

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

---

Lukas Freund

Boston College

Lukas Mann

Arizona State University

*October 10, 2025*

*Workshop: The Macro & Labor Market Consequences of AI*

# Who will gain and who will lose from AI-induced task automation?

# Who will gain and who will lose from AI-induced task automation?

- Much of the discourse: job elimination [*Frey and Osborne, 2017; Susskind, 2020*]

# Who will gain and who will lose from AI-induced task automation?

- Much of the discourse: job elimination *[Frey and Osborne, 2017; Susskind, 2020]*
- Our focus: **job transformation** ~ shift in the task content of jobs

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

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
<b>Handloom</b>	●	●	●	●	●	●	●		●		●		●	●	●	●	●
<b>Early power loom (~1820)</b>							●	●	●	●	●	●	●	●	●	●	●
<b>1833</b>							●	●	●	●		●	●	●	●	●	●
<b>1883</b>							○	●	●	●			●	●	●	●	○

Notes. ● = Task performed; ○ = Reduced frequency; Empty = Task not performed.

Based on Bessen (2012), who draws on the records of the Lawrence Company, MA.

# Who will gain and who will lose from AI-induced task automation?

- Much of the discourse: job elimination *[Frey and Osborne, 2017; Susskind, 2020]*
- Our focus: **job transformation** ~ shift in the task content of jobs
  - weavers *[Bessen, 2012]* & machinists *[Bartel et al., 2007]*
  - systematic historical evidence *[Autor et al., 2003; Spitz-Oener, 2006; Atalay et al., 2006]*
  - seems to hold true for AI, too *[Bonney et al., 2024; Gathmann et al., 2024]*

# Who will gain and who will lose from AI-induced task automation?

- Much of the discourse: job elimination *[Frey and Osborne, 2017; Susskind, 2020]*
- Our focus: **job transformation** ~ shift in the task content of jobs
  - weavers *[Bessen, 2012]* & machinists *[Bartel et al., 2007]*
  - systematic historical evidence *[Autor et al., 2003; Spitz-Oener, 2006; Atalay et al., 2006]*
  - seems to hold true for AI, too *[Bonney et al., 2024; Gathmann et al., 2024]*
- 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

# Who will gain and who will lose from AI-induced task automation?

- Much of the discourse: job elimination *[Frey and Osborne, 2017; Susskind, 2020]*
- Our focus: **job transformation** ~ shift in the task content of jobs
  - weavers *[Bessen, 2012]* & machinists *[Bartel et al., 2007]*
  - systematic historical evidence *[Autor et al., 2003; Spitz-Oener, 2006; Atalay et al., 2006]*
  - seems to hold true for AI, too *[Bonney et al., 2024; Gathmann et al., 2024]*
- 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:**
  - develop a task-based **framework of job transformation**
  - show how to **overcome these 2 measurement challenges**
  - **project outcomes** from LLM automation for heterogeneously skilled workers



- ① **Theory:** task-based model of job transformation
- ② **Measurement:** map model tasks to data + estimate task-specific skills
- ③ **Application:** project LLM-induced job transformation effects

- ① **Theory:** task-based model of job transformation
  - **occupation = production tech.** that bundles tasks performed by workers or machines
  - workers have heterogeneous portfolios of **task-specific skills**, choose occupation freely
  - **task bundling:** many tasks have to be performed by the same worker
  - partial equilibrium
  
- ② **Measurement:** map model tasks to data + estimate task-specific skills
  
  
  
  
  
  
  
  
  
  
- ③ **Application:** project LLM-induced job transformation effects

## ① **Theory:** task-based model of job transformation

- **occupation = production tech.** that bundles tasks performed by workers or machines
- workers have heterogeneous portfolios of **task-specific skills**, choose occupation freely
- **task bundling:** many tasks have to be performed by the same worker
- partial equilibrium

## ② **Measurement:** map model tasks to data + estimate task-specific skills

- NLP: ~ 19,000 O\*NET tasks → 38 task clusters, construct **occupational task weights**
- NLSY: worker panel of occ. choices & wages
  - **estimate skill distribution** via MLE using model structure

## ③ **Application:** project LLM-induced job transformation effects

## ① **Theory:** task-based model of job transformation

- **occupation = production tech.** that bundles tasks performed by workers or machines
- workers have heterogeneous portfolios of **task-specific skills**, choose occupation freely
- **task bundling:** many tasks have to be performed by the same worker
- partial equilibrium

## ② **Measurement:** map model tasks to data + estimate task-specific skills

- NLP:  $\sim 19,000$  O\*NET tasks  $\rightarrow$  38 task clusters, construct **occupational task weights**
- NLSY: worker panel of occ. choices & wages  
 $\rightarrow$  **estimate skill distribution** via MLE using model structure

## ③ **Application:** project LLM-induced job transformation effects

- LLMs automate information-processing tasks *[Eloundou et al., 2023]*

# LLM automation of information- processing: big picture insights

## 1 Occupation-level automation exposure $\Rightarrow$ adverse worker-level impacts

- large reallocation flows following AI automation  $\rightarrow$  shifting worker composition
- ambiguous relationship b/w exposure & average wage change at occupational level
- winners and losers *within* occupation

## 2 Even absent job *elimination*, **LLM automation of information-processing tasks creates large and heterogeneous wage effects through job transformation**

# Theory

---

# Environment: task-based production meets Roy

- Discrete time ( $t$ ), repeated static model
- **Production technology:**
  - **occupation**  $o \in \mathcal{O}$  (economist, teacher,...)
  - **bundles discrete tasks**  $\tau \in \mathcal{T}$  (analyzing data, moving objects,...) with weights  $\{\alpha_{o,\tau}\}_{\tau \in \mathcal{T}}$
  - production is Cobb-Douglas in task inputs

# Environment: task-based production meets Roy

- Discrete time ( $t$ ), repeated static model
- **Production technology:**
  - **occupation**  $o \in \mathcal{O}$  (economist, teacher,...)
  - **bundles discrete tasks**  $\tau \in \mathcal{T}$  (analyzing data, moving objects,...) with weights  $\{\alpha_{o,\tau}\}_{\tau \in \mathcal{T}}$
  - production is Cobb-Douglas in task inputs
- **Firms:**
  - perfectly compete for a worker's labor
  - assign tasks ex-ante optimally to humans ( $\rightarrow \mathcal{T}_l$ ) or machines w prod.  $\{\mathbf{z}_\tau\}_{\tau \in \mathcal{T}}$  ( $\rightarrow \mathcal{T}_m$ )
  - hire one worker per job, rent machines from inf. elastic capital market at exog. rate  $r$



