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

Lukas Freund
Boston College

Lukas Mann
Arizona State University

February 18, 2026

Federal Reserve Bank of Boston

Motivation: job transformation through AI

- What will be the labor market consequences of AI?

Motivation: job transformation through AI

- What will be the labor market consequences of AI?

- Our focus: **job transformation** $\sim$ shift in the task content of jobs
  - rich empirical literature *[e.g., Autor et al., 2003; Spitz-Oener, 2006; Atalay et al., 2020]*

Job Transformation – a present-day example

junior associates [...] will historically have been doing a lot of document review work [...]

A lot of that can be automated [...]

But that just means actually those associates can be used more efficiently on other things [. . .] It's upscaling the type of work they're able to do [like] interacting with clients and just doing more sophisticated legal work

The AI Shift **Professional services** + Add to myFT

The AI Shift: If AI is coming for junior lawyers' jobs, why does their pay keep going up?

Automation may be freeing up their time to do more valuable work

© Efi Chalikopoulou

Sarah O'Connor and **John Burn-Murdoch**

Published DEC 18 2025

10

O'Connor and Burn-Murdoch (2025, FT)

Motivation: job transformation through AI

- What will be the labor market consequences of AI?
- Our focus: **job transformation** $\sim$ shift in the task content of jobs
  - rich empirical literature *[e.g., Autor et al., 2003; Spitz-Oener, 2006; Atalay et al., 2020]*

$\Rightarrow$ **How will AI affect wages through job transformation? Winners and losers?**

Motivation: job transformation through AI

- What will be the labor market consequences of AI?
- Our focus: **job transformation** $\sim$ shift in the task content of jobs
  - rich empirical literature *[e.g., Autor et al., 2003; Spitz-Oener, 2006; Atalay et al., 2020]*

$\Rightarrow$ **How will AI affect wages through job transformation? Winners and losers?**

- **State-of-art models abstract from job transformation** as measurement is hard:
  - which tasks will be automated?
  - what are workers' *task-specific* skills?

A quantitative model of AI-induced job transformation effects

1. **Theory**: formalize **job transformation** in a task-based theory

2. **Measurement:** estimate **skill distribution** via MLE using model structure

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

A quantitative model of AI-induced job transformation effects

1. **Theory**: formalize **job transformation** in a task-based theory
   - occupations *bundle* tasks, performed by workers or machines
   - workers have heterogeneous portfolios of task-specific skills, choose occ. & earn wage
   - automation leads to job transformation by shifting weights on labor-produced tasks
2. **Measurement:** estimate **skill distribution** via MLE using model structure
3. **Application:** project **LLM**-induced job transformation effects

A quantitative model of AI-induced job transformation effects

1. **Theory**: formalize **job transformation** in a task-based theory
   - occupations *bundle* tasks, performed by workers or machines
   - workers have heterogeneous portfolios of task-specific skills, choose occ. & earn wage
   - automation leads to job transformation by shifting weights on labor-produced tasks
2. **Measurement:** estimate **skill distribution** via MLE using model structure
   - ensure mapping between model skills and O*NET tasks
   - validate estimated model (steady state, historical routine-biased tech. change)
3. **Application:** project **LLM**-induced job transformation effects

A quantitative model of AI-induced job transformation effects

1. **Theory**: formalize **job transformation** in a task-based theory
   - occupations *bundle* tasks, performed by workers or machines
   - workers have heterogeneous portfolios of task-specific skills, choose occ. & earn wage
   - automation leads to job transformation by shifting weights on labor-produced tasks

2. **Measurement:** estimate **skill distribution** via MLE using model structure
   - ensure mapping between model skills and O*NET tasks
   - validate estimated model (steady state, historical routine-biased tech. change)

3. **Application:** project **LLM**-induced job transformation effects
   - LLMs automate information-processing tasks *[Eloundou et al., 2024]*

Who wins and who loses? Three key results.

1. Exposure: **Wage effects of AI are non-monotonic**—*positive* for low exposure & *negative* for high exposure—**and heterogeneous** even conditional on occupation

2. Skills: **AI will *raise* the return to social & non-routine manual skills, *reduce* that to analytical skills**

3. Distribution: **AI is progressive**—low-earners benefit more than high-earners

Who wins and who loses? Three key results.

1. Exposure: **Wage effects of AI are non-monotonic**—*positive* for low exposure & *negative* for high exposure—**and heterogeneous** even conditional on occupation

2. Skills: **AI will *raise* the return to social & non-routine manual skills, *reduce* that to analytical skills**

3. Distribution: **AI is progressive**—low-earners benefit more than high-earners

Job transformation drives each one of these results

What's new? Position in the literature.

We develop a formal model of job transformation and quantitatively demonstrate its central role in shaping the labor market consequences of AI.

- **Job transformation (empirical)** *[**Autor et al., 2003**; Spitz-Oener, 2006; Autor and Handel, 2013; Atalay et al., 2020; Autor et al., 2024; Gathmann et al., 2024]*

  $\Rightarrow$ **formalize & link with skills** $\rightarrow$ structurally quantify *wage* effects

- **Task-based theory** *[Acemoglu-Autor, 2011; Aghion-Jones-Jones, 2017; Acemoglu-Restrepo, 2018; **Acemoglu-Restrepo, 2022**; Hemous-Olsen, 2022; Freund, 2023; Autor-Thompson, 2025]*

  $\Rightarrow$ introduce jobs and task bundling $\rightarrow$ enable study of **job transformation**

- **Model-based analysis of AI** *[Acemoglu, 2025; **Hampole et al., 2025**; Fan, 2025; Restrepo, 2025; Althoff-Reichardt, 2025; Lashkari et al., 2026; Tonetti-Jones, 2026]*

