For Whom the Bot Tolls: Specialization and the Earnings Effects of AI

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Columbia University

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Minneapolis Fed

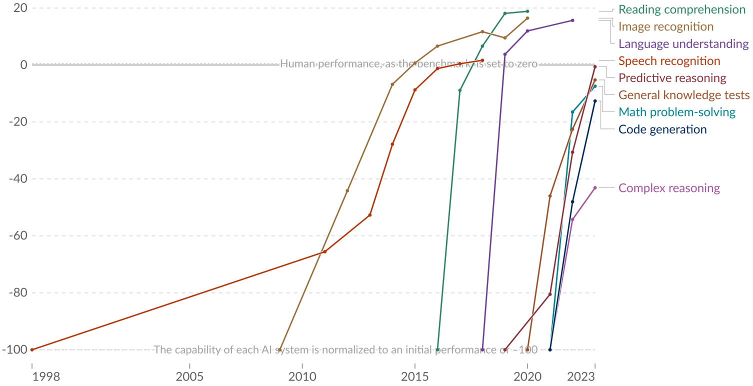
BSE Summer Forum 2025: Firms in a Changing Background
June 3, 2025

AI capabilities are rapidly improving relative to humans

Test scores of AI systems on various capabilities relative to human performance

Our World in Data

Within each domain, the initial performance of the AI is set to −100. Human performance is used as a baseline, set to zero. When the AI's performance crosses the zero line, it scored more points than humans.



Data source: Kiela et al. (2023)

Note: For each capability, the first year always shows a baseline of −100, even if better performance was recorded later that year.

Large-scale automation *exposure*

FINANCIAL TIMES

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Artificial intelligence + Add to myFT

Higher earners face greater AI exposure, study finds

Research estimates how much the fast-evolving technology hits various jobs, from software engineers to mechanics

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Jobs most affected included blockchain engineers, clinical data managers, public relations specialists and financial quantitative analysts © Getty Images

Michael Peel in London

Published JUN 20 2024

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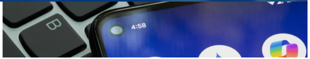
RESEARCH

Generative AI, the American worker, and the future of work

Molly Kinder, Xavier de Souza Briggs, Mark Muro, and Sifan Liu
October 10, 2024

- Existing generative AI technology already has the potential to significantly disrupt a wide range of jobs. We find that more than 30% of all workers could see at least 50% of their occupation's tasks disrupted by generative AI.
- Unlike previous automation technologies that primarily affected routine, blue collar work, generative AI is likely to disrupt a different … tasks, especially in middle- to higher-paid profe…
- Despite the high stakes for workers, we are not … opportunities that generative AI is poised to brin…
- The report emphasizes the importance of devel… AI's impact on work and workers. This includes f… design and implementation, enhancing worker v… and developing public policies that ensure work… harms such as job loss and inequality.



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IMF report: 40 percent of jobs exposed to AI

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The report landed on Sunday, right before the World Economic Forum (WEF) in Davos, where the rise of artificial intelligence, and generative AI in particular, will be a major talking point | Stefani Reynolds/AFP via Getty Images

JANUARY 15, 2024 3:33 PM CET
BY PIETER HAECK

What will be the implications for earnings & their distribution?

- **Q: Who will gain and who will lose from AI-induced task automation?**

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- Task-based **theory** formalizes the intuition
  [Zeira, 1998; Acemoglu-Autor, 2011; Acemoglu-Restrepo, 2018; ...]

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- But **measurement** is hard
  1. workers' portfolios of **task-specific skills**
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     ✓ *[Webb, 2020; Eloundou et al., 2023; ...]*

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This paper:
unify theory & measurement to quantify how specialization governs individual earnings effects of AI

What we do: theory-guided measurement & counterfactuals

1. **Theory**: canonical task-based model + Roy occupational choice

2. **Measurement**: distribution of task-specific skills

3. **Quantitative analysis** of automation based on task exposure measures

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   - LLMs: occupational task weights for 30 tasks (clustering of $\sim$ 20,000 O*NET tasks)
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     $\rightarrow$ estimate skill distribution using model structure

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3. **Quantitative analysis** of automation based on task exposure measures
   - **Industrial robots**: automation of material handling tasks
   - **AI**: automation of information-processing tasks

What's new?

- **AI: measurement of job exposure**

  [Brynjolfsson et al., 2018; Webb, 2019; Felten et al., 2021; Eloundou et al., 2023; ...]

  $\Rightarrow$ map to **structural** model $\rightarrow$ individual **earnings effects** as a function of skills

- **Task-based framework** *[Acemoglu-Autor, 2011; Acemoglu-Restrepo, 2022; Freund, 2024; ...]*

  $\Rightarrow$ empirically operationalize $\rightarrow$ link to **forward-looking** automation measures

- **Multi-dimensional skills**

  [Lindenlaub, 2017; Guvenen et al., 2020; Lise-PostelVinay, 2021; Deming, 2023; Grigsby, 2023]

  $\Rightarrow$ **estimate** distribution of high-dim. task-specific skills $\rightarrow$ **skill specialization**

- **Applications of LLMs in economics research** *[Korinek, 2023; Athey et al., 2024; Dell, 2024]*

  $\Rightarrow$ use LLMs for clustering & time-share measurement $\rightarrow$ **flexible** tool

Theory

Environment: task-based production meets Roy

- Discrete time (t), repeated static model
- **Production technology:**
  - production is Cobb-Douglas over discrete task set $\mathcal{T}$
  - **occupation** $o \in \mathcal{O}$ **bundles tasks** with weights $\{\alpha_{o,\tau}\}_{\tau \in \mathcal{T}}$

economist, teacher, ...

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- **Firms:**
    - infinite supply of entrepreneurs who perfectly compete for a worker's labor
    - assign tasks ex-ante optimally to humans ($\rightarrow \mathcal{T}_l$) or machines w prod. $\{z_\tau\}_{\tau \in \mathcal{T}}$ ($\rightarrow \mathcal{T}_m$)
    - match with 1 worker, rent machines from inf. elastic capital market at exog. rate r

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- **Workers:**

  $|\mathcal{T}_l| \times 1$ *vector*

  - log utility over consumption
  - heterogeneous, fixed **task-specific skills** $s_i = \{s_{i,\tau}\}_{\tau \in \mathcal{T}_l}$ where $s_i \sim \mathcal{N}(\bar{s}, \Sigma_s)$
  - period t: draw shocks, choose occupation o, match with entrepreneur, produce & earn

Firm's optimal production problem

- **Output** of firm in occ o with worker i given idiosyncratic shock $\varepsilon_{i,t} \sim \mathcal{N}(0, \varrho)$:

$$y_{i,o,t}(\cdot) = \underbrace{\prod_{\tau \in \mathcal{T}_l} \left(\exp\left(s_{i,\tau} + \varepsilon_{i,t}\right) \cdot \ell_{i,\tau,t}\right)^{\alpha_{o,\tau}}}_{\text{worker-produced}} \underbrace{\prod_{\tau \in \mathcal{T}_m} \left(\exp\left(z_\tau\right) \cdot m_{i,\tau,t}\right)^{\alpha_{o,\tau}}}_{\text{machine-produced}}$$