# Environment: task-based production meets Roy

- Discrete time ( $t$ ), repeated static model
- **Production technology:**
  - **occupation**  $o \in \mathcal{O}$  (economist, teacher,...)
  - **bundles discrete tasks**  $\tau \in \mathcal{T}$  (analyzing data, moving objects,...) with weights  $\{\alpha_{o,\tau}\}_{\tau \in \mathcal{T}}$
  - production is Cobb-Douglas in task inputs
- **Firms:**
  - perfectly compete for a worker's labor
  - assign tasks ex-ante optimally to humans ( $\rightarrow \mathcal{T}_l$ ) or machines w prod.  $\{z_\tau\}_{\tau \in \mathcal{T}}$  ( $\rightarrow \mathcal{T}_m$ )
  - hire one worker per job, rent machines from inf. elastic capital market at exog. rate  $r$
- **Workers:**
  - log utility over consumption
  - heterogeneous, fixed **task-specific skills**  $s_i = \{s_{i,\tau}\}_{\tau \in \mathcal{T}_l}$  where  $\downarrow s_i \sim \mathcal{N}(\bar{s}, \Sigma_s)$
  - period  $t$ : draw shocks, choose occupation  $o$ , produce & earn

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



# Firm's optimal production problem

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

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

- **Profits:**

$$\pi_{i,o,t} = \max_{\{m_{i,\tau}\}_{\tau \in \mathcal{T}_m}, \{\ell_{i,\tau}\}_{\tau \in \mathcal{T}_l}} y_{i,o,t}(\{\ell_{i,\tau,t}\}_{\tau \in \mathcal{T}_l}, \{m_{i,\tau,t}\}_{\tau \in \mathcal{T}_m}) - \exp(w_{i,o,t}) - r \sum_{\tau \in \mathcal{T}_m} m_{i,\tau,t}$$
$$\text{s.t. } \sum_{\tau \in \mathcal{T}_l} \ell_{i,\tau,t} = 1$$

# Firm's optimal production problem

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

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

- **Profits:**

$$\pi_{i,o,t} = \max_{\{m_{i,\tau}\}_{\tau \in \mathcal{T}_m}, \{\ell_{i,\tau}\}_{\tau \in \mathcal{T}_l}} y_{i,o,t}(\{\ell_{i,\tau,t}\}_{\tau \in \mathcal{T}_l}, \{m_{i,\tau,t}\}_{\tau \in \mathcal{T}_m}) - \exp(w_{i,o,t}) - r \sum_{\tau \in \mathcal{T}_m} m_{i,\tau,t}$$
$$\text{s.t. } \sum_{\tau \in \mathcal{T}_l} \ell_{i,\tau,t} = 1$$

- **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

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

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

- **Profits:**

$$\pi_{i,o,t} = \max_{\{m_{i,\tau}\}_{\tau \in \mathcal{T}_m}, \{\ell_{i,\tau}\}_{\tau \in \mathcal{T}_l}} y_{i,o,t}(\{\ell_{i,\tau,t}\}_{\tau \in \mathcal{T}_l}, \{m_{i,\tau,t}\}_{\tau \in \mathcal{T}_m}) - \exp(w_{i,o,t}) - r \sum_{\tau \in \mathcal{T}_m} m_{i,\tau,t}$$
$$\text{s.t. } \sum_{\tau \in \mathcal{T}_l} \ell_{i,\tau,t} = 1$$

- **Optimality:**

► FOC capital

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

# Occupational task-weight matrix

## Remark: Task-weight matrix.

The matrix  $A$  summarizes the relative weights attached to each task  $\tau \in \mathcal{T}_l$  across occupations  $o \in \mathcal{O}$ :

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

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

The row vector  $A_o := A_{o,\cdot}$  contains the task weights for occupation  $o$ .

Wage equation:

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

which implies

$$\begin{aligned}
 w_{i,o,t} &= \underbrace{\mu_o}_{\text{occ.-specific intercept}} + \underbrace{\sum_{\tau_l} \frac{\alpha_{o,\tau}}{LS_o} \cdot s_{i,\tau}}_{\text{weighted skills}} + \underbrace{\varepsilon_{i,t}}_{\text{idiosyncratic productivity shock}} \\
 &= \mu_o + \underbrace{\frac{1}{n_{\text{skill}}} \sum_{\tau_l} s_{i,\tau}}_{\text{scalar absolute advantage}} + \text{Cov} \left( n_{\text{skill}} \cdot \frac{\alpha_{o,\cdot}}{LS_o}, \underbrace{s_{i,\cdot} - \frac{1}{n_{\text{skill}}} \sum_{\tau_l} s_{i,\tau}}_{\text{specialization vector}} \right) + \varepsilon_{i,t}
 \end{aligned}$$

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

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

- Occupational choice probabilities:**

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

# Automation and job transformation in the model

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

$$\mathcal{T}'_l = \mathcal{T}_l \setminus \tau^* \quad \mathcal{T}'_m = \mathcal{T}_m \cup \tau^*$$

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

$$\begin{aligned} A'_o - A_o &= \begin{pmatrix} \frac{\alpha_{o,1}}{LS'_o} \cdot \frac{\alpha_{o,\tau^*}}{LS_o} & \frac{\alpha_{o,2}}{LS'_o} \cdot \frac{\alpha_{o,\tau^*}}{LS_o} & \dots & -\frac{\alpha_{o,\tau^*}}{LS_o} & \dots \end{pmatrix} \\ &= \frac{\alpha_{o,\tau^*}}{LS_o} \times \begin{pmatrix} \frac{\alpha_{o,1}}{LS'_o} & \frac{\alpha_{o,2}}{LS'_o} & \dots & -1 & \dots \end{pmatrix} \end{aligned}$$