  $\Rightarrow$ directly estimate granular skills $\rightarrow$ **demonstrate key role of JT**

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

  $\Rightarrow$ **estimate** distribution of task-specific skills $\rightarrow$ tie Δ skill returns to automation

Theory

Model environment: task-based production meets Roy

▸ Equilibrium definition

Technology

Final good: CES (σ) aggregator over occupational output

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

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

where $X_{i,\tau,t} = X_{i,\tau,t}^{\text{machines}} + X_{i,\tau,t}^{\text{labor}}$

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

Firm/job: Hires 1 worker (i), chooses machine quantity $M_{i,\tau,t}$ $\rightarrow X_{i,\tau,t}^{\text{machines}} = \exp(z_\tau) M_{i,\tau,t}$

Model environment: task-based production meets Roy

Equilibrium definition

Technology

Final good: CES (σ) aggregator over occupational output

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

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

where $X_{i,\tau,t} = X_{i,\tau,t}^{\text{machines}} + X_{i,\tau,t}^{\text{labor}}$

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

Firm/job: Hires 1 worker (i), chooses machine quantity $M_{i,\tau,t}$ $\rightarrow X_{i,\tau,t}^{\text{machines}} = \exp(z_\tau) M_{i,\tau,t}$

Workers

Skills: **Task-specific**, time-invariant

$$s_i \equiv \{s_{i,\tau}\}_{\tau \in \mathcal{T}_l} \sim \mathcal{N}(\bar{s}, \Sigma_s)$$
$$\rightarrow X_{i,\tau,t}^{\text{labor}} = \exp(s_{i,\tau}) \ell_{i,\tau,t}$$

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

Time: Inelastic unit supply

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

Model environment: task-based production meets Roy

Equilibrium definition

Technology

Final good: CES (σ) aggregator over occupational output

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

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

where $X_{i,\tau,t} = X_{i,\tau,t}^{\text{machines}} + X_{i,\tau,t}^{\text{labor}}$

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

Firm/job: Hires 1 worker (i), chooses machine quantity $M_{i,\tau,t}$ $\rightarrow X_{i,\tau,t}^{\text{machines}} = \exp(z_\tau) M_{i,\tau,t}$

Workers

Skills: **Task-specific**, time-invariant

$$s_i \equiv \{s_{i,\tau}\}_{\tau \in \mathcal{T}_l} \sim \mathcal{N}(\bar{s}, \Sigma_s)$$
$$\rightarrow X_{i,\tau,t}^{\text{labor}} = \exp(s_{i,\tau}) \ell_{i,\tau,t}$$

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

Time: Inelastic unit supply

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

Markets

Labor: Competitive

Capital: Infinitely elastic supply, machines can be rented at rate r

Occupational output: Competitive

Final good: Competitively traded numeraire

Optimal time allocation is proportional to weight matrix A

▸ Firm problem ▸ Capital FOC

Firm's profit maximization problem yields:

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

The **occupational 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 and intuitive log-linear wage equation

Intercept term

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

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

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

Automation leads to job transformation *given* task bundling

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

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

- **Job transformation:** weight on $\tau^\star \downarrow$ & weight on other entries $\uparrow$ proportional to their occupation-specific weight, i.e. $A_o' - A_o = \frac{\alpha_{o,\tau^\star}}{LS_o} \times \begin{pmatrix} \frac{\alpha_{o,1}}{LS_o'} & \frac{\alpha_{o,2}}{LS_o'} & \dots & -1 & \dots \end{pmatrix}$

	$\tau^\star$	Task 2	Task 3	Task 4	Task 5
Occ 1 (Pre)	0.2	0	0.4	0.1	0.3
Occ 1 (Post)	0	0	0.5	0.125	0.375
Occ 2 (Pre)	0	0.5	0.4	0.1	0
Occ 2 (Post)	0	0.5	0.4	0.1	0

Automation leads to job transformation *given* task bundling

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

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

- **Job transformation:** weight on $\tau^\star \downarrow$ & weight on other entries $\uparrow$ proportional to their occupation-specific weight
  - We nest "**partial automation**": only a fraction $\zeta_{\tau^\star} \in [0, 1]$ is automated

▸ Details

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

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

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

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

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

where

$$\underbrace{(A'_o - A_o) \cdot s_i}_{\text{job transformation effects}} = \underbrace{\frac{\alpha_{o,\tau^\star}}{LS_o}}_{\text{occupational exposure}} \times \left(\sum_{\mathcal{T}_l \setminus \tau^\star} \underbrace{\frac{\alpha_{o,\tau}}{LS_o - \alpha_{o,\tau^\star}} s_{i,\tau} - s_{i,\tau^\star}}_{i\text{'s relative specialization}} \right)$$

and

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

Measurement

Measurement

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

- **Step 1: map model tasks & occupations to data, *construct* A**
  - tasks: NLP tools to cluster ∼19,000 O*NET task statements → 38 task clusters Details
  - occupations: 3-digit, SOC-2000
  - occ. task weights (A): identified off of LLM-generated time diaries given $\ell_{i,\tau,t} = \frac{\alpha_{o,\tau}}{\sum_{\tau \in \mathcal{T}_l} \alpha_{o,\tau}} := A_{o,\tau}$
  - robustness: aggregated O*NET weights
  - time-varying (pre-2000, post-2000)

- **Step 2: *estimate* skill distribution** $(\bar{s}, \Sigma_s)$ Details
  - data: A + NLSY '79 panel of worker occ. choices and wages Details
  - identifying variation: realized wages & occupational choices
  - validation: Monte Carlo exercise Graphs

