Job Transformation, Specialization, and the Labor Market Effects of AI

Lukas Freund
Boston College

Lukas Mann
Arizona State University

October 24, 2025

NBER EFG Program Meeting, Federal Reserve Bank of New York

Motivation: job transformation through AI

- Focus of much of discourse on **automation**: job *elimination* *[e.g., Frey and Osborne, 2017]*

Motivation: job transformation through AI

▸ Weavers

- Focus of much of discourse on **automation**: job *elimination* *[e.g., Frey and Osborne, 2017]*
- Our focus: ***job transformation*** $\sim$ shift in the task content of jobs *[Autor et al., 2003]*
  - example: power looms and weavers *[Bessen, 2012]*
  - $\downarrow$ routine intensity mostly due to within-occupation changes *[e.g., Atalay et al., 2021]*
  - early evidence for AI: task ($\neq$ job) displacement predominant *[e.g., Bonney et al., 2024]*

Motivation: job transformation through AI

▸ Weavers

- Focus of much of discourse on **automation**: job *elimination* *[e.g., Frey and Osborne, 2017]*
- Our focus: ***job transformation*** $\sim$ shift in the task content of jobs *[Autor et al., 2003]*
  - example: power looms and weavers *[Bessen, 2012]*
  - $\downarrow$ routine intensity mostly due to within-occupation changes *[e.g., Atalay et al., 2021]*
  - early evidence for AI: task ($\neq$ job) displacement predominant *[e.g., Bonney et al., 2024]*

$\Rightarrow$ **(How) will AI affect earnings through job transformation? Winners and losers?**

Motivation: job transformation through AI

▸ Weavers

- Focus of much of discourse on **automation**: job *elimination* *[e.g., Frey and Osborne, 2017]*
- Our focus: ***job transformation*** $\sim$ shift in the task content of jobs *[Autor et al., 2003]*
  - example: power looms and weavers *[Bessen, 2012]*
  - $\downarrow$ routine intensity mostly due to within-occupation changes *[e.g., Atalay et al., 2021]*
  - early evidence for AI: task ($\neq$ job) displacement predominant *[e.g., Bonney et al., 2024]*

$\Rightarrow$ **(How) will AI affect earnings through job transformation? Winners and losers?**

- State-of-the-art models abstract from job transformation as **measurement** is hard
  1. workers' portfolios of **task-specific skills**
  2. **which tasks** will be automated

This paper

An applied quantitative theory of AI-induced job transformation effects

What we do:

1. develop a task-based framework of job transformation
2. estimate the multi-dimensional skill distribution
3. project effects of LLM automation for heterogeneously skilled workers

This paper

An applied quantitative theory of AI-induced job transformation effects

What we do:

1. develop a task-based framework of job transformation
2. estimate the multi-dimensional skill distribution
3. project effects of LLM automation for heterogeneously skilled workers

What we find:

→ AI-induced job transformation leads to large and heterogeneous earnings effects, even conditional on occupation

A task-based theory of job transformation

- **Occupations** are heterogeneous *bundles* of tasks
- **Tasks** can be performed by either labor or machines (AI)
- Workers have **task-specific skills**
- **Automation** leads to job transformation by shifting weights on labor-produced tasks

Model environment: task-based production meets Roy

▸ Equilibrium definition

Model environment: task-based production meets Roy

▸ Equilibrium definition

Technology and firms

Occupation: $o \in \mathcal{O}$ **bundles** discrete tasks $\mathcal{T}$ with weights $\{\alpha_{o,\tau}\}_{\tau \in \mathcal{T}}$

$$Y_{i,o} = \prod_{\tau \in \mathcal{T}} x_{i,\tau}^{\alpha_{o,\tau}}$$

where $x_{i,\tau} = x_{i,\tau}^{\text{machines}} + x_{i,\tau}^{\text{human}}$

Tasks: Assigned to humans ($\mathcal{T}_l$) or machines ($\mathcal{T}_m$)

Firm/job: Hires 1 worker (i), chooses machine quantity

Model environment: task-based production meets Roy

Equilibrium definition

Technology and firms

Occupation: $o \in \mathcal{O}$ **bundles** discrete tasks $\mathcal{T}$ with weights $\{\alpha_{o,\tau}\}_{\tau \in \mathcal{T}}$

$$Y_{i,o} = \prod_{\tau \in \mathcal{T}} x_{i,\tau}^{\alpha_{o,\tau}}$$

where $x_{i,\tau} = x_{i,\tau}^{\text{machines}} + x_{i,\tau}^{\text{human}}$

Tasks: Assigned to humans ($\mathcal{T}_l$) or machines ($\mathcal{T}_m$)

Firm/job: Hires 1 worker (i), chooses machine quantity

Workers

Skills: Heterogeneous, fixed **task-specific**:

$$s_i \equiv \{s_{i,\tau}\}_{\tau \in \mathcal{T}_l} \sim \mathcal{N}(\bar{s}, \Sigma_s)$$

$$\rightarrow x_{i,\tau}^{\text{human}} = \exp(s_{i,\tau}) \cdot l_{i,\tau}$$

Occupational choice: Choose $o \in \mathcal{O}$ s.t. Gumbel preference shocks

Time: Supplied inelastically

$$\sum_{\tau \in \mathcal{T}_l} \ell_{i,\tau,t} = 1$$

Model environment: task-based production meets Roy

Equilibrium definition

Technology and firms

Occupation: $o \in \mathcal{O}$ **bundles** discrete tasks $\mathcal{T}$ with weights $\{\alpha_{o,\tau}\}_{\tau \in \mathcal{T}}$

$$Y_{i,o} = \prod_{\tau \in \mathcal{T}} x_{i,\tau}^{\alpha_{o,\tau}}$$

where $x_{i,\tau} = x_{i,\tau}^{\text{machines}} + x_{i,\tau}^{\text{human}}$

Tasks: Assigned to humans ($\mathcal{T}_l$) or machines ($\mathcal{T}_m$)

Firm/job: Hires 1 worker (i), chooses machine quantity

Workers

Skills: Heterogeneous, fixed **task-specific**:

$$s_i \equiv \{s_{i,\tau}\}_{\tau \in \mathcal{T}_l} \sim \mathcal{N}(\bar{s}, \Sigma_s)$$

$$\rightarrow x_{i,\tau}^{\text{human}} = \exp(s_{i,\tau}) \cdot l_{i,\tau}$$

Occupational choice: Choose $o \in \mathcal{O}$ s.t. Gumbel preference shocks

Time: Supplied inelastically

$$\sum_{\tau \in \mathcal{T}_l} \ell_{i,\tau,t} = 1$$

Markets

Labor: Competitive wages

Capital: Infinitely elastic supply of machines at rate r

Goods: Fixed occupational prices $\rightarrow$ partial equilibrium

Optimal time allocation is proportional to weight matrix A

▸ Problem ▸ Capital

Firm's profit maximization problem yields:

$$\ell_{i,\tau,t} = \frac{\alpha_{o,\tau}}{\sum_{\tau \in \mathcal{T}_l} \alpha_{o,\tau}} = \frac{\alpha_{o,\tau}}{\mathrm{LS}_o}$$

Remark: Task-weight matrix.