# Wage effects of automation

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

$$\begin{aligned}\mathbb{E} [w_{i,o,t+1} - w_{i,o,t}] &= \Delta\mu_o + \underbrace{(A'_o - A_o)s_i}_{\text{job transformation effects}} \\ &= \Delta\mu_o + \underbrace{\frac{\alpha_{o,\tau^*}}{LS_o}}_{\text{occupational exposure}} \left( \sum_{\tau \setminus \tau^*} \underbrace{\frac{\alpha_{o,\tau}}{LS_o - \alpha_{o,\tau^*}} s_{i,\tau} - s_{i,\tau^*}}_{\text{relative specialization}} \right)\end{aligned}$$

where

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

# The role of task bundling

## Remark: Task bundling

An occupation features **task-bundling** if

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

The economy features a **no-bundling property** if no occupation features task-bundling:

$$|\{\tau \in \mathcal{T}_l : \alpha_{o,\tau} > 0\}| = 1 \quad \forall o \in \mathcal{O}.$$

⇒ In a no-bundling economy, wage changes are solely driven by  $\Delta\mu_o$

⇒ With task bundling, wages also change due to **job transformation**

## Remark: Decomposition

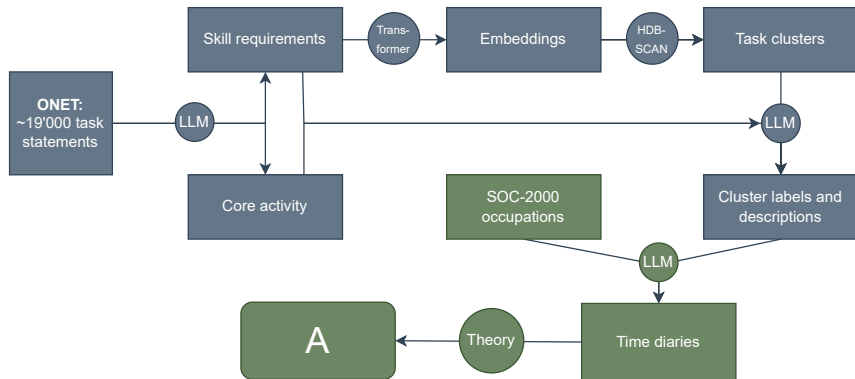
$$\begin{aligned}
 & \mathbb{E}[w'_o | \hat{o}' = o] - \mathbb{E}[w_o | \hat{o} = o] \\
 &= \underbrace{\mathbb{E}[w'_o | \hat{o} = o] - \mathbb{E}[w_o | \hat{o} = o]}_{\Delta w_o \text{ of incumbents}} + \underbrace{\mathbb{E}[w'_o | \hat{o}' = o] - \mathbb{E}[w'_o | \hat{o} = o]}_{\text{re-sorting}} \\
 &= \underbrace{\Delta \mu_o}_{\text{productivity and displacement}} + \underbrace{(A'_o - A_o) \cdot \bar{s}}_{\text{task shift}} + \underbrace{(A'_o - A_o)(\bar{s}_{|o} - \bar{s})}_{\text{selection}} \\
 &\quad + \underbrace{\mathbb{E}[w'_o | \hat{o}' = o] - \mathbb{E}[w'_o | \hat{o} = o]}_{\text{re-sorting}}
 \end{aligned}$$

# Measurement

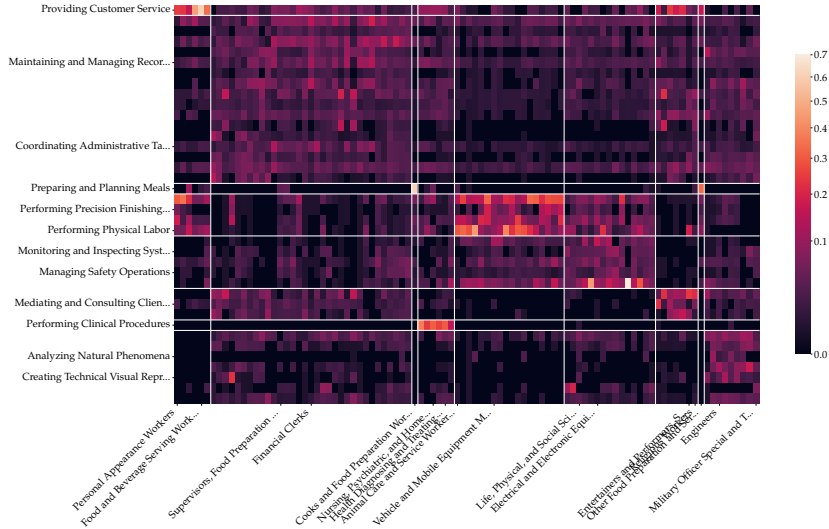
---

- **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 ( $\sim 3d$ )
- **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](#)

# Task-weight matrix A



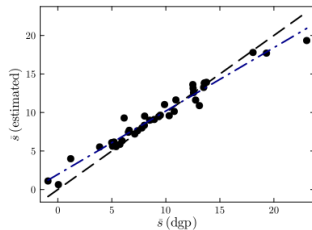
## Step 2: estimation of task-specific skills

- **Measurement challenge #1:** 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
  - NLSY '97 yields v similar parameter estimates
- **Formalization:** maximum likelihood [▶ Details](#)
- **Implementation:** MC integration + auto-diff. + stochastic gradient descent
- **Validation:** Monte Carlo exercise