Measurement

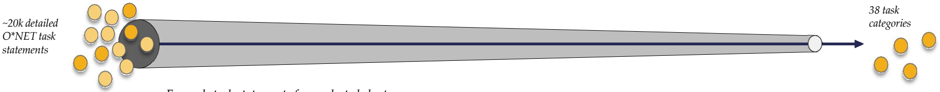
- **Goal:** parametrize the model at same 'resolution' as task-exposure measures

- **Step 1: map model tasks & occupations to data, *construct* A**
  - tasks: NLP tools to cluster $\sim$19,000 O*NET task statements $\rightarrow$ 38 task clusters Details
  - occupations: 3-digit, SOC-2000
  - occ. task weights (A): identified off of LLM-generated time diaries given $\ell_{i,\tau,t} = \frac{\alpha_{o,\tau}}{\sum_{\tau \in \mathcal{T}_l} \alpha_{o,\tau}} := A_{o,\tau}$
  - robustness: aggregated O*NET weights
  - time-varying (pre-2000, post-2000)

- **Step 2: *estimate* skill distribution** $(\bar{s}, \Sigma_s)$ Details
  - data: A + NLSY '79 panel of worker occ. choices and wages Details
  - identifying variation: realized wages & occupational choices
  - validation: Monte Carlo exercise Graphs

Examples of mapping from detailed tasks to clusters

We cluster O*NET's unstructured, detailed task statements into 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.
- *Etc.*

Performing Detailed Manual Tasks

- Prepare reports of activities, evaluations, recommendations, or decisions.
- Prepare, examine, or analyze accounting records, financial statements, or other financial report.
- *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.
- *Etc.*

Coordinating Project Initiatives

For each task, we extract skill requirements, create semantic vector embeddings for these requirements using a transformer, and perform HDBSCAN-clustering (with hyperparameters tuned to maximize the DBCV score) on these embeddings to create broad task categories.

Measurement

▸ Validation: task weights ▸ Task $\longrightarrow$ cluster examples ▸ A_{pre}

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

- **Step 1: map model tasks & occupations to data, *construct* A**
  - tasks: NLP tools to cluster ∼19,000 O*NET task statements → 38 task clusters ▸ Details
  - occupations: 3-digit, SOC-2000
  - occ. task weights (A): identified off of LLM-generated time diaries given $\ell_{i,\tau,t} = \frac{\alpha_{o,\tau}}{\sum_{\tau \in \mathcal{T}_l} \alpha_{o,\tau}} := A_{o,\tau}$
  - robustness: aggregated O*NET weights
  - time-varying (pre-2000, post-2000)

- **Step 2: *estimate* skill distribution** $(\bar{s}, \Sigma_s)$ ▸ Details
  - data: A + NLSY '79 panel of worker occ. choices and wages ▸ Details
  - identifying variation: realized wages & occupational choices
  - validation: Monte Carlo exercise ▸ Graphs

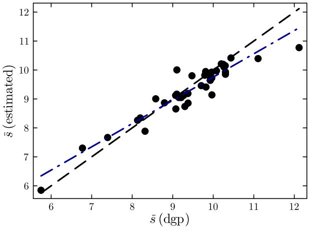
Performing Skilled Manual Oper...
Performing Physical Labor
Producing Technical Documentat...
Administering Regulatory Compl...
Preparing and Planning Meals
Mediating and Consulting Clien...
Creating Technical Visual Repr...
Providing Customer Service
Performing Clinical Procedures
Other Installation, Maintenanc...
Electrical and Electronic Equi...
Supervisors, Building and Grou...
Media and Communication Worker...
Cooks and Food Preparation Wor...
Health Diagnosing and Treating...
Other Healthcare Support Occup...
Military Officer Special and T...
Sales Representatives, Service...
Funeral Service Workers
Retail Sales Workers
Occupational and Physical Ther...
Other Food Preparation and Ser...
0.5
0.4
0.3
0.2
0.1
0.0

Measurement

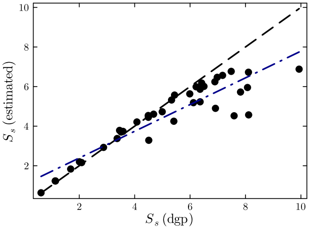
- **Goal:** parametrize the model at same 'resolution' as task-exposure measures
- **Step 1: map model tasks & occupations to data, *construct* A**
  - tasks: NLP tools to cluster ~19,000 O*NET task statements → 38 task clusters
  - occupations: 3-digit, SOC-2000
  - occupational task weights: identified off of time diaries (baseline: LLM)
  - time-varying (pre-2000, post-2000)
- **Step 2: *estimate* skill distribution** $(\bar{s}, \Sigma_s)$ ▸ Details
  - data: A + NLSY '79 panel of worker occ. choices and wages ▸ Details
  - identifying variation: realized wages & occupational choices
  - validation: Monte Carlo exercise ▸ Graphs