A summarizes relative weights attached to tasks $\tau \in \mathcal{T}_l$ across occupations $o \in \mathcal{O}$:

$$A = \begin{pmatrix} \frac{\alpha_{1,1}}{LS_1} & \frac{\alpha_{1,2}}{LS_1} & \cdots & \frac{\alpha_{1,n_{\text{skill}}}}{LS_1} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\alpha_{n_{\text{occ}},1}}{LS_{n_{\text{occ}}}} & \frac{\alpha_{n_{\text{occ}},2}}{LS_{n_{\text{occ}}}} & \cdots & \frac{\alpha_{n_{\text{occ}},n_{\text{skill}}}}{LS_{n_{\text{occ}}}} \end{pmatrix} \in \mathbb{R}^{|\mathcal{O}| \times |\mathcal{T}_l|}$$

where $\mathrm{LS}_o = \sum_{\tau \in \mathcal{T}_l} \alpha_{o,\tau}$ denotes the labor share in occupation o.

Model yields a tractable log-linear wage equation

▸ Intercept term

$$w_{i,\cdot,t} = \mu + As_i + \varepsilon_{i,t}$$

$$\overbrace{w_{i,o,t}}^{\text{log wage of } i \text{ if choose } o \text{ in } t} = \overbrace{\mu_o}^{\text{occ.-specific intercept}} + \overbrace{\sum_{\mathcal{T}_l} \frac{\alpha_{o,\tau}}{LS_o} \cdot s_{i,\tau}}^{\text{weighted skills}} + \overbrace{\varepsilon_{i,t}}^{\text{idiosyncratic productivity shock (not crucial)}}$$

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

Automation leads to job transformation *given* task bundling

- **Automation**: rise in machine productivity $z_{\tau^\star}$ making it optimal to reassign τ^*

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

- **Job transformation:** weight on $\tau^* \downarrow$ & weight on other entries $\uparrow$ proportional to their occupation-specific weight

$$A_o' - A_o = \frac{\alpha_{o,\tau^\star}}{LS_o} \times \begin{pmatrix} \frac{\alpha_{o,1}}{LS_o'} & \frac{\alpha_{o,2}}{LS_o'} & \dots & -1 & \dots \end{pmatrix}$$

- Job transformation meaningful ($A_o' - A_o \neq 0$) if an occ. features **task bundling**:

$$\left|\{\tau \in \mathcal{T}_l : \alpha_{o,\tau} > 0\}\right| > 1$$

Wages change due to canonical *and* job-transformation effects

▸ Occupation-level decomposition

- **Change** in expected ($\mathbb{E}[\varepsilon_{i,t}] = 0$) potential log wage for i in occupation o :

$$\mathbb{E}\left[w_{i,o,t+1} - w_{i,o,t}\right] = \Delta\mu_o + \underbrace{(A'_o - A_o)s_i}_{\text{job transformation effects}}$$

$$= \Delta\mu_o + \underbrace{\frac{\alpha_{o,\tau^\star}}{LS_o}}_{\text{occupational exposure}} \left(\sum_{\mathcal{T}_l \setminus \tau^\star} \underbrace{\frac{\alpha_{o,\tau}}{LS_o - \alpha_{o,\tau^\star}} s_{i,\tau} - s_{i,\tau^\star}}_{\text{relative specialization}} \right)$$

where

$$\Delta\mu_o = \underbrace{\frac{\alpha_{o,\tau^\star}}{LS_o - \alpha_{o,\tau^\star}} \left(z_{\tau^\star} - \log r + \mu_o\right)}_{\text{productivity \& displacement effect}}$$

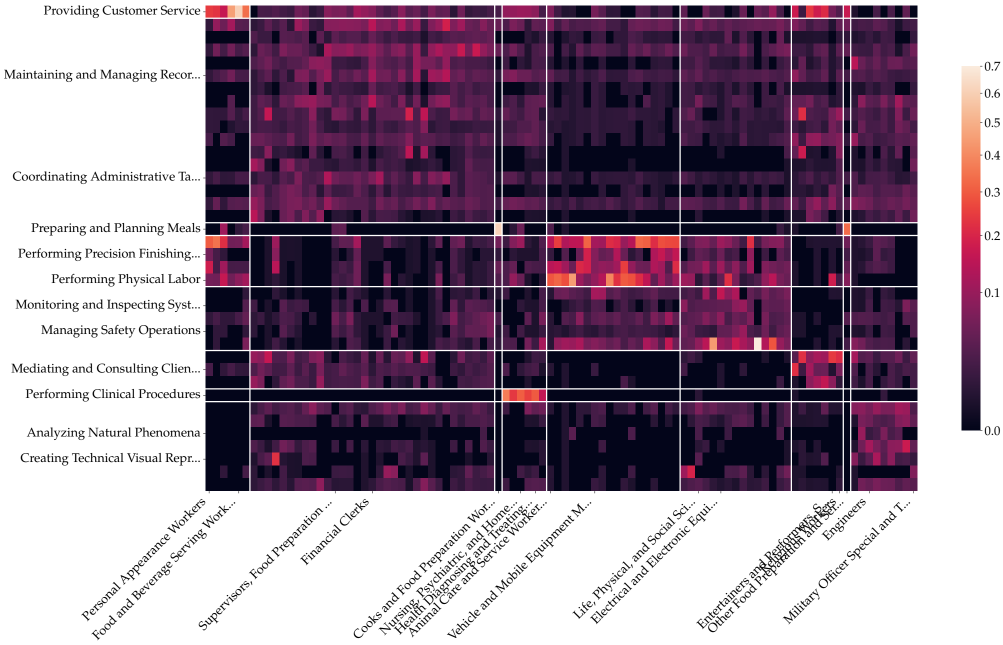
Measurement

- **Goal:** parametrize the model at same ‘resolution’ as task-exposure measures

Measurement

- **Goal:** parametrize the model at same 'resolution' as task-exposure measures

- **Step 1:** map model tasks & occupations to data $\rightarrow$ ***construct*** A ▸ Details
  - tasks: $\sim$19,000 task statements from O*NET ($\sim$ most exposure measures)
  - 90+ occupations
  - cluster tasks using NLP techniques based on similarity of inferred skill requirements
  - measure occupational task weights (baseline: LLM)



