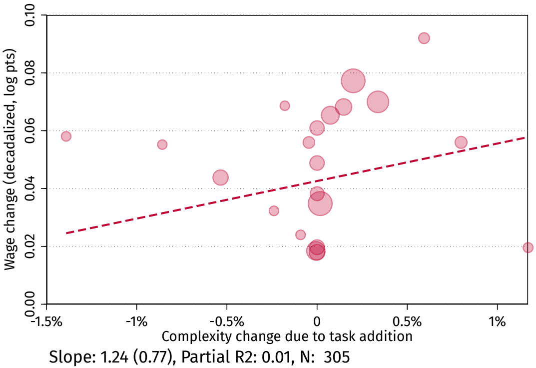
△ Dale-Chall Complexity: Removal

Removing inexpert tasks and adding expert tasks: Both ↑ wages

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

table





△ Dale-Chall Complexity: Removal

△ Dale-Chall Complexity: Addition

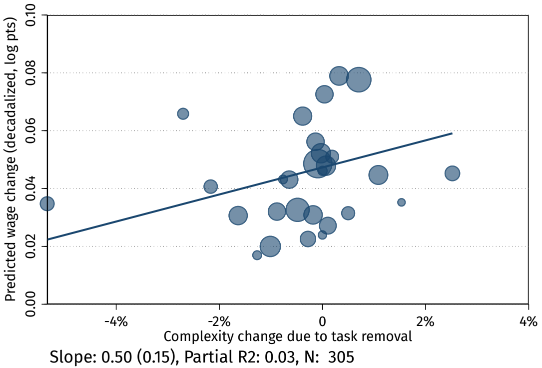
Task removal and addition→

Either can raise or lower expertise demands

Removing inexpert tasks, adding expert tasks: Both ↑ incumbent expertise

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

▸ table

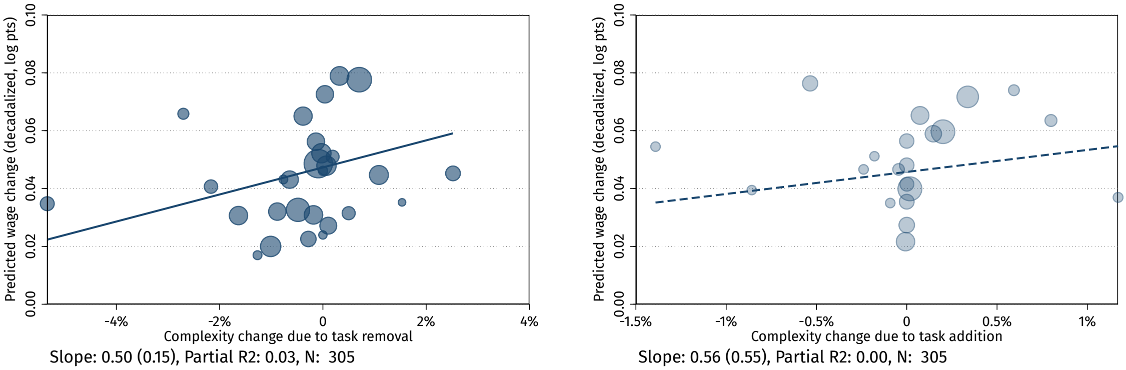


△ Dale-Chall Complexity: Removal

Removing inexpert tasks, adding expert tasks: Both ↑ incumbent expertise

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

table



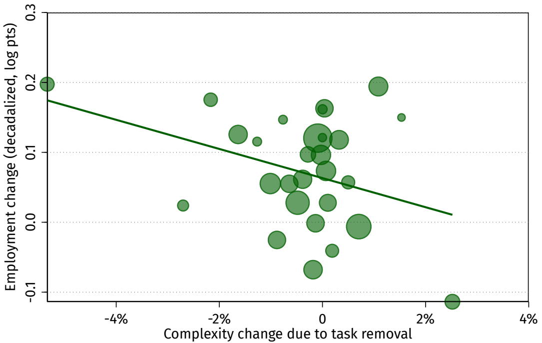
△ Dale-Chall Complexity: Removal

△ Dale-Chall Complexity: Addition