Validation: Monte-Carlo study

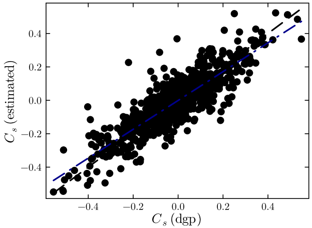
(a) Means



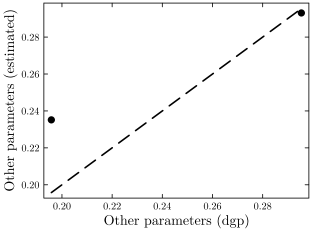
(b) Standard deviation



(c) Correlation



(d) Other parameters



Model properties & validation: overview

▸ Parameter values

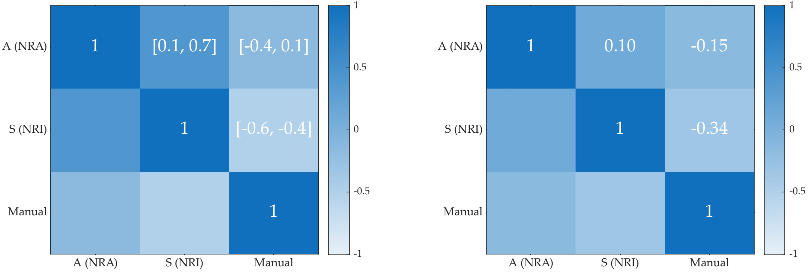
- Parameter estimates
  - Skill correlations vs. literature ▸ Details
  - Skills along the wage distribution vs. literature ▸ Details
- Steady state
  - Occ. employment shares ▸ Details
  - Wages ▸ Details
    - Occ. level averages
    - Between-within occ. variance decomposition
  - Occ. transitions:
    - Staying and switching probabilities ▸ Details
    - Switches explained by task distances ▸ Details
    - Individual switching frequency shaped by specialization ▸ Details
- Historical: RBTC
  - Skill returns: ↑ return to social skills *[Deming, 2017]* ▸ Details
  - Employment: polarization *[Autor & Dorn, 2013]* ▸ Details

Estimated skill correlations match empirical literature

▸ Classification ▸ Skill indices

- Literature often studies coarser task classification, esp. NRA/NRI/NRM/RC/RM *[e.g., Autor et al., 2003]* $\rightarrow$ map our granular tasks to this classification & create skill indices
- $\rightarrow$ Estimated correlations match empirical ranges for aggregated skills *[Deming, 2017; Guvenen et al., 2020; Lise & Postel-Vinay, 2020; Girsberger et al., 2022; Barany & Holzheu, 2025]*

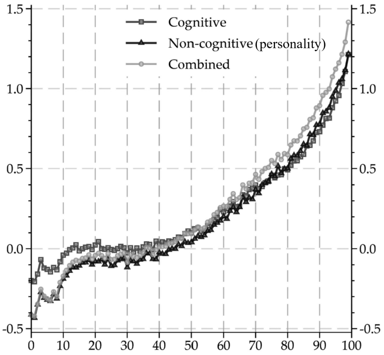
(a) Literature **(b)** Model



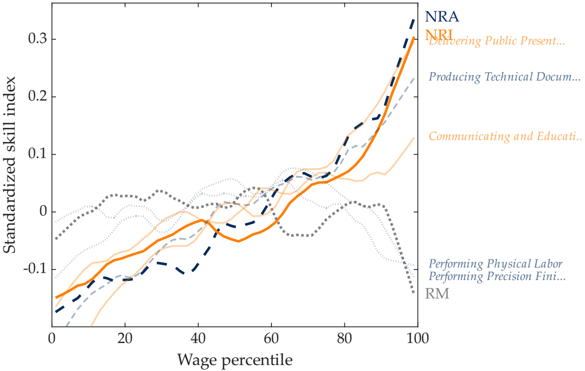
Skills vary along the wage distribution in line with data

→ In model & data, analytical and social (but not manual) skills rise along the wage dist.

(a) Data *[Bratsberg et al., 2025]*

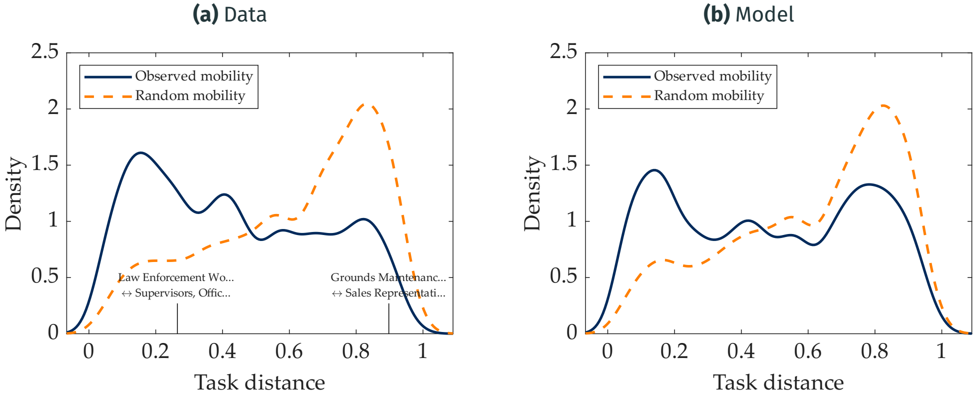


(b) Model



Task requirements explain switching in model and data

→ In model & data, workers tend to move to occupations with similar task requirements—strong evidence for relevance of task-specific skills *[cf. Gathmann-Schoenberg, 2010]*



Historical validation: the case of RBTC

- Large literature on "**routine-biased technological change**" (RBTC)
- **Model analysis:** compare SS under post-2000 vs. pre-2000 *A*
- Model captures RBTC = validation of our *A* measures & model mechanisms

(a) Data *[Atalay et al., 2020]*

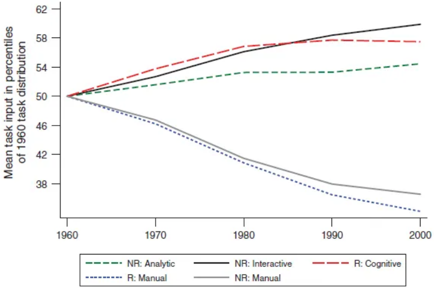
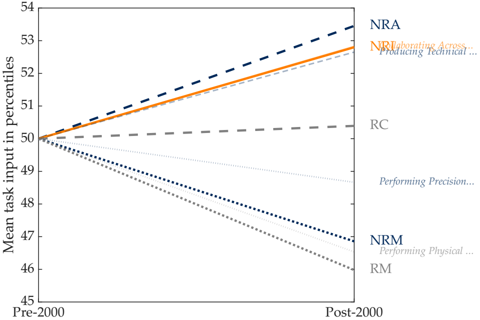