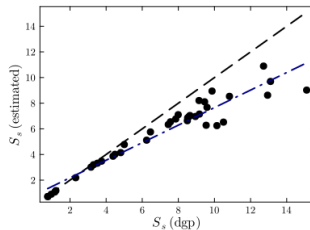


# Validation: Monte-Carlo exercise

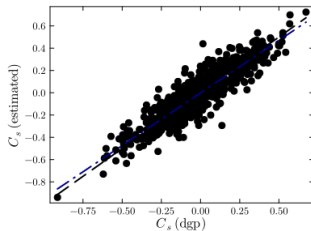
(a) Means



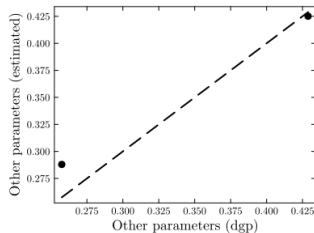
(b) Standard deviations



(c) Correlations

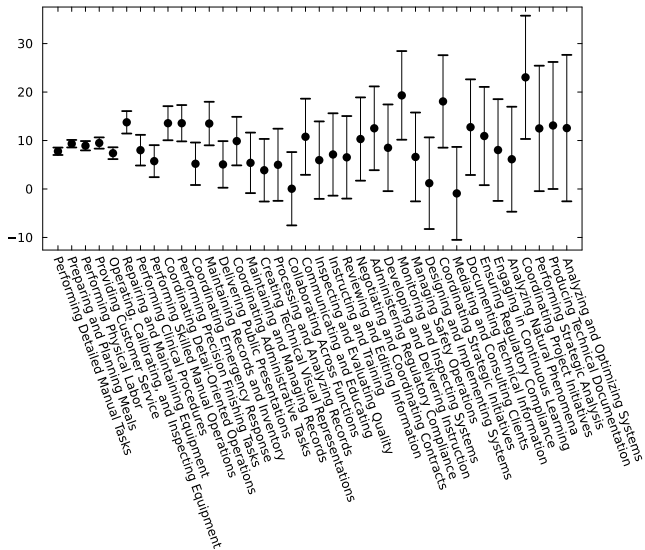


(d) Other parameters



# Estimated mean skills and dispersion

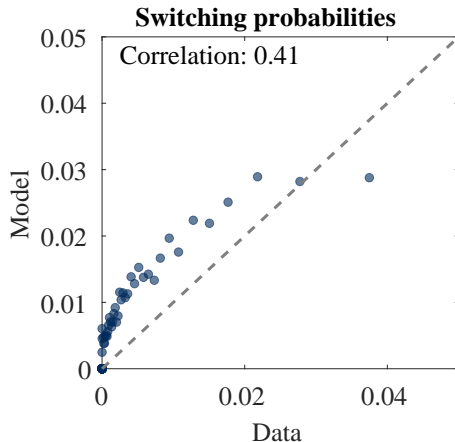
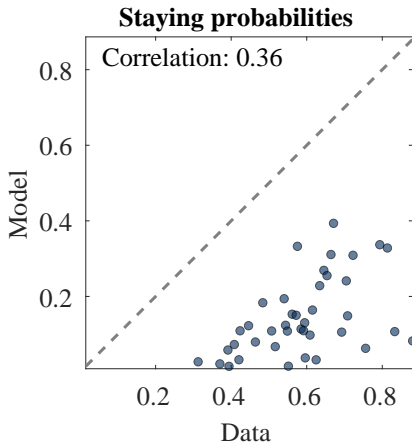
► Other parameters



# Model properties: occupational transition probabilities

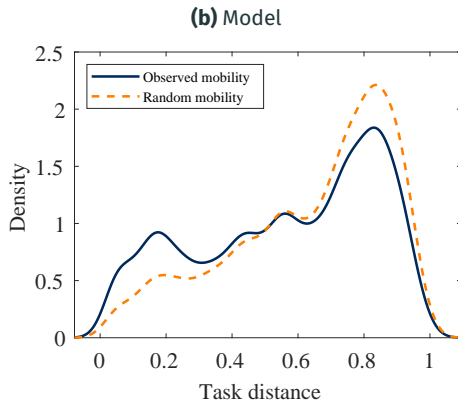
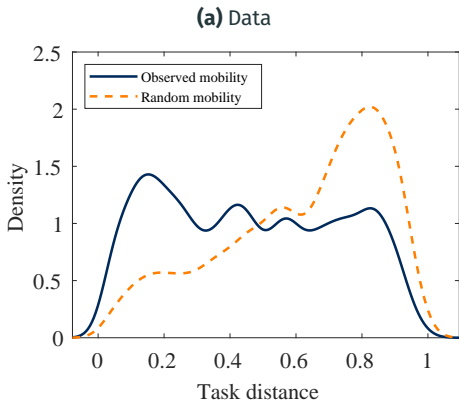
► Learning extension

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



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

[cf. Gathmann-Schoenberg, 2010]



# LLM automation

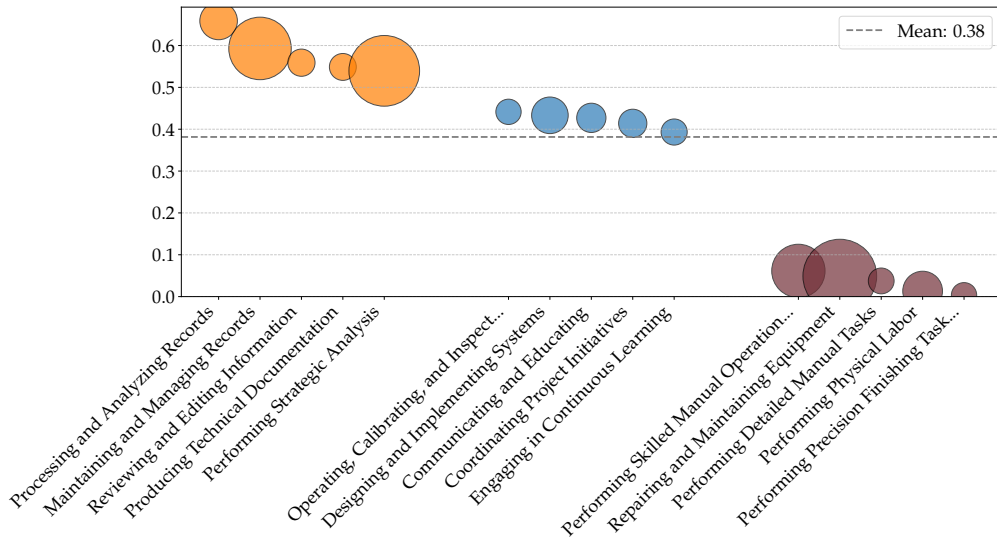
---

# Construction of task-specific automation shocks

- Who wins, who loses from AI-induced job transformation?
- **Measurement challenge #2:** which specific tasks are being automated?
- **Our solution:** exploit the mapping of model tasks — clusters of O\*NET tasks — to existing, technology-specific automation exposure measures  
*[Webb, 2019; Eloundou et al., 2023; Anthropic—Handa et al., 2024; ...]*
- **We focus on LLMs**, using task-level measure from Eloundou et al. (2023)