Removing inexpert tasks and adding expert tasks: Both ↓ employment

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

▸ table



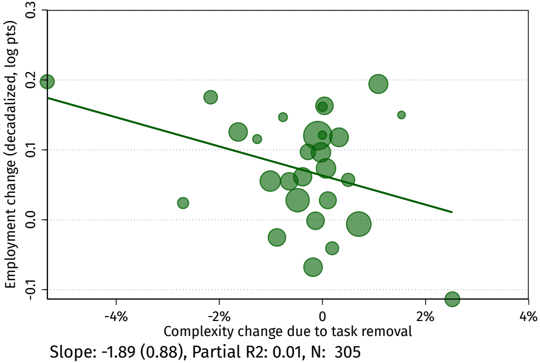
Slope: -1.89 (0.88), Partial R2: 0.01, N: 305

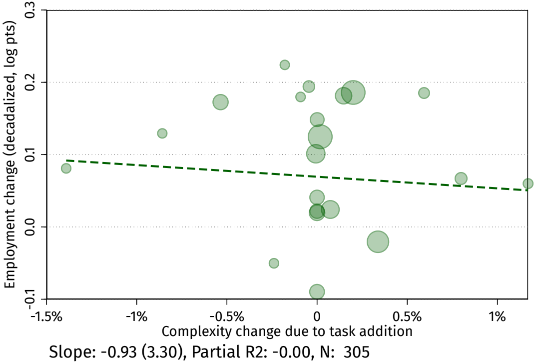
△ Dale-Chall Complexity: Removal

Removing inexpert tasks and adding expert tasks: Both ↓ employment

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

▸ table





△ Dale-Chall Complexity: Removal

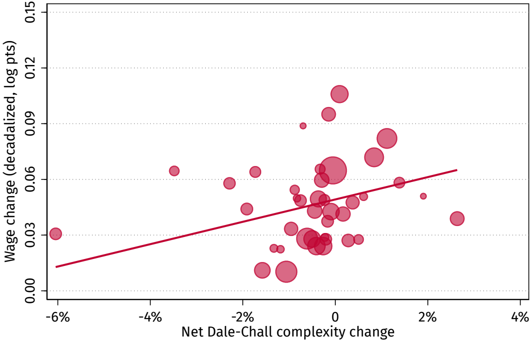
△ Dale-Chall Complexity: Addition

Wage changes—
More tasks or more expertise?

How many tasks vs. which tasks: Wage regressions

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

▸ table



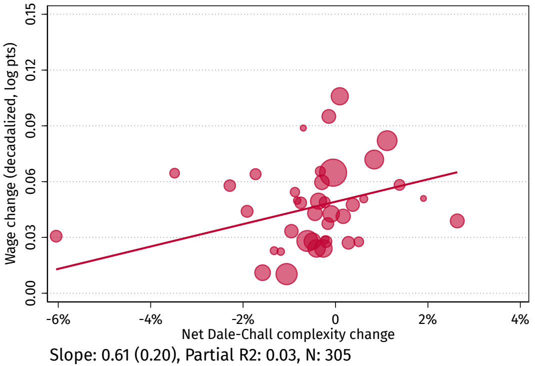
Slope: 0.61 (0.20), Partial R2: 0.03, N: 305

△ Dale-Chall Complexity

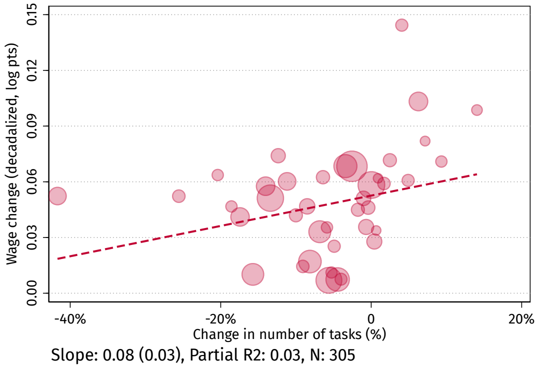
How many tasks vs. which tasks: Wage regressions