- **Profits:**

$$\pi_{i,o,t} = \max_{\{m_{i,\tau}\}_{\tau \in \mathcal{T}_m}, \{\ell_{i,\tau}\}_{\tau \in \mathcal{T}_l}} y_{i,o,t}\left(\{\ell_{i,\tau,t}\}_{\tau \in \mathcal{T}_l}, \{m_{i,\tau,t}\}_{\tau \in \mathcal{T}_m}\right) - \exp\left(w_{i,o,t}\right) - r \sum_{\tau \in \mathcal{T}_m} m_{i,\tau,t}$$

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FOC capital

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▸ FOC capital

$$\ell_{i,\tau,t} = \frac{\alpha_{o,\tau}}{\sum_{\tau \in \mathcal{T}_l} \alpha_{o,\tau}} \longrightarrow \textit{matrix A: } |\mathcal{O}| \times |\mathcal{T}_l|$$

Wage equation

▸ Intercept term

$$w_{i,o,t} = \overbrace{\mu_o}^{\text{occ.-specific intercept}} + \overbrace{\sum_{\mathcal{T}_l} \frac{\alpha_{o,\tau}}{LS_o} \cdot s_{i,\tau}}^{\text{weighted skills}} + \overbrace{\varepsilon_{i,t}}^{\text{idiosyncratic productivity shock}}$$

$$= \mu_o + \underbrace{\frac{1}{n_{\text{skill}}} \sum_{\mathcal{T}_l} s_{i,\tau}}_{\text{scalar absolute advantage}} + \text{Cov}\left(n_{\text{skill}} \cdot \frac{\alpha_{o,\cdot}}{LS_o}, \underbrace{s_{i,\cdot} - \frac{1}{n_{\text{skill}}} \sum_{\mathcal{T}_l} s_{i,\tau}}_{\text{specialization vector}} \right) + \varepsilon_{i,t}$$

$\text{LS}_o = \sum_{\tau \in \mathcal{T}_l} \alpha_{o,\tau}$: labor share in occupation o

Occupational choice

- Each period, worker i chooses occ. subject to preference shock $u_{i,o,t} \sim \text{Gumbel}(0, \nu)$:

$$\hat{o}_{i,t} = \text{argmax}_o w_{i,o,t} + u_{i,o,t}$$

- **Occupational choice probabilities:**

$$P(\hat{o} = o | w_{i,\cdot,t}) = \frac{\exp(w_{i,o,t}/\nu)}{\sum_{o'} \exp(w_{i,o',t}/\nu)}$$

- No *exogenous* switching costs

Automation in the model

- **Automation** of task τ^*: a one-time, permanent rise in machine productivity $z_{\tau^\star}$ that is *just* large enough to make it optimal to reassign τ^* from humans to machines

$$\mathcal{T}_l' = \mathcal{T}_l \backslash \tau^\star \qquad \mathcal{T}_m' = \mathcal{T}_m \cup \tau^\star$$

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- **Change** in expected log (potential) wage for *i* in occupation *o*

$$\mathbb{E}\left[w_{i,o,t+1} - w_{i,o,t}\right] = \mu_{o,t+1} - \mu_{o,t} + \overbrace{\frac{\alpha_{o,\tau^\star}}{LS_o}}^{\text{occupational exposure}} \left(\sum_{\mathcal{T}_l \backslash \tau^\star} \frac{\alpha_{o,\tau}}{LS_o - \alpha_{o,\tau^\star}} \overbrace{s_{i,\tau} - s_{i,\tau^\star}}^{\text{worker specialization}} \right)$$

$\Rightarrow$ **A worker is more likely to win if *relatively* skilled in non-automated tasks**