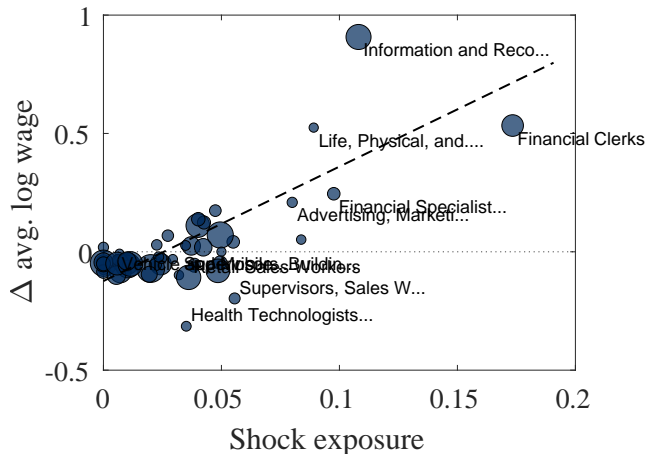
# Aggregated task exposure measures from Eloundou et al. (2023)

► Webb (2020)



# Occupation-level effects

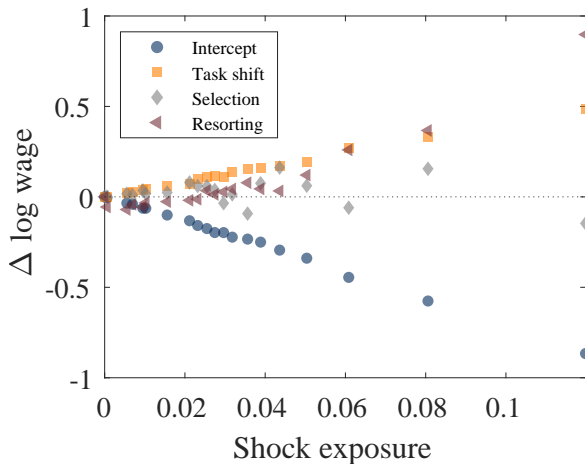
⇒ More exposed occupations experience *larger* wage gains on average





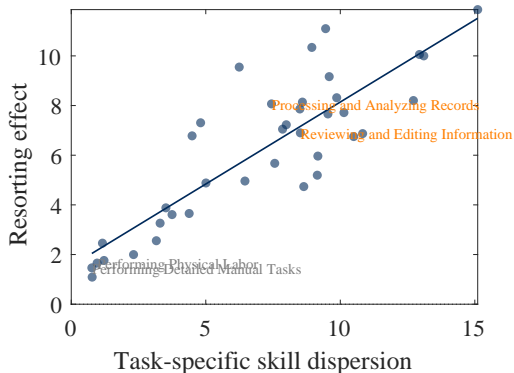
## Decomposition: positive slope driven by task upgrading and resorting

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



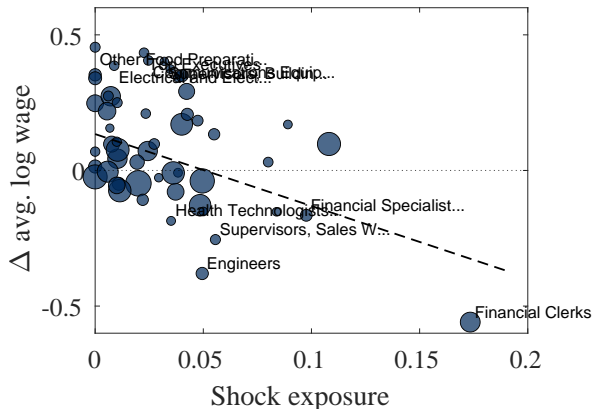
# Resorting effect: comparison across tasks

- ⇒ AI-exposed tasks → larger skills dispersion → larger re-sorting wage effects
- ⇒ occupational averages provide worse guidance to worker-level outcomes



# Individual-level effects for incumbents

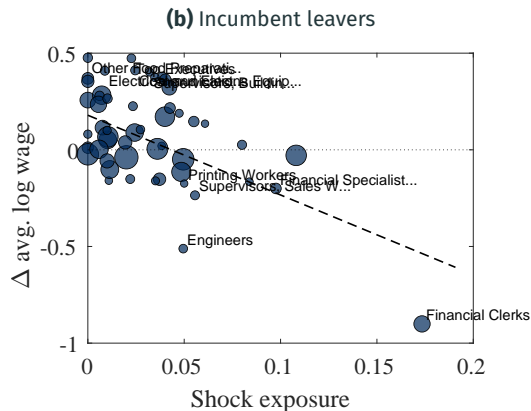
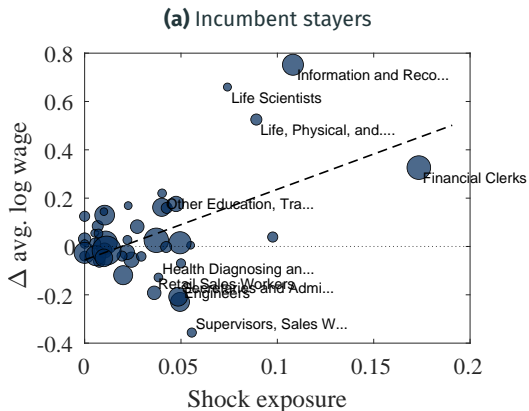
⇒ Incumbent workers' wages in highly exposed origin occupations decline on average



# Heterogeneity among incumbents

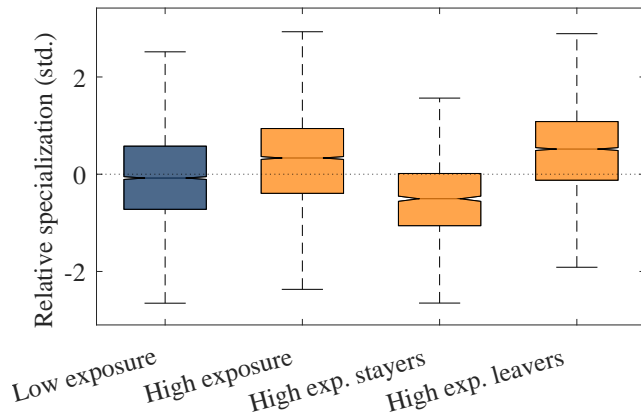
► Relative specialization

⇒ Stayers win, leavers lose (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])