FIGURE 3. COMPARISON TO AUTOR, LEVY, AND MURNANE (2003, FIGURE 1)

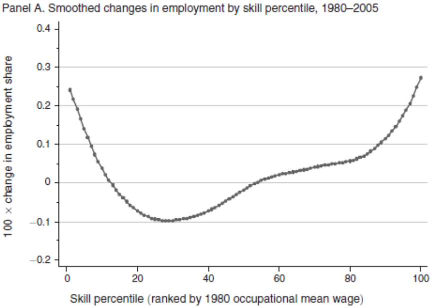
(b) Model



RBTC effects in the literature: employment polarization

→ The empirical literature documents a U-shaped change in employment by "skill" (wage percentile) and attributes it to RBTC

(a) Data *[Autor & Dorn, 2013]*



(b) Data *[Goos et al., 2009]*

Figure 1. Percentage Changes in Employment Shares over 1993–2006 for Jobs Ranked by Their 1994 Log Wage

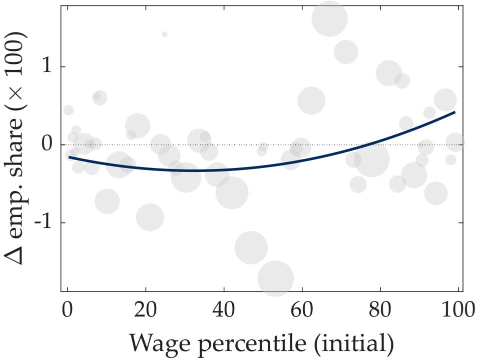
Note: Jobs are industry-occupation cells weighted by their 1993 employment shares, pooled across countries, and ranked by their UK 1994 log mean wage.

Sources: European Union Labour Force Survey 1993–2006, United Kingdom Labour Force Survey 1994.

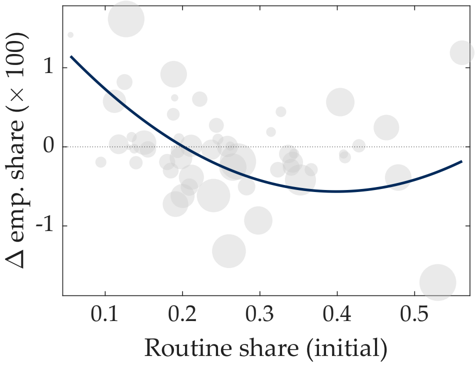
Model matches empirical employment polarization

→ Model matches this U-shaped change in employment and the role of declining routine jobs

(a) Model: by wage percentile



(b) Model: by routine share

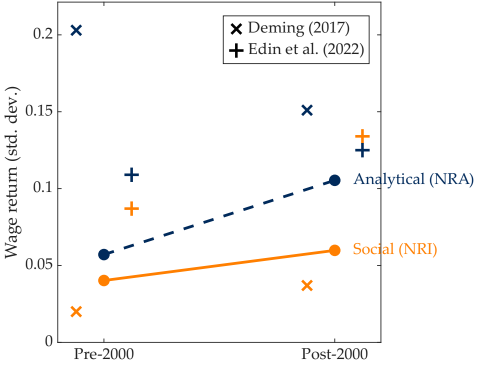


Model matches evidence on rising return to social skills

▸ Polarization

→ Model implies rising return to “social” skills, consistent with empirical literature

[Deming, 2017; Edin et al., 2022]



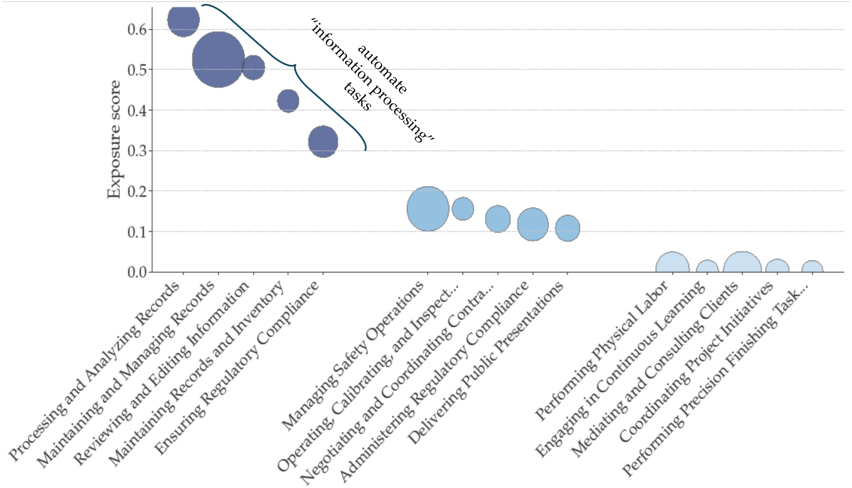
Vertical axis indicates the log wage change associated with a one std. dev. increase in the respective skill index. Markers indicate estimates from the empirical literature; solid lines indicate model predictions.