Measurement

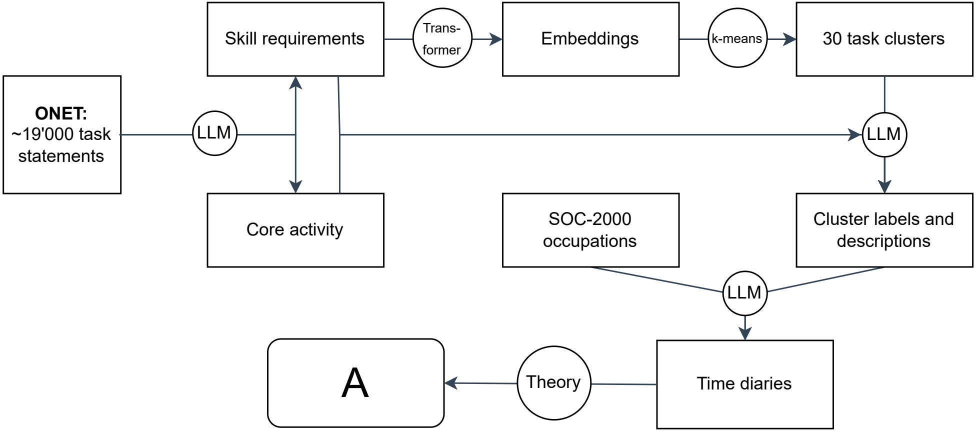
Theory meets data: overview

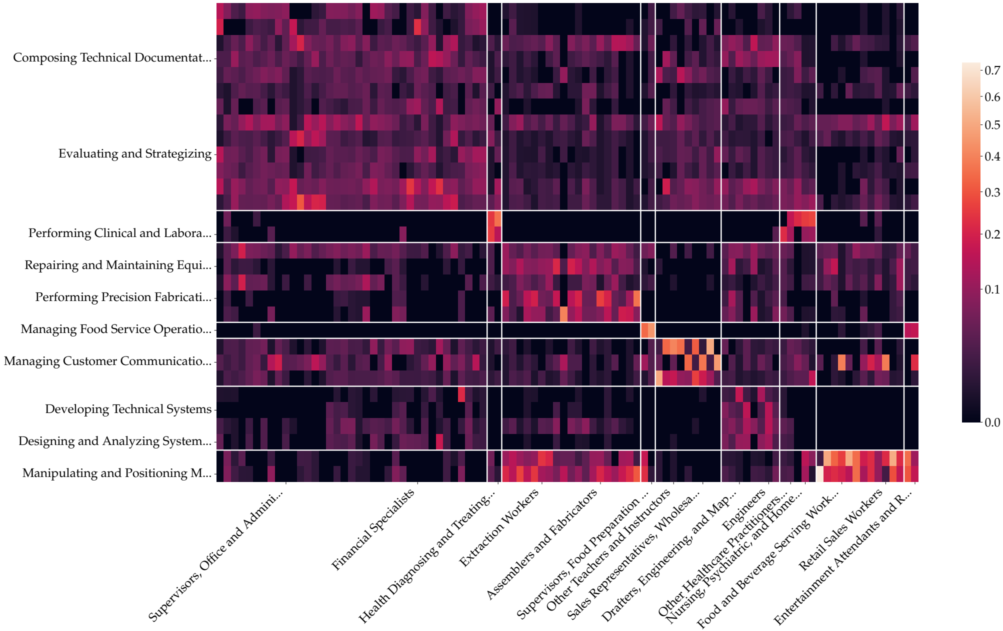
▸ Why not O*NET GWAs/importance weights

- **Goal:** parametrize the model at same 'resolution' as task exposure measures
- **Step 1:** map model tasks & occupations to data, construct A
  - O*NET: $\sim$ 19,000 task statements ($\sim$ most exposure measures) $\rightarrow$ *cluster* them
  - occupations: 90+ SOC-2000 minor groups ($\sim$ 3d)
  - task-weights $A_{o,\tau} = \frac{\alpha_{o,\tau}}{\sum_{\tau \in \mathcal{T}_l} \alpha_{o,\tau}}$ for all occupations & tasks
- **Step 2:** estimate unobserved skill distribution $(\bar{s}, \Sigma_s)$ using MLE
  - given A + NLSY '79 + model structure

Step 1: constructing the task-weight matrix *A*

▸ Validation ▸ Examples: occ ▸ Examples: tasks





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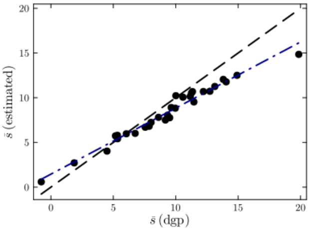
Evaluating and Strategizing
Performing Clinical and Labora...
Repairing and Maintaining Equi...
Performing Precision Fabricati...
Managing Food Service Operatio...
Managing Customer Communicatio...
Developing Technical Systems
Designing and Analyzing System...
Manipulating and Positioning M...
Supervisors, Office and Admini...
Financial Specialists
Health Diagnosing and Treating...
Extraction Workers
Assemblers and Fabricators
Supervisors, Food Preparation ...
Other Teachers and Instructors
Sales Representatives, Wholesa...
Drafters, Engineering, and Map...
Engineers
Other Healthcare Practitioners...
Nursing, Psychiatric, and Home...
Food and Beverage Serving Work...
Retail Sales Workers
Entertainment Attendants and R...
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0

Step 2: estimation of task-specific skills

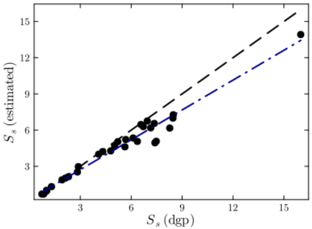
- **Challenge:** skill distribution is unobserved
- **Solution:** use the structure of the model to estimate $(\bar{s}, \Sigma_s)$
    - variation: realized wages & occupational choices
    - intuition: economist vs software engineer
- **Data:** NLSY '79 + A matrix
    - worker-level panel of occupational choices and wages
- **Formalization:** max. likelihood
- **Implementation:** MC integration + auto-diff. + stochastic gradient descent ▸ Details
- **Validation:** Monte Carlo exercise

Validation: Monte-Carlo study

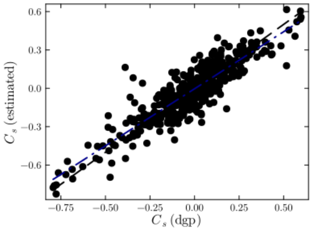
(a) Means



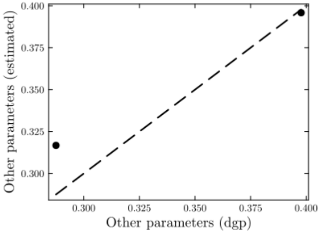
(b) Standard deviation



(c) Correlation



(d) Other parameters



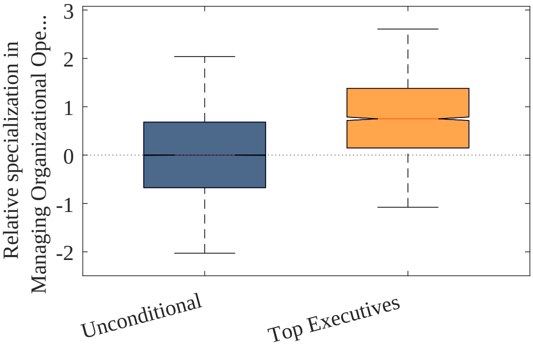
Model properties: selection based on comparative advantage

▸ Transition vs. specialization

- Workers tend to select into occupations which load heavily on tasks they are relatively skilled at – example of *Top Executives*

relative specialization:

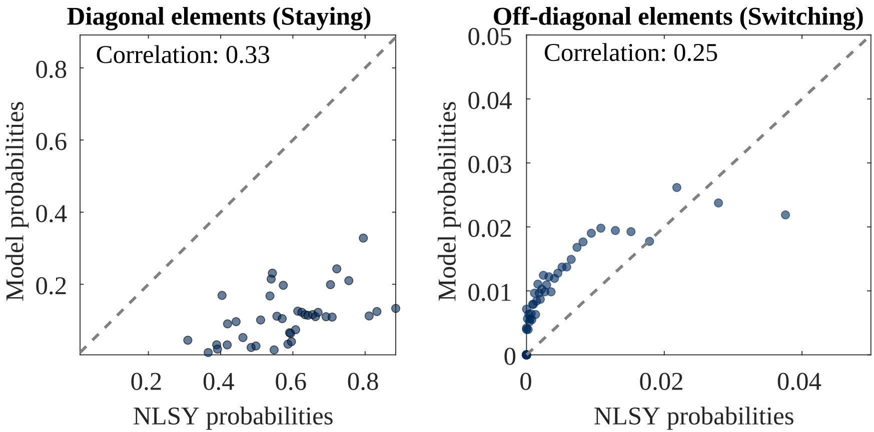
$s_{i,\cdot} - \frac{1}{n_{\text{skill}}} \sum_{\mathcal{T}_l} s_{i,\tau}$



Model properties: occupational transition probabilities

Wages and emp. shares

- Some persistence (but not quite enough)
- Model directionally tracks switching patterns

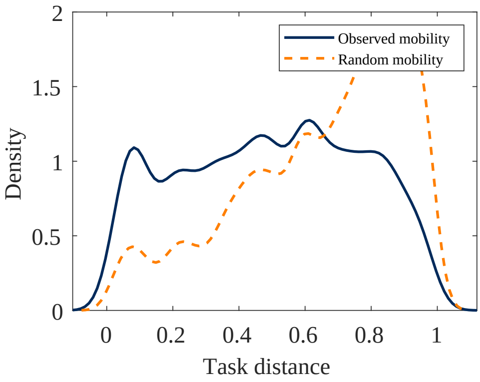


Model properties: occupational transitions reflect task requirements

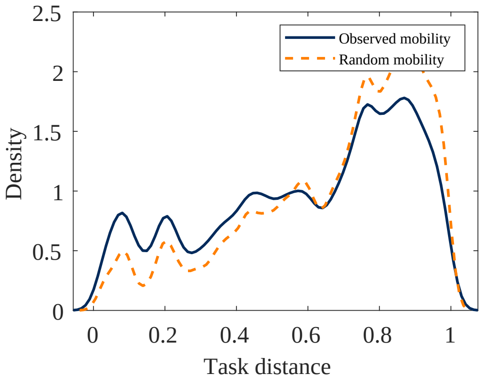
- Workers are more likely to move to occupations with similar task requirements