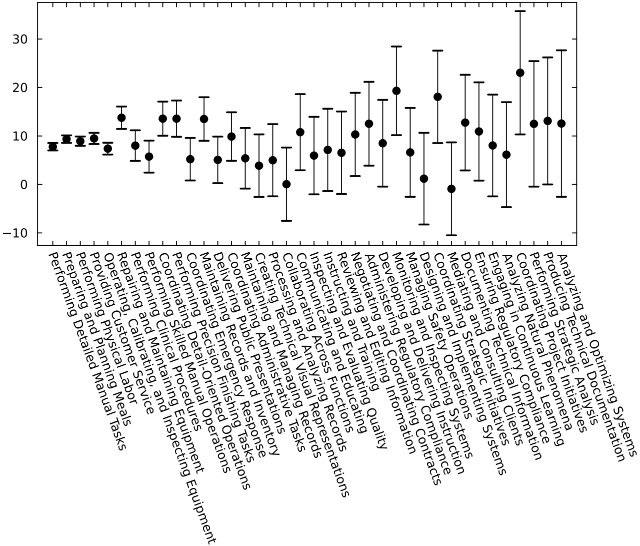
Providing Customer Service
Maintaining and Managing Recor...
Coordinating Administrative Ta...
Preparing and Planning Meals
Performing Precision Finishing...
Performing Physical Labor
Monitoring and Inspecting Syst...
Managing Safety Operations
Mediating and Consulting Clien...
Performing Clinical Procedures
Analyzing Natural Phenomena
Creating Technical Visual Repr...
Personal Appearance Workers
Food and Beverage Serving Work...
Supervisors, Food Preparation ...
Financial Clerks
Cooks and Food Preparation Wor...
Nursing, Psychiatric, and Home...
Health Diagnosing and Treating...
Animal Care and Service Worker...
Vehicle and Mobile Equipment M...
Life, Physical, and Social Sci...
Electrical and Electronic Equi...
Entertainers and Performers, S...
Other Food Preparation and Ser...
Religious Workers
Engineers
Military Officer Special and T...
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0

Measurement

- **Goal:** parametrize the model at same 'resolution' as task-exposure measures
- **Step 1:** map model tasks & occupations to data $\rightarrow$ ***construct*** A Details
    - tasks: $\sim$19,000 task statements from O*NET ($\sim$ most exposure measures)
    - 90+ occupations
    - cluster tasks using NLP techniques based on similarity of inferred skill requirements
    - measure occupational task weights (baseline: LLM)
- **Step 2:** use NLSY, A and MLE $\rightarrow$ ***estimate* skill distribution** $(\bar{s}, \Sigma_s)$ Details
    - data: A + NLSY '79 panel of worker occ. choices and wages
    - identifying variation: realized wages & occupational choices
    - validation: Monte Carlo exercise Graphs

Estimated mean skills and dispersion

▸ Model validation ▸ Other parameters



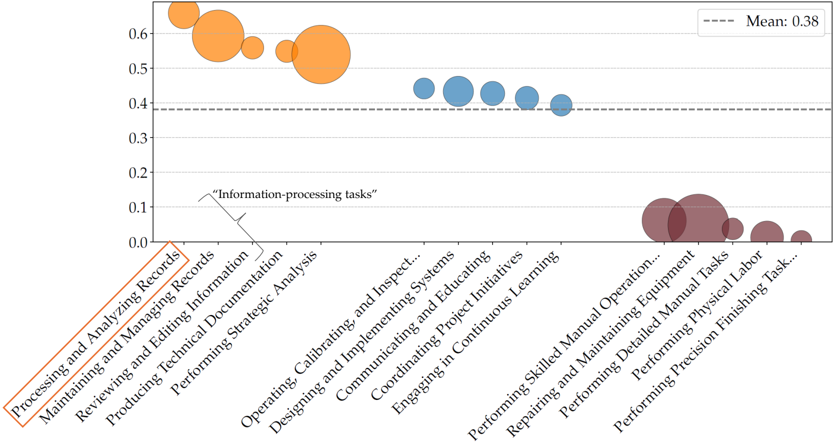
We use the model to project the wage effects due to LLM automation

- **Scenario:** What happens if LLMs automate certain tasks?
- **Measurement challenge:** which specific tasks will be/are being automated?
- **Solution:** exploit mapping of model tasks to LLM task exposure measures
  - exposure measures from Eloundou et al. (2024)
  - framework is flexible enough to map to many other exposure measures from literature
    [Webb, 2019; Eloundou et al., 2024; Anthropic/Handa et al., 2024; ...]
  - scenario where $z_{\tau^\star}$ is *just* high enough for task to be fully automated in all occ.'s

Scenario: LLMs automate information-processing task(s)

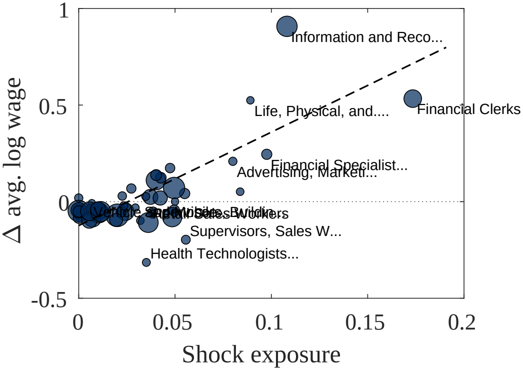
▸ Webb (2020)

Task exposure measures from Eloundou et al. (2024) aggregated to our task clusters:



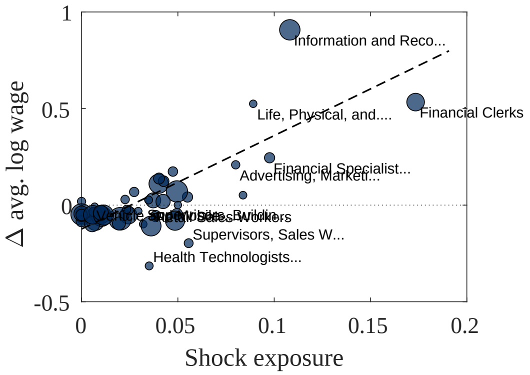
Occupation-level effects...

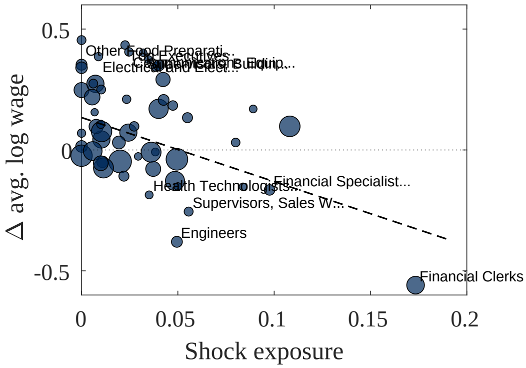
(a) Occupation-level



Occupation- & individual-level effects diverge due to resorting

Large changes in occupational skill composition (job transformation + large dispersion in automated skills) $\implies$ occupational wage change $\neq$ incumbent wage change