AI

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?
  - forward-looking analysis
  - labor share $\neq$ sufficient statistic when considering job transformation effects
- **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 tasks



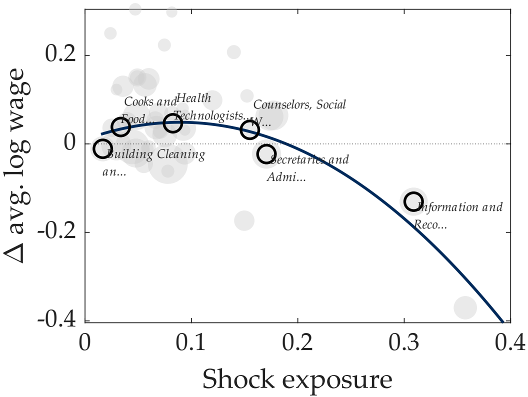
Task automation exposure measures from Eloundou et al. (2024) aggregated to our task clusters.

Exposure: What are the implications for wages of being in an AI-exposed occupation?

Result #1: The wage effects of AI exposure are non-monotonic

▸ PE

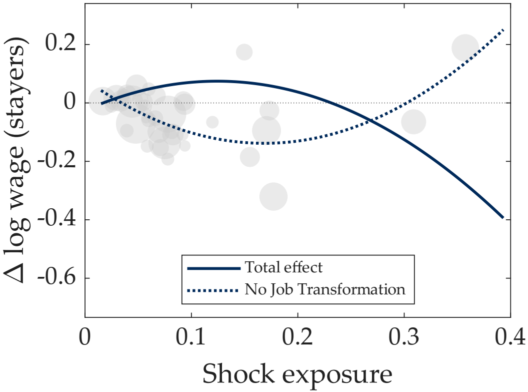
→ On average, incumbents in occupations with *some* exposure win, but those in heavily exposed occupations lose *[consistent with early evidence, e.g., in Eisfeldt et al., 2025]*



Vertical axis indicates change in individual wage, horizontal axis is the exposure of the origin occupation.

Job transformation drives this pattern

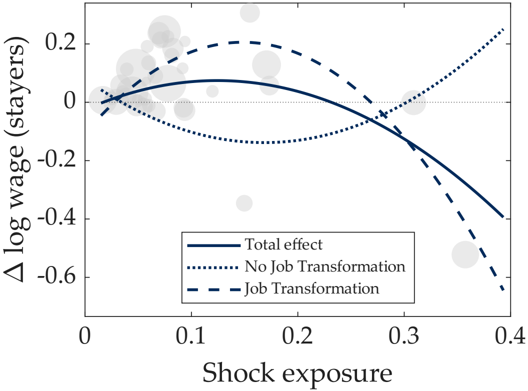
→ Holding *A* fixed, i.e. absent job transformation, the inverted-U shape disappears



Focusing on stayers for clarity of exposition.

Job transformation interacts with selection

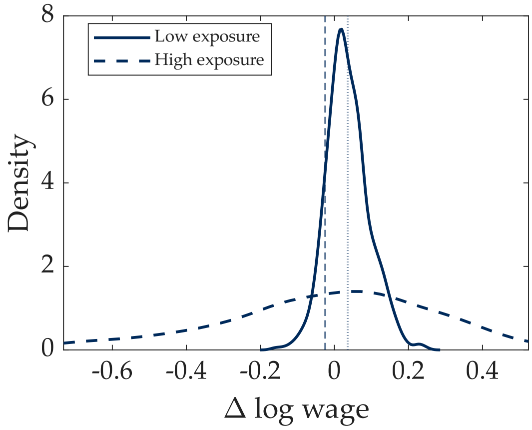
→ Job transformation ($\Delta A \cdot s$) is *positive* for low exposure (greater focus on what you're best at) but *negative* at high exposure (machines take over what you're best at)



Result 1b: But the average masks large heterogeneity

▸ JT drives dispersion

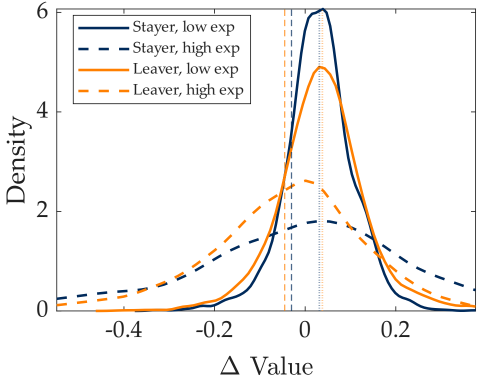
→ Dispersion in outcomes is greater among workers in high-exposure occupations



Exposure represents *potential* for change

→ The biggest gains are among stayers in high-exposure occupations

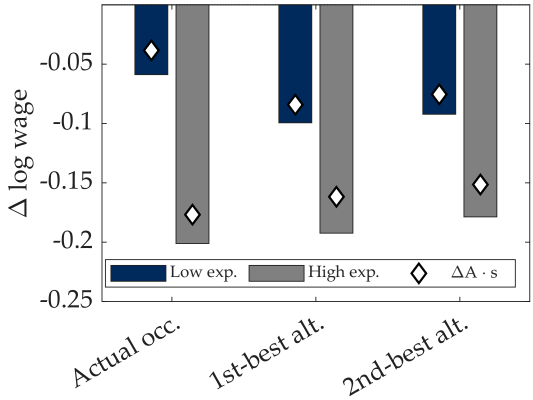
→ The biggest losses are among workers leaving high-exposure occupation



Value is defined as $V_{i,t} = \nu \log \left(\sum_{o \in \mathcal{O}} \exp \left(\frac{w_{i,o,t}}{\nu} \right) \right)$ *and average out wage changes due preference-shock driven switches.*

Stayers whose lose see are “trapped”

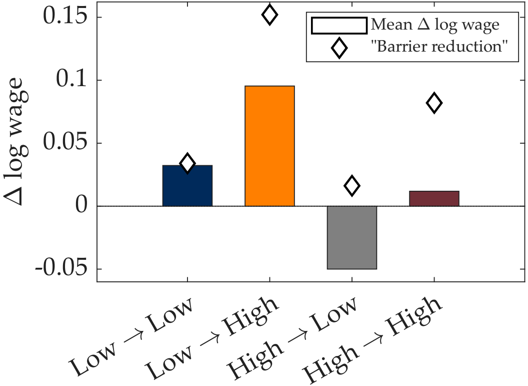
→ Job transformation leads to correlated ↓ in potential wages across likely occupations



Sub-sample of stayers experiencing negative wage changes.