[cf. Gathmann-Schoenberg, 2010]

(a) Data



(b) Model

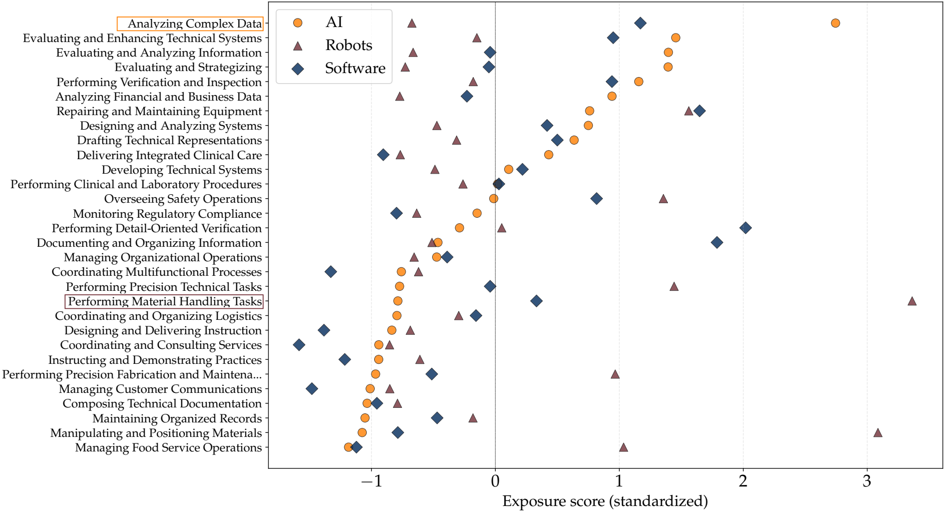


Application: AI

Webb's (2020) exposure measures

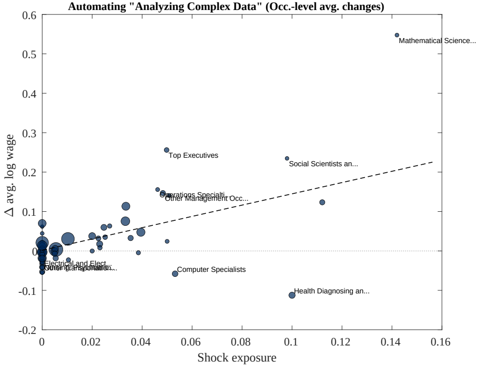
Patent criteria

Eloundou et al. (2023)



AI: automating "analyzing complex data"

(a) Occupation-level effects



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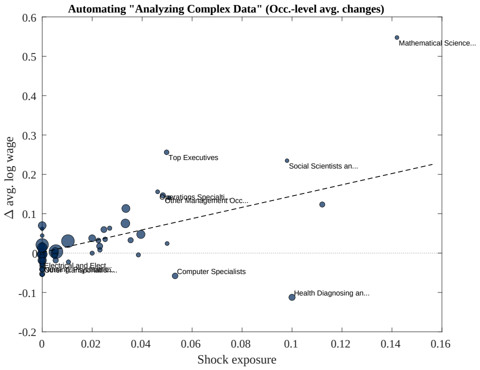
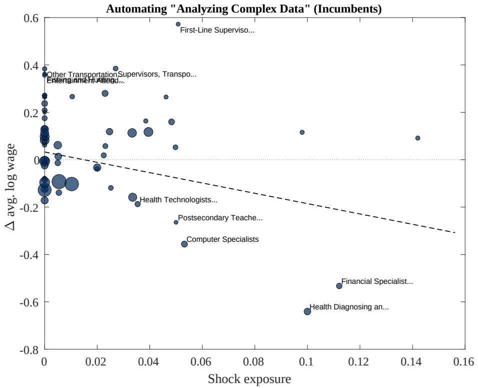


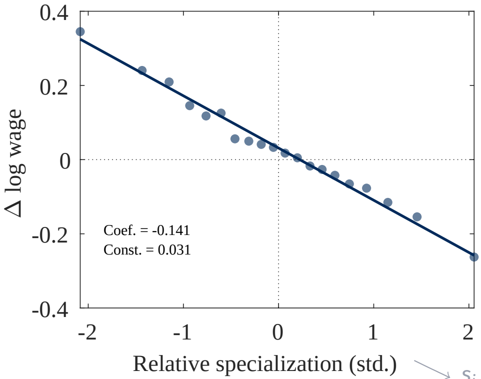
(b) Yet for incumbents...



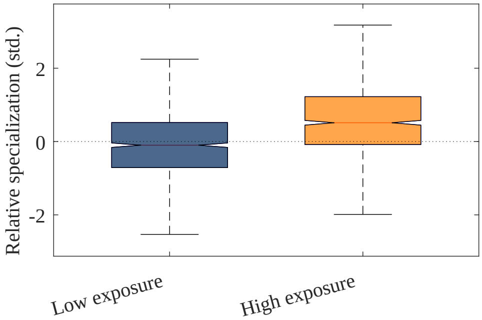
Mechanism: specialization + selection

$\Rightarrow$ As workers *select* into occupations by comparative advantage, high *occupational* exposure also tends to imply *relative skill specialization* in the automated task

(a) Specialization and wages



(b) Selection on specialization



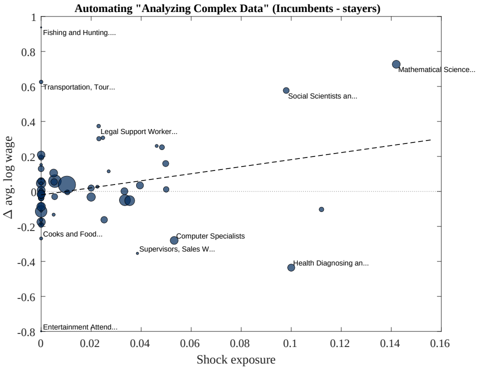
$s_{i,\tau^*} - \frac{1}{n_{\text{skill}}} \sum_{\tau \in \mathcal{T}_l} s_{i,\tau}$