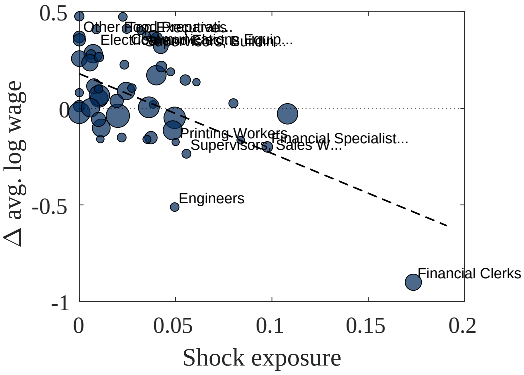


Leavers lose, *but* stayers win

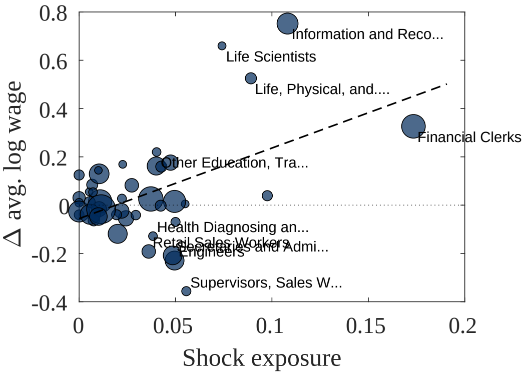
▸ Gains for in-switchers

⇒ Systematic heterogeneity that reflects selection: *task upgrading* for stayers *[cf. Bartel et al., 2007; Dauth et al., 2021]* and erosion of comparative advantage for leavers

(a) Incumbent leavers



(b) Incumbent stayers



The model's predictions chime with the anecdata

- **NYT** (May 14. '25): **"Your A.I. Radiologist Will Not Be With You Soon"**
  - *"Radiologists do far more than study images. They advise other doctors and surgeons, talk to patients, write reports and analyze medical records."*
  - G. Hinton in '25: *"[In a few years, most medical image interpretation will be done by] a combination of A.I. and a radiologist, and it will make radiologists a whole lot more efficient in addition to improving accuracy."*

- **FT** (Jun. 08 '25): **"Disrupted or displaced? How AI is shaking up jobs"**

  "According to PwC, the mix of capabilities sought by employers is changing 66 per cent faster in occupations most exposed to AI, such as financial analysts, than in those least exposed, such as physical therapists."

- **CNN** (Oct. 11 '25): **"Your plumber has a new favorite tool: ChatGPT"**

  "People go into the trades because they like doing the hands-on work itself, and if some of the administrative tasks can be automated, then that should help those workers lean into the parts of the job they like and do smarter work."

A framework to quantify worker effects of AI-induced job transformation

▸ Literature

- **Main contribution:** a tractable framework to quantify the labor market consequences of AI-induced job transformation

- **Find** AI-induced job transformation leads to large and heterogeneous wage effects, even conditional on occupation

  → losers: workers specialized in information-processing tasks, leave transformed jobs
  → winners: workers specialized in customer-facing and coordination tasks, stay or switch in

- **Big picture takeaways:**

  1. occupational exposure $\neq$ adverse individual wage effects
  2. absence of AI-induced job destruction $\neq$ absence of large labor market effects

Thank You!

Extra Slides

Job transformation: the case of weavers in the 19th century

Back

Period	Preparatory tasks		Tasks while machine running							Tasks while power loom stopped							
	Prepare warp	Dress warp	Let off warp	Pick shuttle	Beat reed	Take up cloth	Adjust warp tension	Replace empty bobbin	Monitoring	Fix smashes	Adjust temples	Back up loom	Replace empty shuttle	Fix broken weft	Fix broken warp end	Remove cloth, cleaning	Replace warp
Handloom	●	●	●	●	●	●	●		●		●		●	●	●	●	●
Early power loom (∼1820)							●	●	●	●	●	●	●	●	●	●	●
1833							●	●	●	●		●	●	●	●	●	●
1883							○	●	●	●			●	●	●	●	○

Notes. ● = Task performed; ○ = Reduced frequency; Empty = Task not performed.
Based on Bessen (2012), who draws on the records of the Lawrence Company, MA.

What's new?

Back

- **Measurement of job exposure to technologies** *[Brynjolfsson et al., 2018; Webb, 2019; Felten et al., 2021;* ***Eloundou et al., 2023****; Gathmann et al., 2024; Kogan et al., 2024]*

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

- **Model-based analysis of AI** *[****Hampole et al., 2025****; Fan, 2025]*

  $\Rightarrow$ model with **bundling & skill heterogeneity** $\rightarrow$ quantify how **job transformation** affects heterogeneous worker's earnings

- **Task-based theory** *[Acemoglu-Autor, 2011; Acemoglu-Restrepo, 2018; Acemoglu-Restrepo, 2022; Freund, 2023;* ***Autor-Thompson, 2025****]*

  $\Rightarrow$ introduce **task bundling** $\rightarrow$ highlight automation effects due to **job transformation**

- **Empirical literature on job transformation** *[****Autor et al., 2003****; Autor and Handel, 2013; Spitz-Oener, 2006; Atalay et al., 2020; Autor et al., 2024]*

  $\Rightarrow$ **link tasks with skills** $\rightarrow$ quantify *earnings* effects

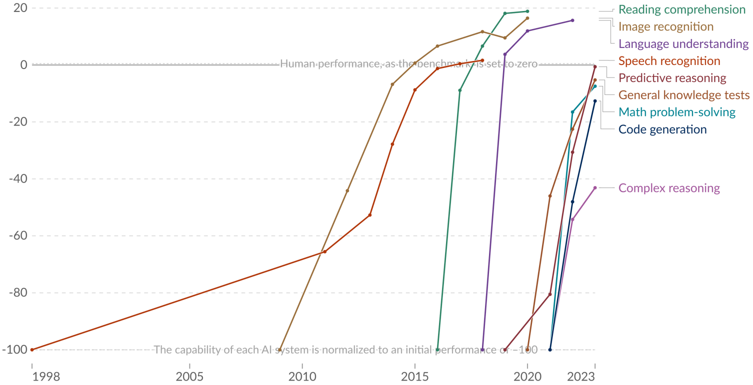
- **Multi-dimensional skills** *[Lindenlaub, 2017; Lise-PostelVinay, 2021; Deming, 2023; Grigsby, 2023]*

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

AI capabilities are rapidly improving relative to humans

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

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.