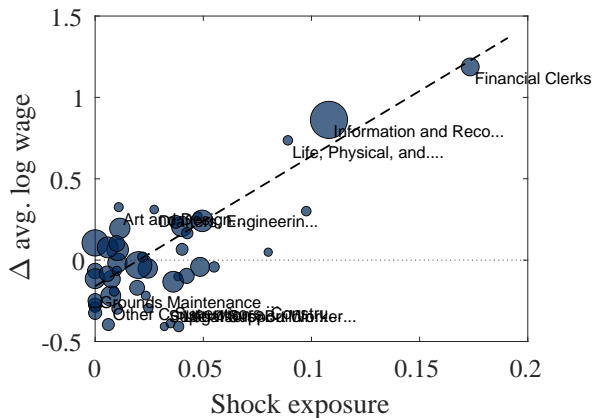
## Explanation: selection

⇒ Leavers are, as a matter of selection, specialized in now-automated task



## In-switchers experience large wage gains

⇒ Workers previously deterred from highly exposed occupations experience wage gains



## Recap of results: LLM-driven automation of information- processing tasks

- LLM-driven automation generates more occupational reallocation than in past
  - occupation-level averages offer limited guidance for worker-level outcomes
- **Selection** on specialization generates neg. link b/w exposure & incumbent wages
  - incumbent leavers specialized in information-processing tasks
- + Automation **benefits** those reallocating time to tasks in which they're more skilled
  - incumbent stayers who excel in customer-facing and coordination tasks
- + Or enabled to access better occupations by **reducing skill-based entry barriers**
  - in-switchers (think of “vibe coding”)

- **Question:** Who will win and who will lose from AI-driven job transformation?
- **This paper:** tractable framework to quantify an answer to this question
- **Big picture insights:**
  - ① occupational exposure  $\neq$  adverse individual wage effects
  - ② absence of AI-induced job destruction  $\neq$  absence of large labor market effects



## Extra Slides

---

# What's new?

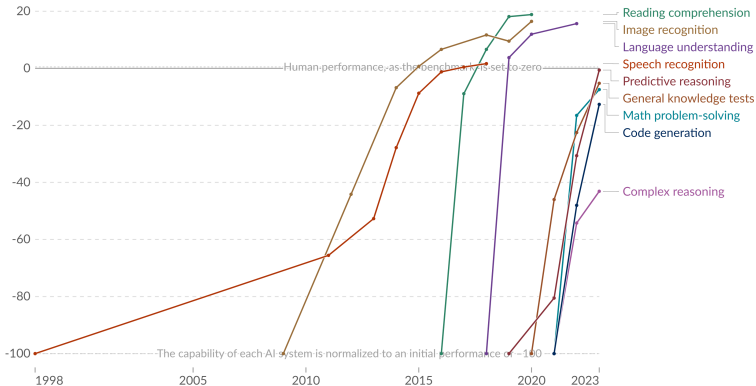
- **Measurement of job exposure to technologies** [Brynjolfsson et al., 2018; Webb, 2019; Felten et al., 2021; Eloundou et al., 2023; Gathmann et al., 2024; Kogan et al., 2024]  
⇒ map to **structural** model → individual **earnings effects** as a function of skills
- **Model-based analysis of AI** [Hampole et al., 2025; Fan, 2025]  
⇒ model with **bundling & skill heterogeneity** → 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]  
⇒ introduce task bundling → highlight automation effects due to  $\Delta$  task content
- **Empirical literature on job transformation** [Autor et al., 2003; Autor and Handel, 2013; Spitz-Oener, 2006; Atalay et al., 2020; Autor et al., 2024]  
⇒ **link tasks with skills** → quantify *earnings* effects
- **Multi-dimensional skills** [Lindenlaub, 2017; Lise-Postel-Vinay, 2021; Deming, 2023; Grigsby, 2023]  
⇒ **estimate** distribution of high-dim. task-specific skills → **measure specialization**

# 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)

OurWorldinData.org/artificial-intelligence | CC BY

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

- 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:  $\mu_o$  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  $A \perp \mu_o$

- 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

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

# Wage equation: details

- 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  $\mu_o$  is known for all occupations.

# Occupation-level decomposition: approximation

$$\begin{aligned}
 & \mathbb{E}[w'_o | \hat{o}' = o] - \mathbb{E}[w_o | \hat{o} = o] \\
 &= \overbrace{\underbrace{\Delta\mu_o}_{\text{productivity and displacement}} + \underbrace{(A'_o - A_o) \cdot \bar{s}}_{\text{task shift}} + \underbrace{\nu^{-1}(A'_o - A_o)\Sigma \left( A_o^T - \sum_{o''} h_{o''}(\bar{s}_{|o}) A_{o''}^T \right)}_{\text{selection}}}_{\Delta w_o \text{ of incumbents}} \\
 &+ \underbrace{\nu^{-1} A'_o \Sigma \left( \left( (A'_o - A_o)^T - \sum_{o''} (h'_{o''}(\bar{s}'_{|o}) (A'_{o''})^T - h_{o''}(\bar{s}_{|o}) A_{o''}^T \right) \right)}_{\text{re-sorting}}. \tag{1}
 \end{aligned}$$

where

$$\bar{s}_{|o} = \bar{s} + \nu^{-1} \Sigma \overbrace{\left( A_o^T - \sum_{o''} h_{o''}(\bar{s}_{|o}) A_{o''}^T \right)}^{\text{relative task intensity of occupation } o}, \quad h_o(s) = \frac{\exp(\nu^{-1} \mu_{o'} + \nu^{-1} A_{o'} \cdot s)}{\sum_{o''} \exp(\nu^{-1} \mu_{o''} + \nu^{-1} A_{o''} \cdot s)} \tag{2}$$

# Equilibrium

## Remark: Equilibrium

An equilibrium is defined as a joint distribution  $\Gamma$  of occupation choices, log wages  $w$ , log skills  $s$  and idiosyncratic productivity shocks  $\varepsilon$ , such that:

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

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

- 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  $\varepsilon$  follow  $\mathcal{N}(\bar{s}, \Sigma_s)$  and  $\mathcal{N}(0, \varsigma^2 I)$ , respectively.