Switching *into* high-exposure occ.'s yields gains

→ Transformed occ.'s pull in new workers whose skills align better with new task profile



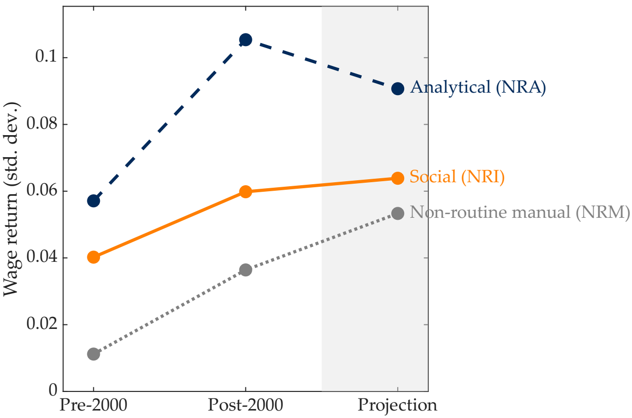
Sub-sample of occupational leavers.

Skills: What type of skills become more or less valuable due to AI?

Result #2: AI raises the return to social & NRM skills

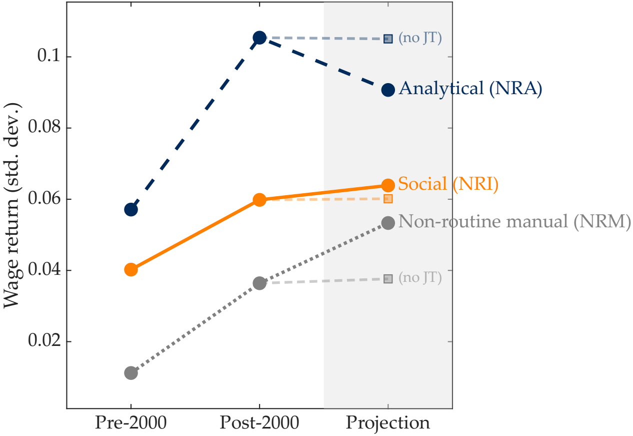
▸ Robustness ▸ AI-proof Trades

⇒ Continued *increase* in return to social skills as well as non-routine manual skills (“skilled trades are AI-proof”), but *decrease* in return to analytical skills



Job transformation drives these shifts in returns

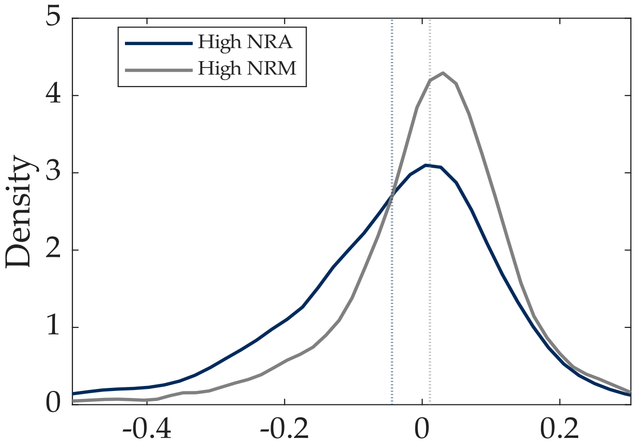
→ We miss these shifts if we abstract from job transformation



These shifts explain who the winners & losers tend to be

▸ Wage version

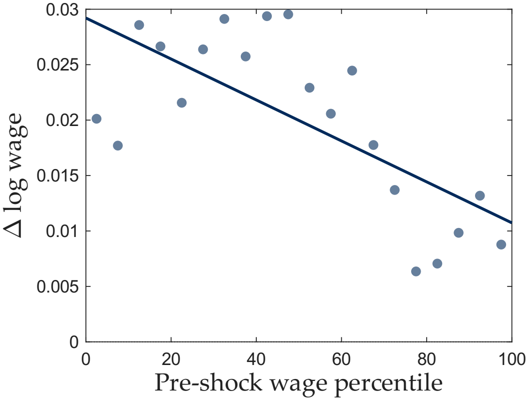
→ High-NRA workers are over-represented among losers, high-NRM workers are over-represented among winners



Distribution: Will the rich or the poor do better due to AI?

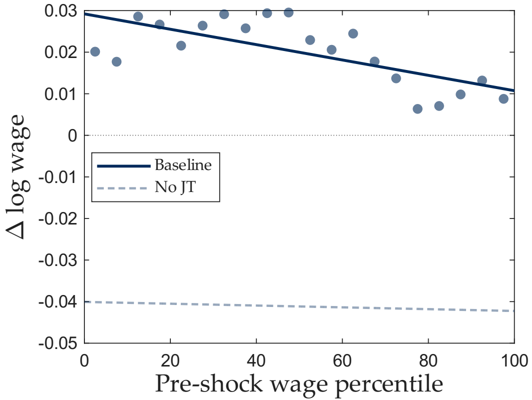
Result #3: AI shock is mildly "progressive"