Firm's optimal production problem

Back

- **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:**

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

$$\text{s.t.} \sum_{\tau \in \mathcal{T}_l} \ell_{i,\tau,t} = 1$$

Firm's optimal production problem

Back

- **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:**

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

$$\text{s.t.} \sum_{\tau \in \mathcal{T}_l} \ell_{i,\tau,t} = 1$$

- **Optimality:**

FOC capital

$$\ell_{i,\tau,t} = \frac{\alpha_{o,\tau}}{\sum_{\tau \in \mathcal{T}_l} \alpha_{o,\tau}}$$

Firm's optimal production problem

Back

- **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:**

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

$$\text{s.t.} \sum_{\tau \in \mathcal{T}_l} \ell_{i,\tau,t} = 1$$

- **Optimality:**

FOC capital

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

FOCs

Back

- 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

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

- Plugging into production function yields

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

Wage equation: details

Back

- Intercept

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

- **Assumption:**

  initially one composite machine task with productivity normalized to $\log r$

  $\implies \mu_o$ is known for all occupations

Decomposition of occupation-level wage changes

Back

Remark: Decomposition

$$\mathbb{E}[w'_o|\hat{o}' = o] - \mathbb{E}[w_o|\hat{o} = o]$$

$$= \overbrace{\mathbb{E}[w'_o|\hat{o} = o] - \mathbb{E}[w_o|\hat{o} = o]}^{\Delta w_o \text{ of incumbents}} + \overbrace{\mathbb{E}[w'_o|\hat{o}' = o] - \mathbb{E}[w'_o|\hat{o} = o]}^{\text{re-sorting}}$$

$$= \underbrace{\Delta\mu_o}_{\text{productivity and displacement}} + \underbrace{(A'_o - A_o)\cdot\bar{s}}_{\text{task shift}} + \underbrace{(A'_o - A_o)(\bar{s}_{|o} - \bar{s})}_{\text{selection}}$$

$$+ \underbrace{\mathbb{E}[w'_o|\hat{o}' = o] - \mathbb{E}[w'_o|\hat{o} = o]}_{\text{re-sorting}}$$

Occupation-level decomposition: approximation

Back

$$
\begin{aligned}
&\mathbb{E}[w'_o|\hat{o}' = o] - \mathbb{E}[w_o|\hat{o} = o] \\
&= \overbrace{\underbrace{\Delta\mu_o}_{\text{productivity and displacement}} + \underbrace{(A'_o - A_o)\cdot\bar{s}}_{\text{task shift}} + \underbrace{\nu^{-1}(A'_o - A_o)\Sigma\left(A_o^{\intercal} - \sum_{o''} h_{o''}(\bar{s}_{|o})A_{o''}^{\intercal}\right)}_{\text{selection}}}^{\Delta w_o \text{ of incumbents}} \\
&\quad \underbrace{+\nu^{-1}A'_o\Sigma\left(\left((A'_o - A_o)^{\intercal} - \sum_{o''}\left(h'_{o''}(\bar{s}'_{|o})(A'_{o''})^{\intercal} - h_{o''}(\bar{s}_{|o})A_{o''}^{\intercal}\right)\right)\right)}_{\text{re-sorting}}. \qquad (1)
\end{aligned}
$$

where

$$
\bar{s}_{|o} = \bar{s} + \nu^{-1}\Sigma\overbrace{\left(A_o^{\intercal} - \sum_{o''} h_{o''}(\bar{s}_{|o})A_{o''}^{\intercal}\right)}^{\text{relative task intensity of occupation } o}, \quad h_o(s) = \frac{\exp(\nu^{-1}\mu_{o'} + \nu^{-1}A_{o'}\cdot s)}{\sum_{o''}\exp(\nu^{-1}\mu_{o''} + \nu^{-1}A_{o''}\cdot s)} \qquad (2)
$$

Equilibrium

Back

Remark: Equilibrium

An equilibrium is defined as a joint distribution Γ of occupation choices, log wages w, log skills s and idiosyncratic productivity shocks $\varepsilon_{\cdot}$, such that:

1. firms make zero profits, i.e., at any point in the distribution:

$$w_{i,o,t} = \mu_o + \sum_{\mathcal{T}_l} \frac{\alpha_{o,\tau}}{LS_o} \cdot s_{i,\tau} + \varepsilon_{i,t}$$

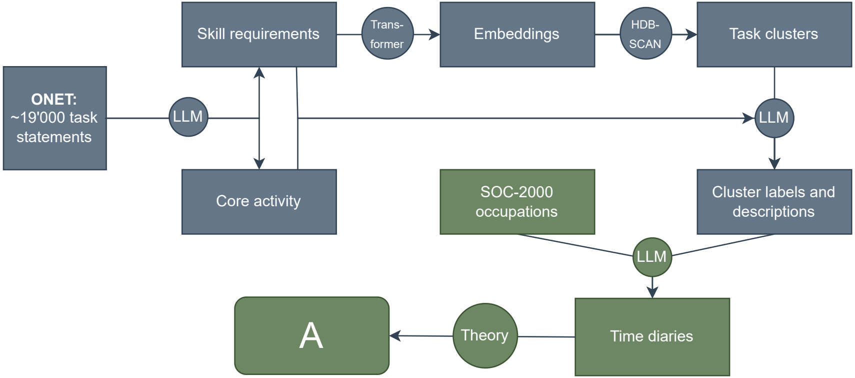
2. workers optimize, i.e., the marginal distribution of occupations conditional on wages follows

$$P(\hat{o} = o | w_{i,\cdot}) = \frac{\exp(w_{i,o}/\nu)}{\sum_{o'} \exp(w_{i,o'}/\nu)}$$

3. the unconditional marginal distributions of skills s and occupational shocks ε follow $\mathcal{N}(\bar{s}, \Sigma_s)$ and $\mathcal{N}(0, \varsigma^2 I)$, respectively.

Constructing the task-weight matrix A

▸ Validation ▸ Examples ◂ Back



Task clustering: example tasks, extraction, assignment

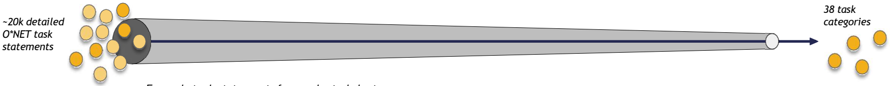
Back

Task	Activity	Skills	Cluster
Smooth rough spots on walls and ceilings, using sandpaper	smooth surfaces	manual dexterity (basic), attention to detail (basic)	Performing Detailed Manual Tasks
Lubricate moving parts on gate-crossing mechanisms and swinging signals	lubricate moving parts	manual dexterity (basic), attention to detail (basic)	Performing Detailed Manual Tasks
Perform physically demanding tasks, such as digging trenches to lay conduit or moving or lifting heavy objects	perform physical labor	physical endurance (advanced), manual dexterity (intermediate)	Performing Physical Labor
Prepare reports of activities, evaluations, recommendations, or decisions	prepare reports	report writing (advanced), analytical reasoning (intermediate), attention to detail (intermediate)	Processing and Analyzing Records
Confer with officials of public health and law enforcement agencies to coordinate interdepartmental activities.	coordinate interdepartmental activities	collaboration (advanced), project management (advanced), communication skills (intermediate)	Coordinating Project Initiatives

Examples of mapping from detailed tasks to clusters

Back

We cluster ~20k unstructured, detailed task statements into 38 task categories based on similarity of skill requirements



Example task statements from selected clusters | *Example task categories*

- Smooth rough spots on walls and ceilings, using sandpaper.
- Lubricate moving parts on gate-crossing mechanisms and swinging signals.
- Clean and polish vehicle windows.
- *Etc.*

→ **Performing Detailed Manual Tasks**

- Prepare reports of activities, evaluations, recommendations, or decisions.
- Prepare, examine, or analyze accounting records, financial statements, or other financial reports to assess accuracy, completeness, and conformance to reporting and procedural standards.
- Prepare and submit reports and charts to treatment team to reflect patients' reactions and evidence of progress or regression.
- *Etc.*

→ **Processing and Analyzing Records**

- Confer with officials of public health and law enforcement agencies to coordinate interdepartmental activities.
- Confer with directors and production staff to discuss issues, such as production and casting problems, budgets, policies, and news coverage.
- Plan and evaluate new projects, consulting with other engineers and corporate executives, as necessary.
- *Etc.*

→ **Coordinating Project Initiatives**

For each task, we extract skill requirements, create semantic vector embeddings for these requirements using a transformer model, and perform HDBSCAN-clustering on these embeddings to create broad task categories.