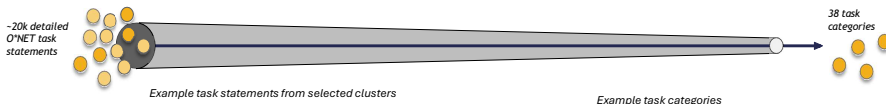


# Task clustering: example tasks, extraction, assignment

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

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



- 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

- 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

- 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

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

- randomly partition individuals into  $n$  groups:

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

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

# Parameter estimates

- For the scalar parameters, we estimate  $\nu = 0.26$  and  $\varrho = 0.43$ .
- The estimate of  $\nu$  implies that reducing prospective wages in a given occupation by 1% lowers the odds of choosing this occupation by about 3.8% since
- $\varrho = 0.43$  indicates that a 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

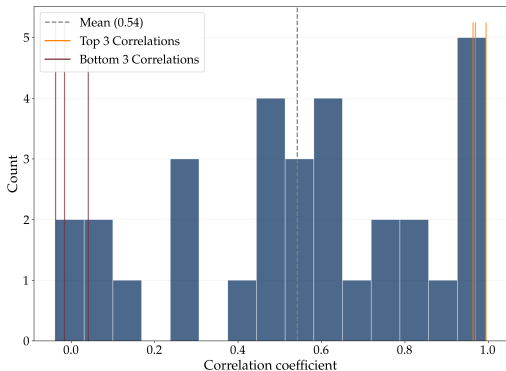
- Potential alternative to our approach: use O\*NET "General Work Activities" (GWAs) and occupational importance weights
- Reasons we prefer our approach:
  - ① GWAs themselves are not mutually exclusive (e.g. "Analyzing Data or Information" vs "Processing Information") nor exhaustive (esp. regarding 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 (→ 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

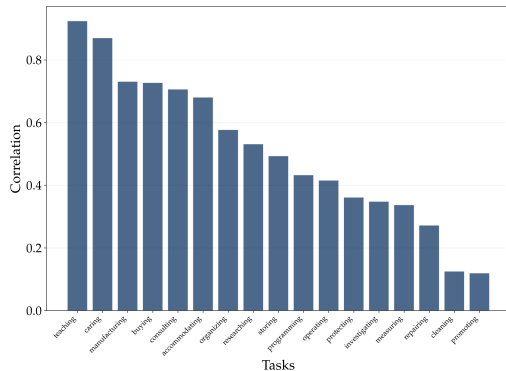
- ① LLM-generated task weights at the occupation-cluster level highly correlated with the average importance rating that O\*NET assigns to detailed tasks within each cluster ✓
- ② Comparison of time share measurement: LLM vs BIBB survey ✓
- ③ Comparison of LLM-generated time shares for GWAs to O\*NET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

# Validation: LLM-generated task shares vs. BIBB

**(a)** Occupation-level correlations



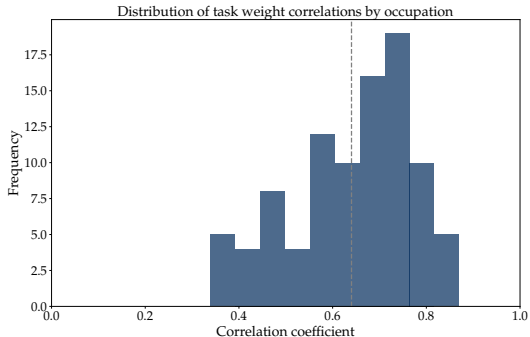
**(b)** Task-level correlations



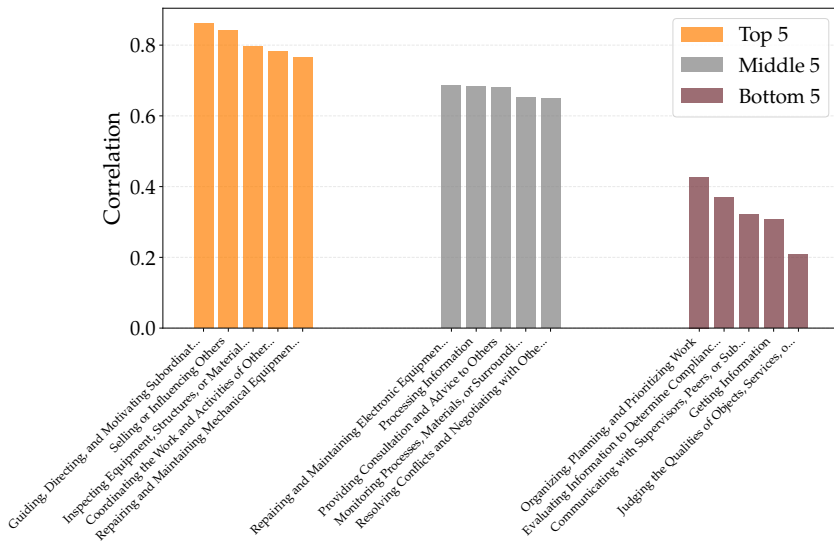


## Validation: O\*NET GWAs (1)

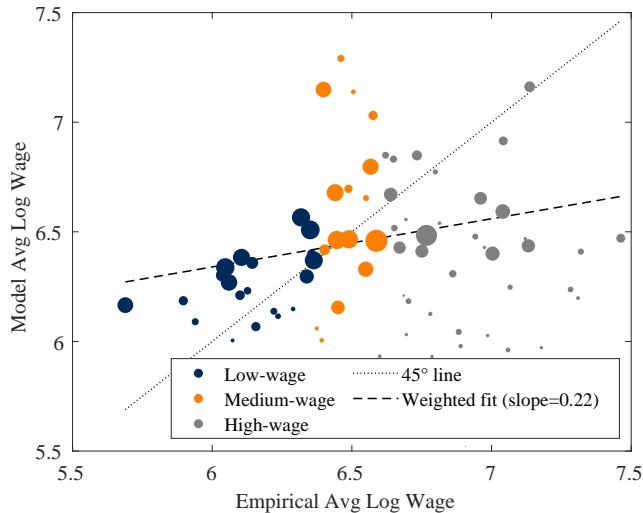
- Take O\*NET GWAs (O\*NET 5.0, consistent with SOC-2000), construct relative importance for each GWA by occupation, aggregate to SOC-2000-3d
- Let LLM generate *time shares* for the GWAs for each SOC-2000-3d occ
- How do LLM-time shares correlate with vector of O\*NET importance weights?