Incumbents: stayers do better than switchers

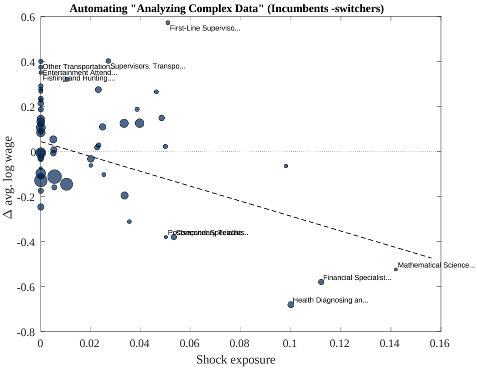
▸ Relative specialization

- Consistent with evidence on task 'upgrading' for stayers *[Bartel et al., 2007; Dauth et al., 2021]* and losses for occupation switchers *[e.g. Huckfeldt, 2022]*

(a) Incumbents: stayers

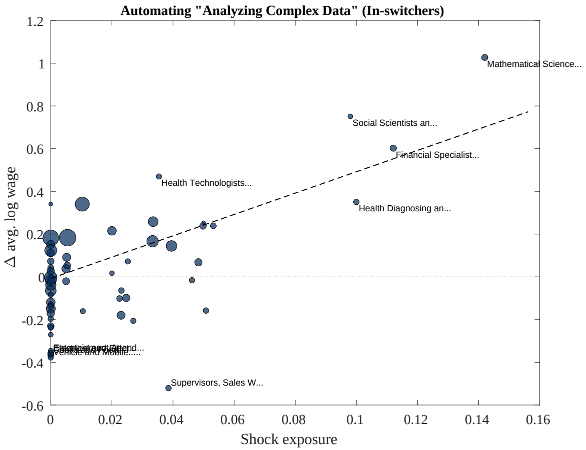


(b) Incumbents: switchers



So why the positive effect at the occupational level? In-switchers!

- Consistent with evidence on positive wage effects from in-switching *[e.g Humlum, 2021]*; magnitude likely overstated (no GE) & too fast (no frictions)

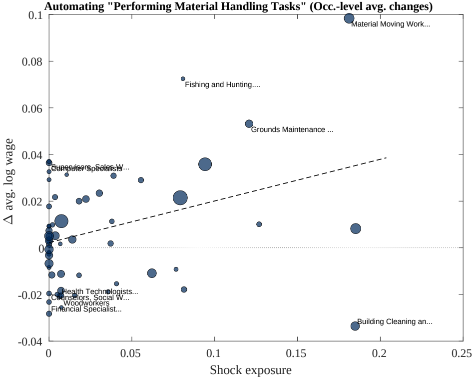


Robots: Partial automation of “performing material handling tasks”

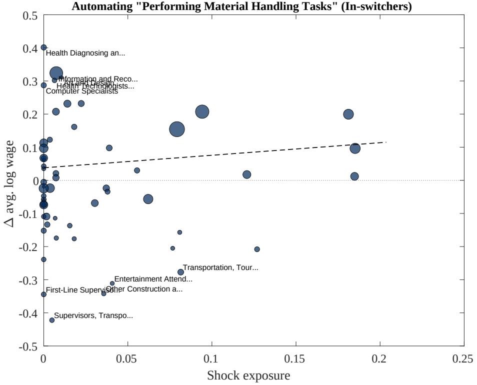
▸ Incumbents

- **Robots:** smaller gradient exposure ↔ wage change
  - in-switching channel weaker

(a) Occupation-level

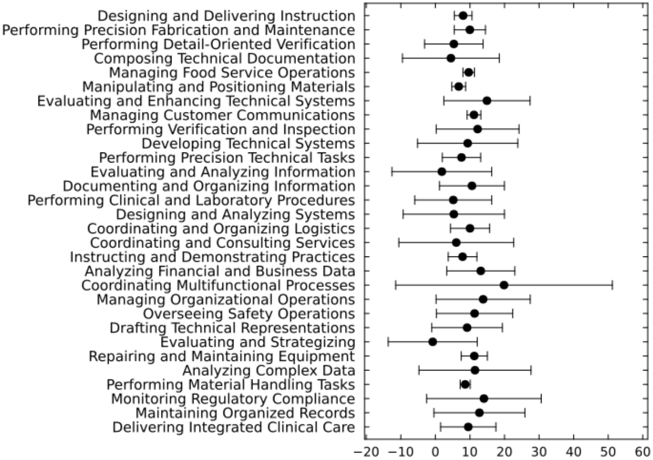


(b) In-switchers



Robots: Partial automation of “performing material handling tasks”

- **Reason:** Much smaller dispersion in specialization



Conclusion

Summary: Specialization and the Earnings Effects of AI

- Early stage – feedback very welcome!
- **Core contribution:** empirically rich tractable framework to quantify & forecast who wins and who loses from (AI-induced) task automation
- **Key insight:** automation effects depend on skill specialization
  - — automation harms you if you are specialized in the automated task
    - → incumbent switchers
  - + *but* benefits you if freed up to pursue tasks in which you're more productive
    - → incumbent stayers & in-switchers
- Next steps: GE; self-driving vehicles; minimum human-in-the-loop regulation

Extra Slides

Automated document review: good or bad?

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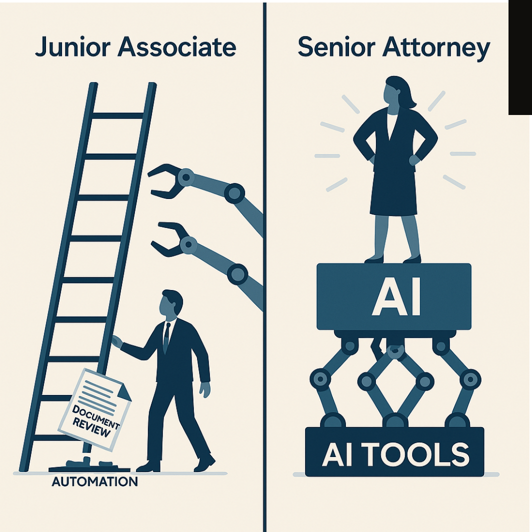

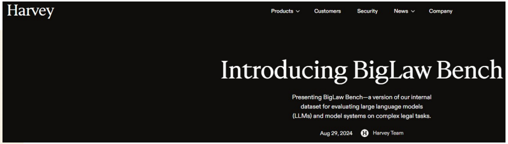

GE: plan

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- Missing important model feature: heterogeneous, endogenous occupation prices
  - steady-state: high-wage occ's involve scarce skills hence high *o* price
  - counterfactual: occupational price response as a function of demand elasticities

- Identification challenge: μ_o becomes endogenous and the following equation is satisfied by more than one pair $(\mu_o, \bar{s})$:

$$\text{mean potential wage}_o = \mu_o + A'_{o,\cdot} \circ \bar{s}$$

  where $\bar{s}$ is vector of average skills

- Options we're exploring:
  1. time variation in task shares
  2. dynamic skill accumulation
  3. identifying restriction $A \perp \mu_o$

FOCs

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- FOC for machines $m := \sum_{\tau \in \mathcal{T}_m} m_\tau$:

$$\left(\sum_{\tau \in \mathcal{T}_m} \alpha_{o,\tau} \right) \frac{y}{r} = m$$

and

$$m_\tau = \frac{\alpha_{o,\tau}}{\sum_{\tau \in \mathcal{T}_m} \alpha_{o,\tau}} m$$