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

▸ table



△ Dale-Chall Complexity



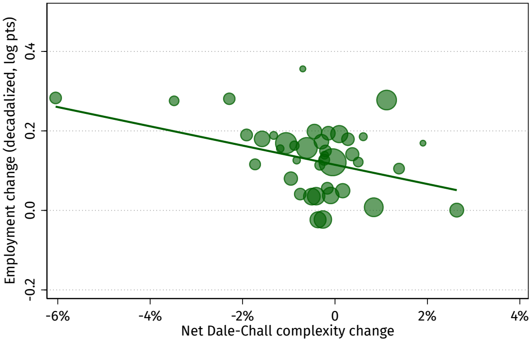
△ Task Count

Employment changes—
More tasks or more expertise?

How many tasks vs. which tasks: Employment regressions

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

table



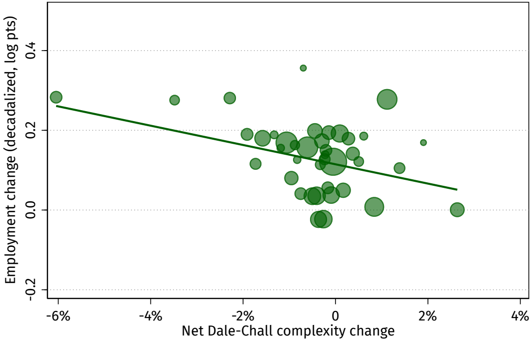
Slope: -2.31 (0.85), Partial R2: 0.02, N: 305

Δ Dale-Chall Complexity

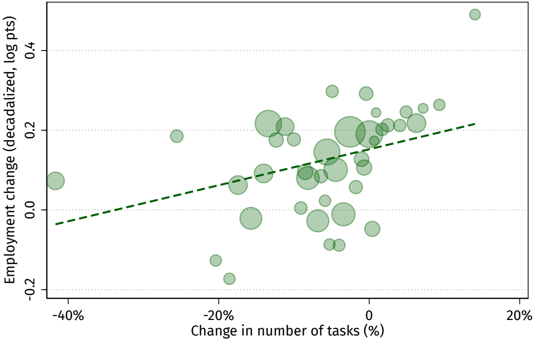
How many tasks vs. which tasks: Employment regressions

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

▸ table



Slope: -2.31 (0.85), Partial R2: 0.02, N: 305



Slope: 0.45 (0.11), Partial R2: 0.05, N: 305

△ Dale-Chall Complexity

△ Task Count

Implications +
Next steps

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

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

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   - Why don't grocery cashiers make high wages given huge productivity gains?
   - Why doesn't everyone apply to pediatric oncology jobs, given the high pay?

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❸ **One-way fungibility** of expertise—key to unpacking **exposure paradox**

- Can also help predict the AI future
- Applying an ‘expertise’ approach, we hope to improve these predictions

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3. **One-way fungibility** of expertise—key to unpacking **exposure paradox**
   - Can also help predict the AI future
   - Applying an 'expertise' approach, we hope to improve these predictions

4. **This is a rough cut — Much more ahead on this agenda**

Acknowledgments – Essential contributors

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

APPENDIX SLIDES

Model Appendix — Production function algebra

Firm optimization

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

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

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

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

Model Appendix — Production function algebra

Simplifications of worker-level production and wages after firm choices

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

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

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

Model Appendix — Real wages before arbitrage

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

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

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

Model Appendix — Simulation procedure

Finite occupations for simulations

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

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

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

Model Appendix — Simulation procedure

Labor arbitrage algorithm

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

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

Model Appendix — Key condition governing labor arbitrage

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

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

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

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

Results Appendix — Main evidence table

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

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Results Appendix — Main evidence table

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

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