Details on the estimation strategy I

Back

- 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

Parameter estimates

Back

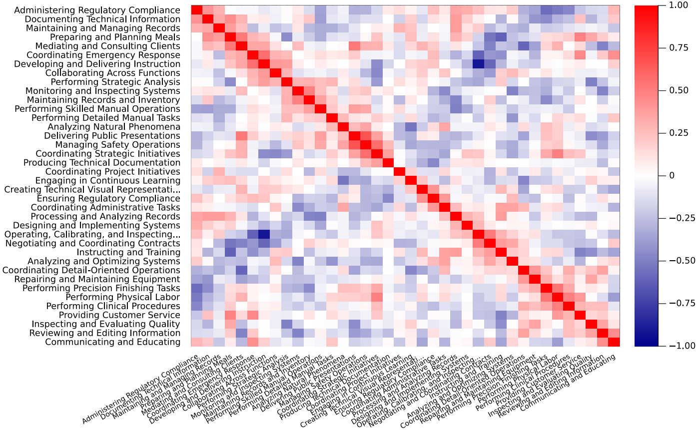


Figure 1: Pair-wise skill correlations

Parameter estimates

Back

- Scalar parameters: $\nu = 0.26$ and $\varrho = 0.43$
  - $\rightarrow$ reducing prospective wages in a given occupation by 1% lowers the odds of choosing this occupation by about 3.8%
  - $\rightarrow$ one standard-deviation occupation-specific random productivity shock can raise or lower wages by about 43% in a given year

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

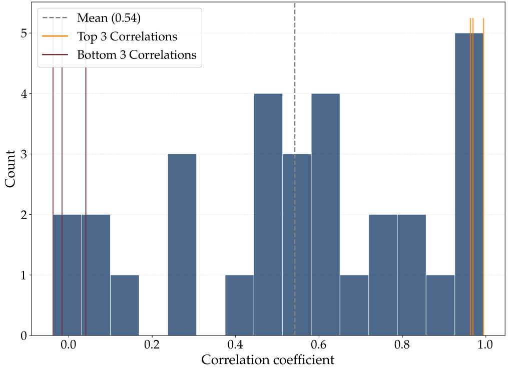
Back

1. LLM-generated task weights at the occupation-cluster level highly correlated with the average importance rating that O*NET assigns to detailed tasks within each cluster ✓
2. Comparison of time share measurement: LLM vs BIBB survey ✓
3. Comparison of LLM-generated time shares for GWAs to O*NET importance weights ✓
4. Internal consistency: do measurements for detailed occupations aggregate up? ✓

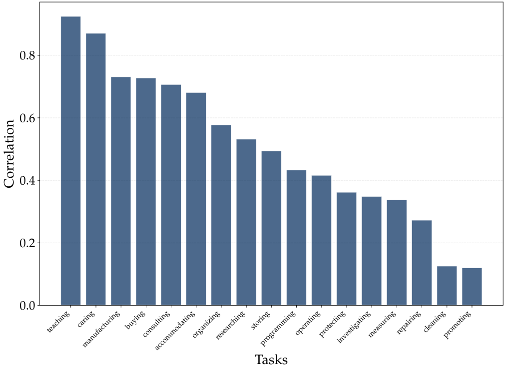
Validation: LLM-generated task shares vs. BIBB

Back

(a) Occupation-level correlations



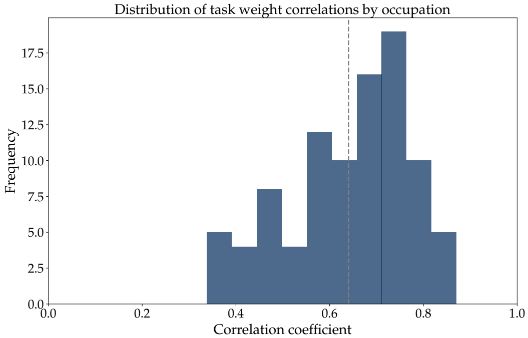
(b) Task-level correlations



Validation: O*NET GWAs (1)

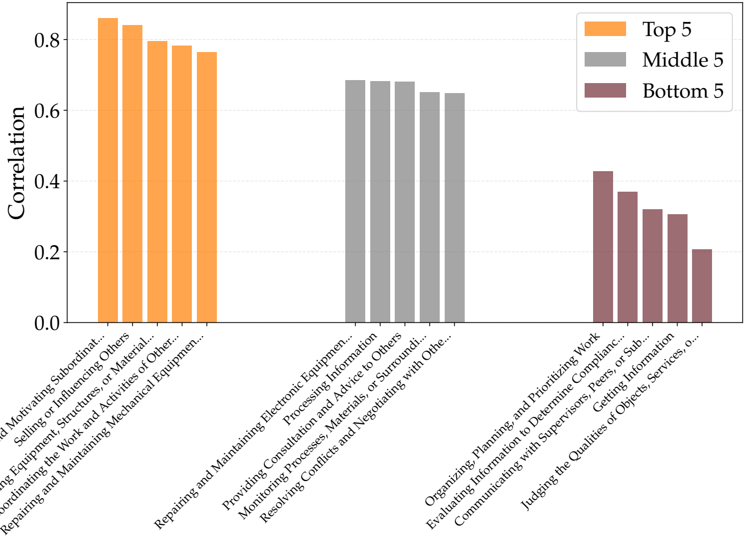
Back

- 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?