- Given

$$\log y_o = \left[\sum_{\tau \in \mathcal{T}_l} \frac{\alpha_{o,\tau}}{\sum_{\tau \in \mathcal{T}_l} \alpha_{o,\tau}} s_{i,\tau} \right] + \varepsilon_{i,o}$$
$$+ \left[\sum_{\tau \in \mathcal{T}} \frac{\alpha_{o,\tau}}{\sum_{\tau \in \mathcal{T}_l} \alpha_{o,\tau}} \log(\alpha_{o,\tau}) \right] - \log \left(\sum_{\tau \in \mathcal{T}_l} \alpha_{o,\tau} \right) + \left[\sum_{\tau \in \mathcal{T}_m} \frac{\alpha_{o,\tau}}{\sum_{\tau \in \mathcal{T}_l} \alpha_{o,\tau}} (z_\tau - \log r) \right],$$

Wage equation: details

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- Intercept

$$\mu_o = \sum_{\tau \in \mathcal{T}} \frac{\alpha_{o,\tau}}{\sum_{\tau \in \mathcal{T}_l} \alpha_{o,\tau}} \log(\alpha_{o,\tau}) + \left(\sum_{\tau \in \mathcal{T}_m} \frac{\alpha_{o,\tau}}{\sum_{\tau \in \mathcal{T}_l} \alpha_{o,\tau}} (z_\tau - \log r) \right)$$

- We assume that in the initial steady state there is only one composite machine task with productivity normalized to $\log r$, which implies that μ_o is known for all occupations.

Details on the estimation strategy I

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- Exact likelihood:

$$\prod_i \int_s \left[\left(\int_{w_{i,\cdot,-\omega.}} \prod_t P(\hat{o}_{i,t} = \omega_{i,t} | w_{i,\cdot,\cdot}, \nu) \cdot f(w_{i,t,-\omega_t} | s, w_{i,\cdot,\omega.}, \varsigma) \right) \cdot f(s | w_{i,\cdot,\omega.}, \varsigma, \bar{s}, \Sigma_s) \right]$$
$$\cdot f(w_{i,\cdot,\omega.} | \varsigma, \bar{s}, \Sigma_s)$$

- **Strategy:** Monte Carlo integration - for all i generate n_o draws from

$$f(w_{i,\cdot,-\omega.} | w_{i,\cdot,\omega.}, \varsigma, \bar{s}, \Sigma_s) = \int_s f(w_{i,\cdot,-\omega.} | s, w_{i,\cdot,\omega.}, \varsigma) f(s | w_{i,\cdot,\omega.}, \varsigma, \bar{s}, \Sigma_s)$$

and evaluate the mean of $P(\hat{o}_{i,t} = \omega_{i,t} | w_{i,\cdot,t}, \nu)$ to obtain an estimator for $\mathcal{L}_i(\theta)$:

$$\hat{\mathcal{L}}_i(w_{i,t,\omega}, \nu, \varsigma, \bar{s}, \Sigma_s) = \left(\frac{1}{n_o} \sum_j \prod_t P(\hat{o}_{i,t} = \omega_{i,t} | w_{j,t,\cdot}, \nu) \right) \cdot f(w_{i,\cdot,\omega.} | \varsigma, \bar{s}, \Sigma_s)$$

Details on the estimation strategy II

Back

- Two numerical techniques help speed up the maximum likelihood computation
- **Auto-differentiation:** efficiently compute the gradient of this function
- **Stochastic gradient descent:**
  - basic technique: gradient descent

$$\theta_{t+1} = \theta_t - \eta \cdot \nabla\left(-\mathcal{L}(\theta_t)\right)$$

  - randomly partition individuals into n groups:

$$\{1, 2, \ldots, I\} = B_1 \cup B_2 \cup \ldots \cup B_n, \quad B_i \cap B_j = \emptyset$$

  - calculate the likelihood based on batch $B_1, \ldots, B_n$ only
  - when done, draw a new partition

Why not use O*NET GWAs and importance weights

Back

- Potential alternative to our approach: use O*NET "General Work Activities" (GWAs) and occupational importance weights
- Reasons we prefer our approach:
  1. GWAs themselves are not mutually exclusive (e.g. "Analyzing Data or Information" vs "Processing Information") nor exhaustive (esp. regarding activities differentiating high-wage occupations, e.g. complex quantitative analyses), and some seem ambiguous ("Getting Information")
  2. Weights available (importance/level/frequency) don't correspond to time shares, as required to map onto the theory
  3. GWAs + LLM-generated time shares: resulting A matrix is low-rank ($\rightarrow$ poor model fit)
  4. Flexibility: our approach is consistent with different occupational classifications (e.g. SOC-2000, which can be x-walked to NLSY) and time periods

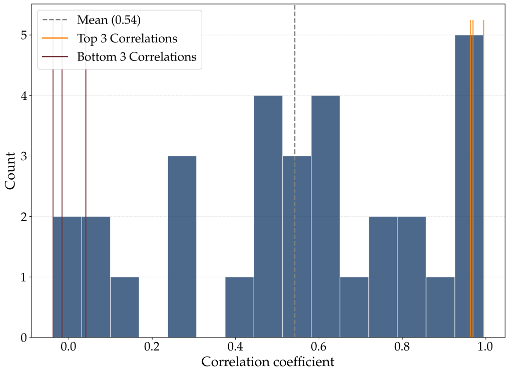
Validation of LLM-generated time shares: overview

1. Comparison of time share measurement: LLM vs BIBB survey ✓
2. Comparison of LLM-generated time shares for GWAs to O*NET importance weights ✓
3. Internal consistency: do measurements for detailed occupations aggregate up? ✓

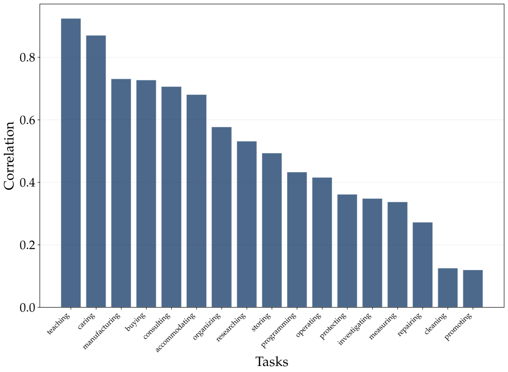
- What else would you like us to check?
  – comparison across LLMs?