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



# Model fit: occupational wages and employment shares

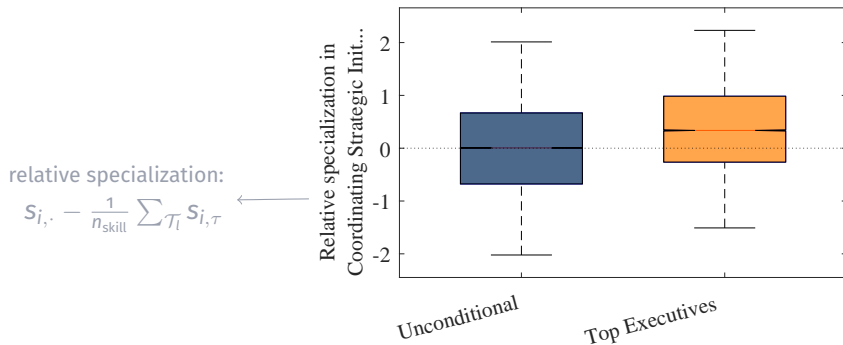
[◀ Back](#)

# A matrix: example tasks - extracted skills - tasks

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

## Selection based on comparative advantage

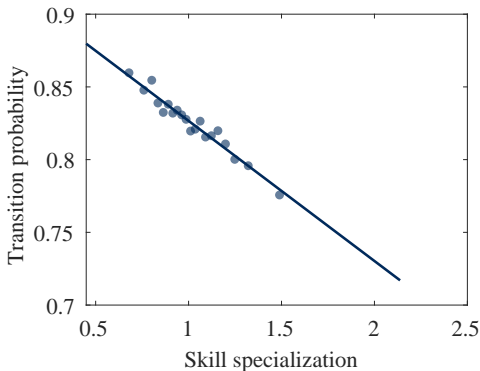
- Workers tend to select into occupations which load heavily on tasks they are relatively skilled at



## Model properties: specialization shapes switching frequency

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

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



# Webb measure: selection criteria

Table A1: Patent selection criteria.

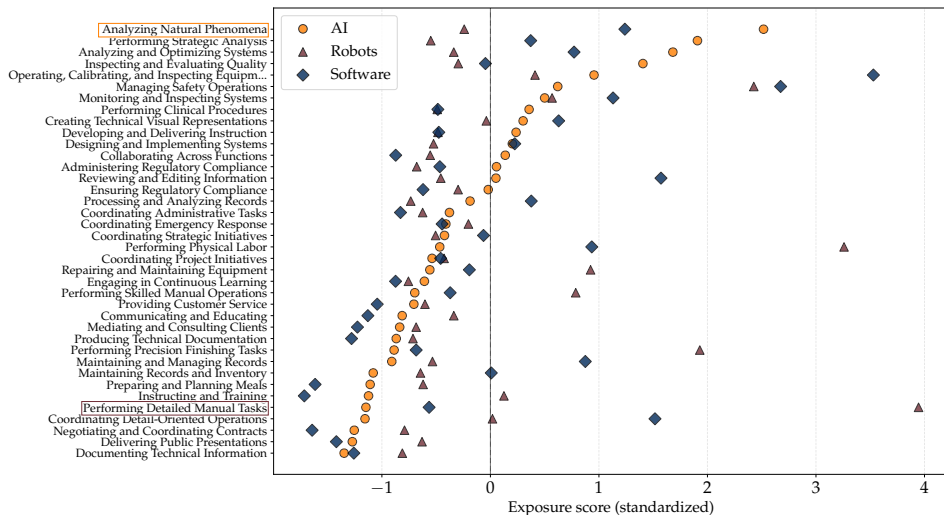
Technology	Definition
AI	Title/abstract include “neural network”, “deep learning”, “reinforcement learning”, “supervised learning”, “unsupervised learning”, or “generative model”
Software	Title/abstract include “software”, “computer”, or “program” AND title/abstract exclude “chip”, “semiconductor”, “bus”,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

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

# Webb's (2020) exposure measures

► Patent criteria

► Eloundou et al. (2023)

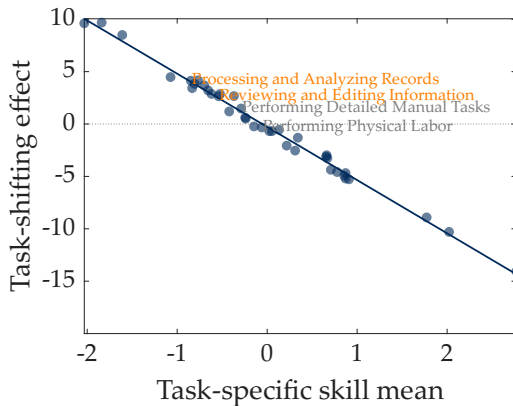




## Task-shift effect: comparison across tasks

[► 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

- **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

$$w_{i,o}^e(o) = \mu_o + A \cdot s_i$$

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

⇒ Worker's (expected) value function satisfies:

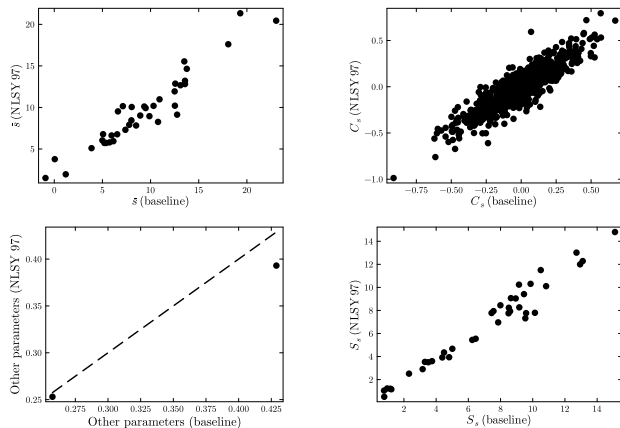
$$V_o(o) = w_{i,o}^e(o) + \beta \nu \log \left[ \exp \left( \frac{V_o(1)}{\nu} \right) + \sum_{o' \neq o} \exp \left( \frac{V_{o'}(o)}{\nu} \right) \right]$$

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

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

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

## NLSY97



**Figure 2:** Estimated parameters from the NLSY97 versus the baseline