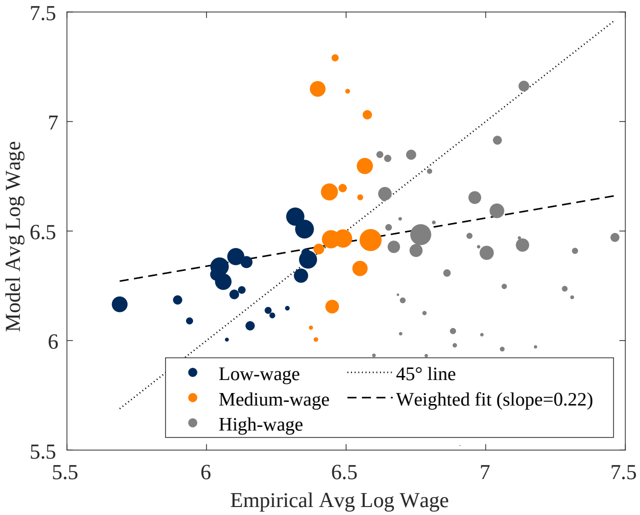
Validation: O*NET GWAs (2): correlation across occupations by task

Back



Model fit: occupational wages and employment shares

Back



A matrix: example tasks - extracted skills - tasks

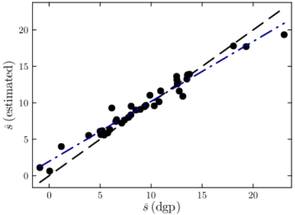
Back

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

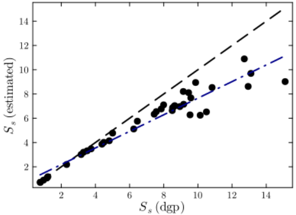
Validation: Monte-Carlo exercise

◂ Back

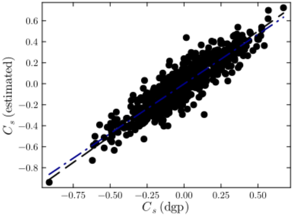
(a) Means



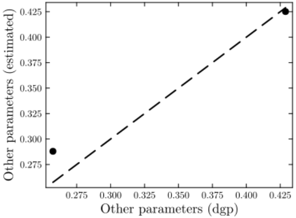
(b) Standard deviations



(c) Correlations



(d) Other parameters

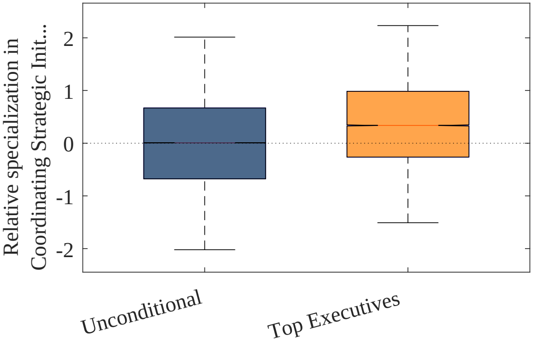


Selection based on comparative advantage

- Workers tend to select into occupations which load heavily on tasks they are relatively skilled at

relative specialization:

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



Model properties & validation

Back

1. Wage variance decomposition: model moments reasonably aligned with data
   - data: std. dev. 0.60, 28% between-occ. share
   - model: std. dev 0.70, 19% between-occ. share

2. Staying and switching probabilities: model generates (some) endogenous persistence and directionally tracks empirical switching patterns Jump

3. In both model & data, direction of moves driven by task requirements Jump

   [cf. Gathman-Schoenberg, 2010]

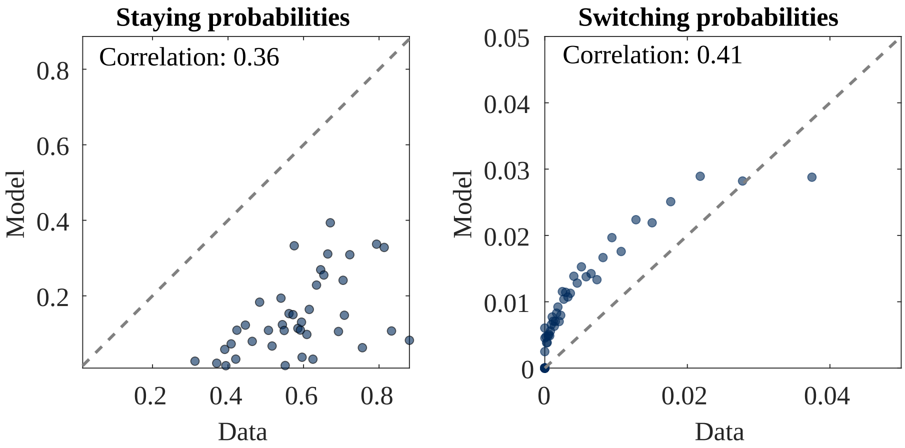
4. Frequency of moves shaped by specialization Jump

   [cf. Kambourov-Manovskii, 2008; Geel et al., 2011]

Model properties: occupational transition probabilities

▸ Learning extension ◂ Back

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

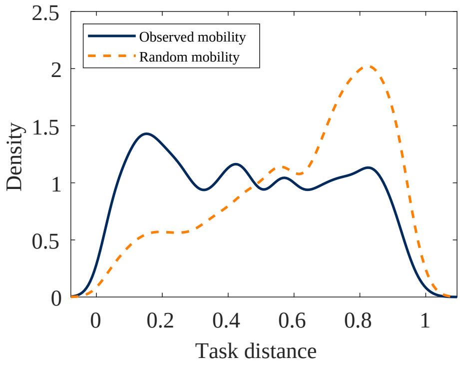


Model properties: task similarity and switching

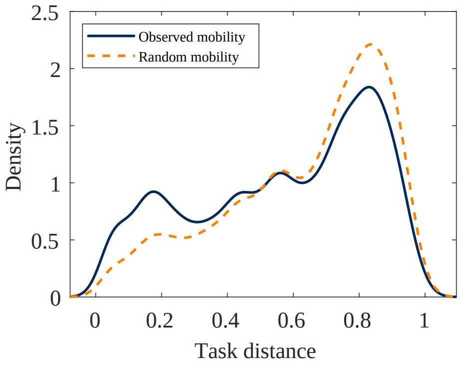
Back

- Workers are more likely to move to occupations with similar task requirements *[cf. Gathmann-Schoenberg, 2010]*

(a) Data



(b) Model

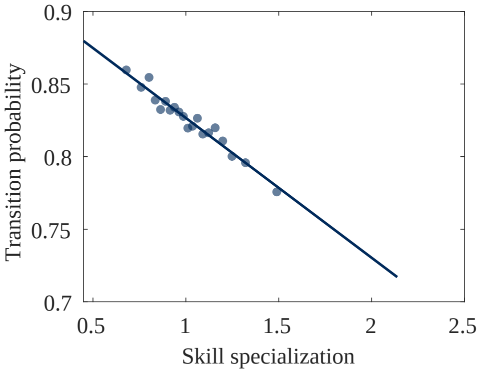


Model properties: specialization shapes switching frequency

Back

- Evidence: skill specialization tends to generate persistence in occupational choice