Validation: LLM-generated task shares vs. BIBB

(a) Occupation-level correlations

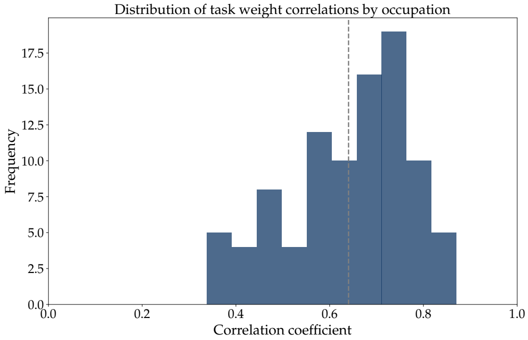


(b) Task-level correlations

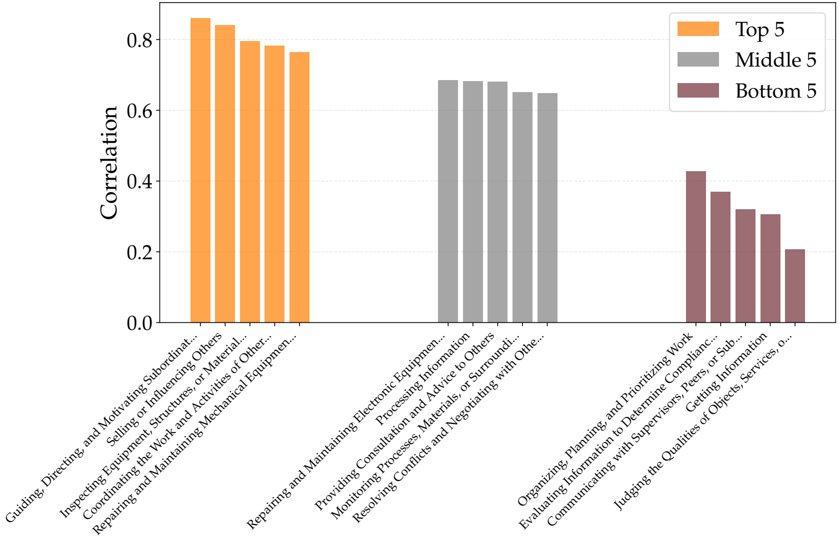


Validation: O*NET GWAs (1)

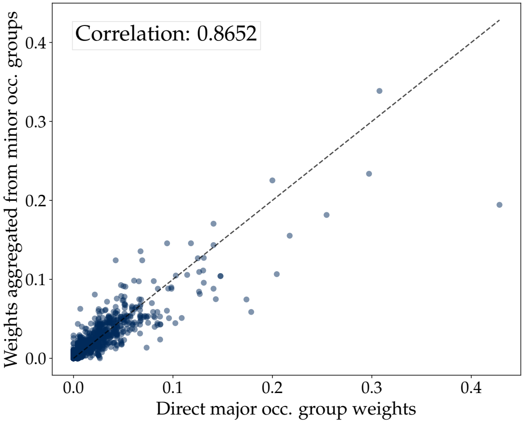
- Take O*NET GWAs (O*NET 5.0, consistent with SOC-2000), construct relative importance for each GWA by occupation, aggregate to SOC-2000-3d
- Let LLM generate *time shares* for the GWAs for each SOC-2000-3d occ
- How do LLM-time shares correlate with vector of O*NET importance weights?



Validation: O*NET GWAs (2): correlation across occupations by task



Validation: internal consistency



Model properties: transition probabilities decline in specialization

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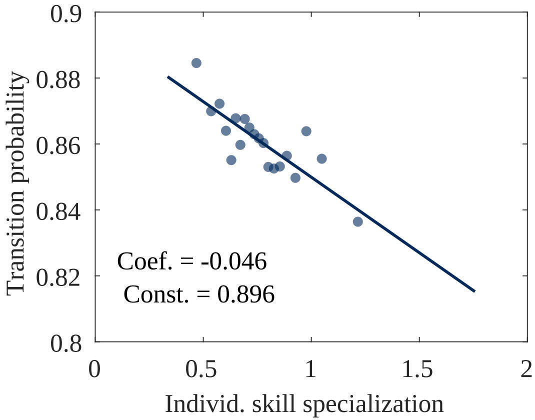
- Workers with v specialized (= dispersed) skills are less likely to switch occupation



Model fit: occupational wages and employment shares

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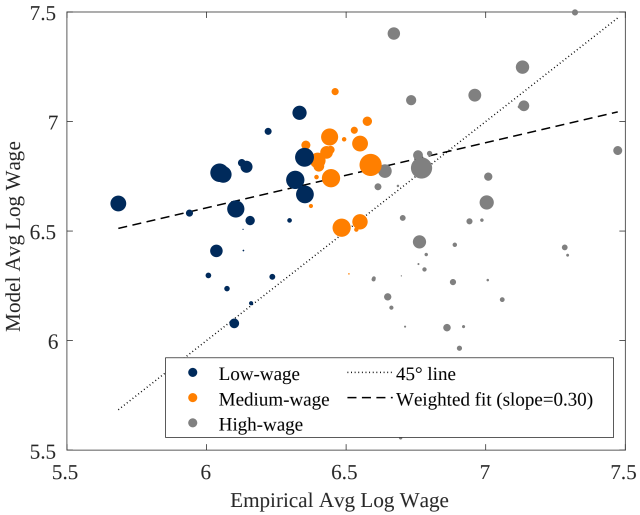

A matrix: example tasks - extracted skills - tasks

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Task	Activity	Skills	Cluster
Direct or coordinate an organization's financial or budget activities to fund operations, maximize investments, or increase efficiency	Direct financial operations	Financial management (expert), strategic planning (advanced), budgeting (advanced), analytical thinking (advanced)	Evaluating and Strategizing
Clean and sterilize vats and factory processing areas	Clean and sterilize processing areas	Manual dexterity (basic)	Performing Material Handling Tasks
Press switches and turn knobs to start, adjust, and regulate equipment, such as beaters, extruders, discharge pipes, and salt pumps	Operate equipment controls	Technical knowledge (intermediate), manual dexterity (basic)	Performing Precision Technical Tasks
Conduct research, data analysis, systems design, or support for software such as Geographic Information Systems (GIS) or Global Positioning Systems (GPS) mapping software	Conduct research and data analysis for GIS software	Research skills (advanced), data analysis (advanced), systems design (advanced)	Analyzing Complex Data

A matrix: example occupations

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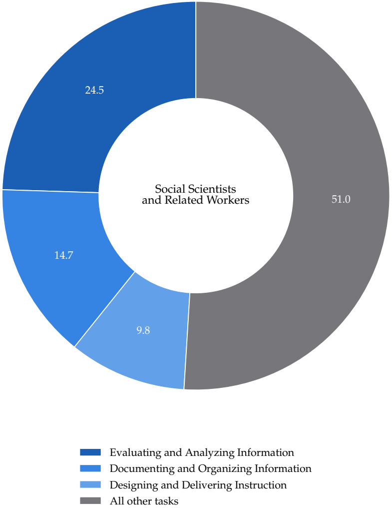
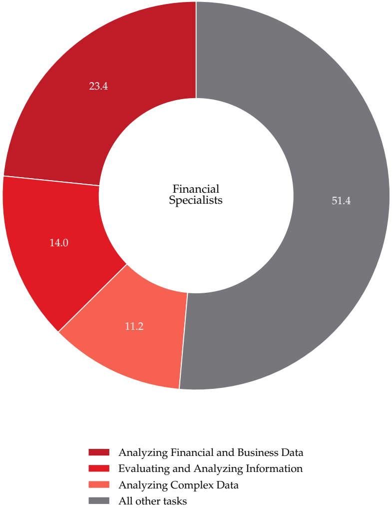
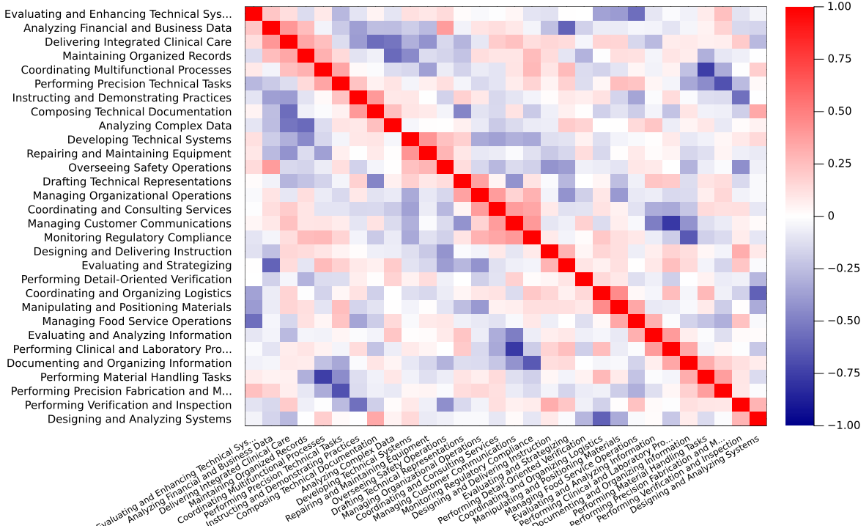




Estimated skill correlation matrix



Webb measure: selection criteria

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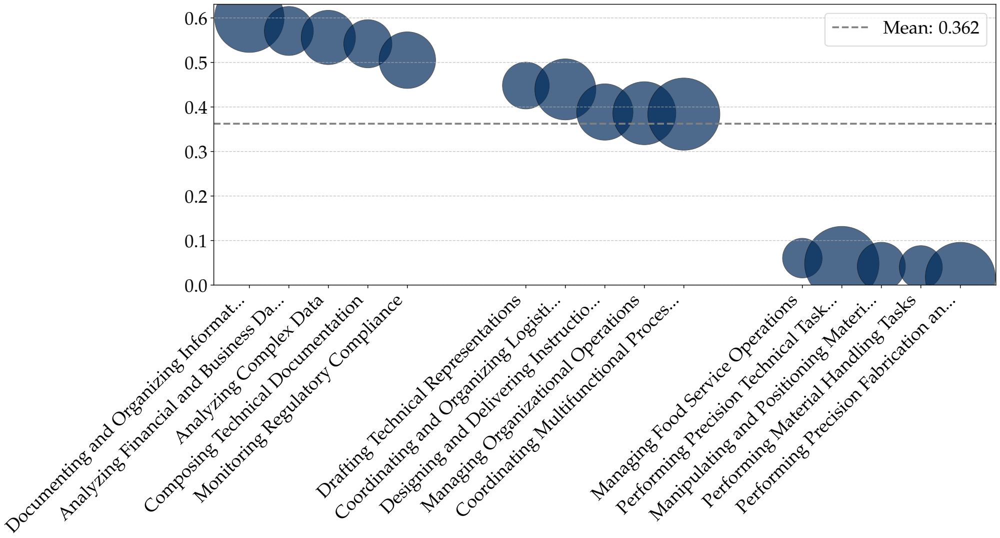
Table A1: **Patent selection criteria.**

Technology	Definition
AI	Title/abstract include "neural network", "deep learning", "reinforcement learning", "supervised learning", "unsupervised learning", or "generative model"
Software	Title/abstract include "software", "computer", or "program" AND title/abstract exclude "chip", "semiconductor", "bus", "circuit", or "circuitry"
Robots	Title/abstract include "robot"

Notes: Patents corresponding to each technology are selected using these keyword inclusion/exclusion criteria.

Aggregated task exposure measures from Eloundou et al. (2023)

Webb (2020)



Webb's historical evidence on effects of robots

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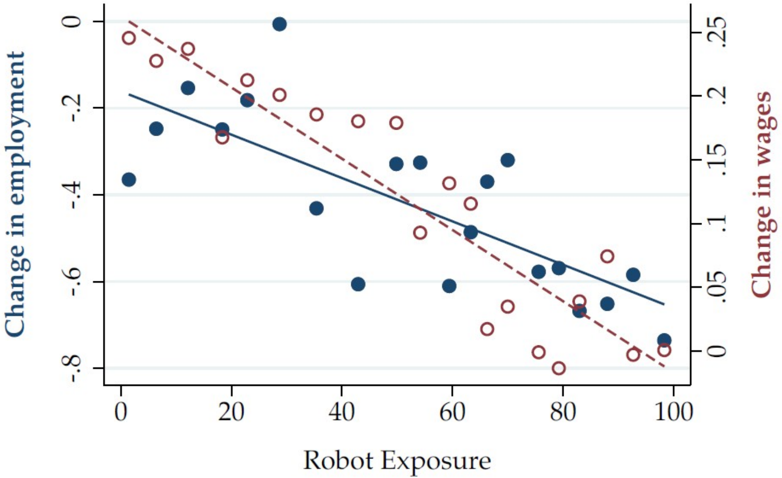

The ins and outs of occupations: robots

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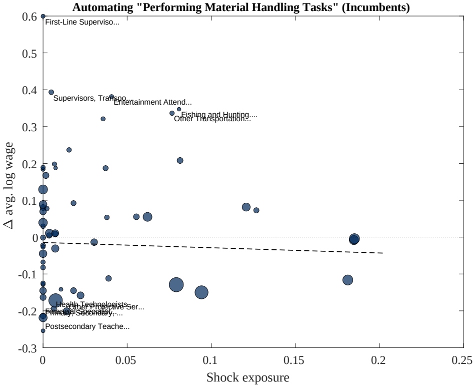
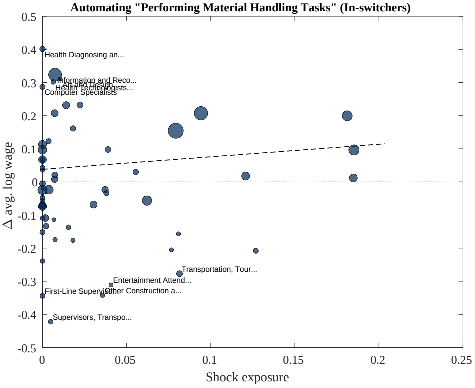
(a) Incumbents



(b) In-switchers



Why stayers do better than switchers

Stayers vs switchers