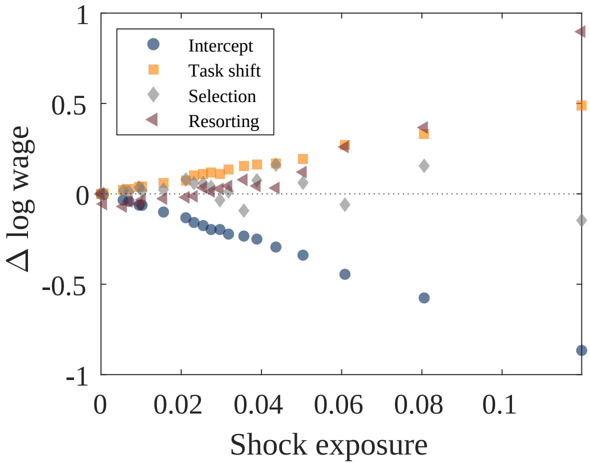
[Kambourov and Manovskii, 2008; Geel et al., 2011]



Decomposition: positive slope driven by task upgrading and resorting

Back

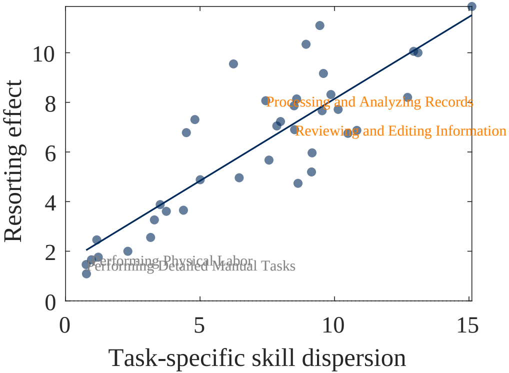
$\Rightarrow$ This is b/c $\Delta\mu_o < 0$ is offset by positive task-shift & resorting effects



Resorting effect: comparison across tasks

Task-shift effect

$\Rightarrow$ AI-exposed tasks tend to be associated with larger skills dispersion $\rightarrow$ larger re-sorting wage effects $\rightarrow$ occupational averages provide worse guidance to worker-level outcomes



Webb measure: selection criteria

Back

Table A1: **Patent selection criteria.**

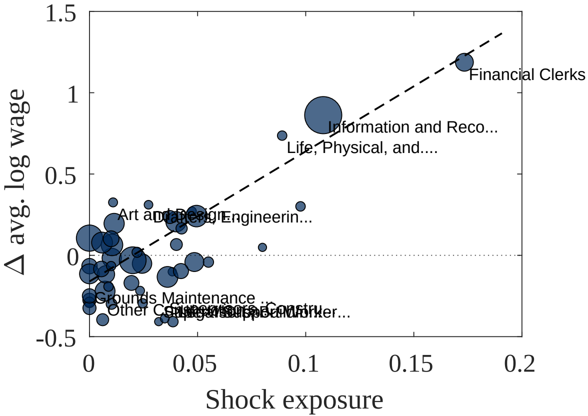
Technology	Definition
AI	Title/abstract include "neural network", "deep learning", "reinforcement learning", "supervised learning", "unsupervised learning", or "generative model"
Software	Title/abstract include "software", "computer", or "program" AND title/abstract exclude "chip", "semiconductor", "bus",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

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

In-switchers experience large wage gains

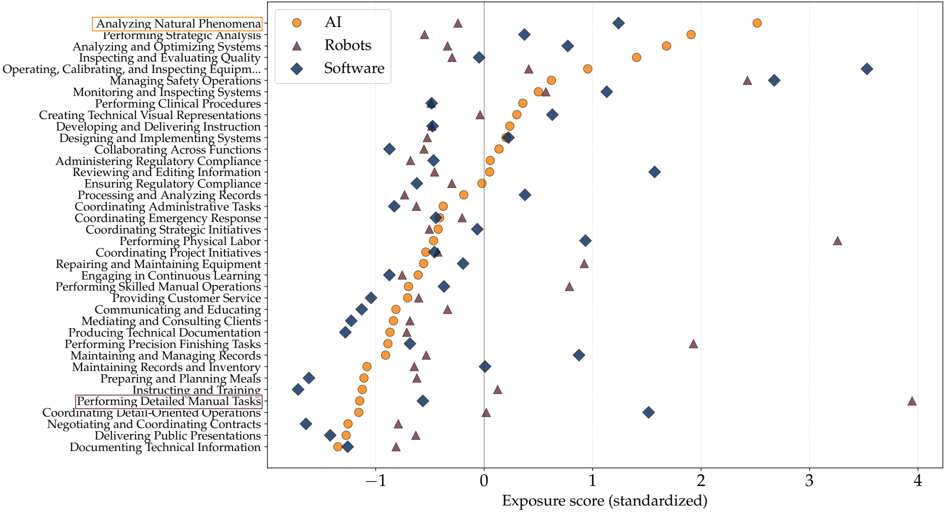
Back

⇒ Workers can enter occupations previously unsuitable as AI removes "skill barriers"



Webb's (2020) exposure measures

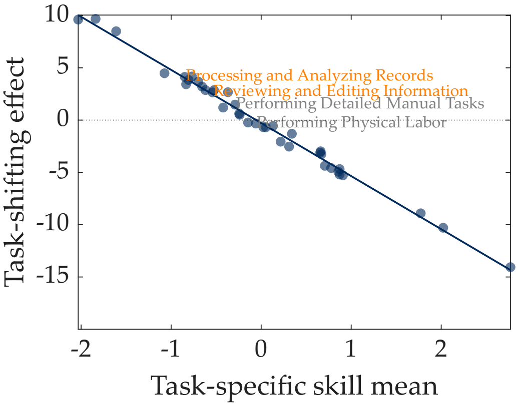
Patent criteria
Back



Task-shift effect: comparison across tasks

▸ Resorting effect

⇒ Task-shifting effects tend to be more positive for tasks exposed to AI than for those most exposed to industrial robots



Returns to occupational experience

Back

- **Limitation** of baseline: lower occupational persistence than in data
- **Simple learning amendment:** if a worker picks o in t, if they didn't work in o in $t-1$, their productivity is 1; if they did work in o in $t-1$, their productivity is $\exp(\Delta)$ with $\Delta \geq 0$. Let the expected wages of a worker with skills s_i be

$$w^e_{i,o}(0) = \mu_o + A \cdot s_i$$

$$w^e_{i,o}(1) = \mu_o + \Delta + A \cdot s_i$$

$\Rightarrow$ Worker's (expected) value function satisfies:

$$V_o(0) = w^e_{i,o}(0) + \beta\nu \log \left[\exp\left(\frac{V_o(1)}{\nu}\right) + \sum_{o' \neq o} \exp\left(\frac{V_{o'}(0)}{\nu}\right) \right]$$

$$V_o(1) = w^e_{i,o}(1) + \beta\nu \log \left[\exp\left(\frac{V_o(1)}{\nu}\right) + \sum_{o' \neq o} \exp\left(\frac{V_{o'}(0)}{\nu}\right) \right]$$

and so $V_o(1) = V_o(0) + \Delta$

- **Paper:** higher persistence but similar counterfactual results

Estimated parameters from the NLSY97 versus the baseline