→ Wage gains disproportionately accrue to low-wage earners



Result #3: AI shock is mildly "progressive" *because* of JT

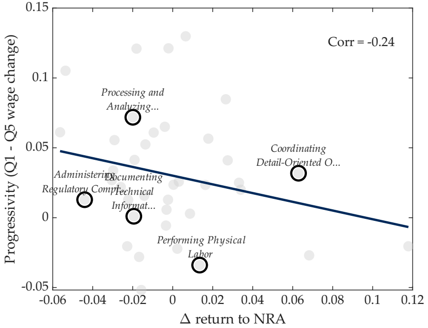
→ Wage gains disproportionately accrue to low-wage earners—once you account for JT
→ JT also endogenously generates substantial increase in *average* wages



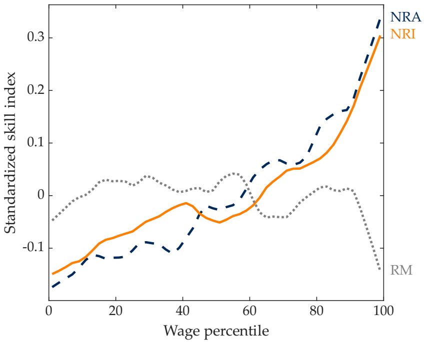
This reflects a decrease in the returns to skills prevalent among high earners

- Automation shocks can be progressive or regressive...
  - ...depending on how they alter the return to skills more prevalent among high earners
- AI is (mildly) progressive
  - ...as it lowers the return to analytical skills (but raises that for social skills)

(a) Comparing shocks



(b) Skills along the distribution



Conclusion

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

We develop a formal model of job transformation and quantitatively demonstrate its central role in shaping the labor market consequences of AI.

1. AI generates positive effects at low exposure, negative effects at high exposure
2. AI raises the return to social skills but lowers that of analytical skills
3. AI is mildly progressive

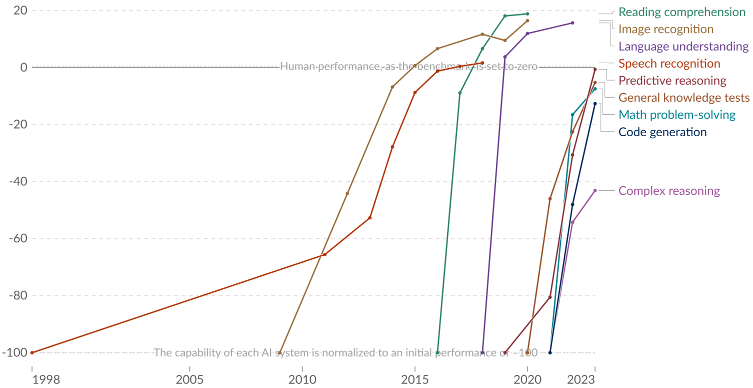
Thank You!

Extra Slides

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.

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)'s analysis of records of the Lawrence Company, MA.

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:**

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

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

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:**

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

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

- **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:**

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

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

- **Optimality:**

FOC capital

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

Capital FOC and production

Back

- FOC for machines $M_{i,o,t} := \sum_{\tau \in \mathcal{T}_m} M_{i,o,\tau,t}$:

$$\left(\sum_{\tau \in \mathcal{T}_m} \alpha_{o,\tau} \right) \frac{p_{o,t} Y_{i,o,t}}{r} = M_{i,o,t}$$

and

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

- Plugging both FOCs into the production function yields

$$y_{i,o,t} = \log Y_{i,o,t} = \left[\sum_{\tau \in \mathcal{T}_l} \frac{\alpha_{o,\tau}}{\sum_{\tau \in \mathcal{T}_l} \alpha_{o,\tau}} s_{i,\tau} \right] + \varepsilon_{i,o} + \frac{1}{\sum_{\tau \in \mathcal{T}_l} \alpha_{o,\tau}} \log P_{o,t}$$
$$+ \left[\sum_{\tau \in \mathcal{T}} \frac{\alpha_{o,\tau}}{\sum_{\tau \in \mathcal{T}_l} \alpha_{o,\tau}} \log(\alpha_{o,\tau}) \right] - \log \left(\sum_{\tau \in \mathcal{T}_l} \alpha_{o,\tau} \right) + \left[\sum_{\tau \in \mathcal{T}_m} \frac{\alpha_{o,\tau}}{\sum_{\tau \in \mathcal{T}_l} \alpha_{o,\tau}} (z_\tau - \log r) \right]$$

Equilibrium

Back

Remark: Equilibrium

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

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

$$w_{i,o,t} = \mu_o + \sum_{\mathcal{T}_l} \frac{\alpha_{o,\tau}}{LS_o} \cdot s_{i,\tau} + \varepsilon_{i,t}, \qquad Y \equiv \left(\sum_{o \in \mathcal{O}} \omega_o^{\frac{1}{\sigma}} Y_o^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} = \sum_{o \in \mathcal{O}} p_o Y_o$$

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.

Wage equation: details

Back

- Intercept

  $$\mu_o = \sum_{\tau \in \mathcal{T}} \frac{\alpha_{o,\tau}}{\sum_{\tau \in \mathcal{T}_l} \alpha_{o,\tau}} \log\left(\alpha_{o,\tau}\right) + \left(\sum_{\tau \in \mathcal{T}_m} \frac{\alpha_{o,\tau}}{\sum_{\tau \in \mathcal{T}_l} \alpha_{o,\tau}} \left(z_\tau - \log r\right) \right) + \frac{1}{\sum_{\tau \in \mathcal{T}_l} \alpha_{o,\tau}} \log P_{o,t}$$

  where $P_{o,t}$ is the price of output of occupation o

- We assume that in the initial steady state there is only one composite machine task with productivity normalized to $\log r$

Partial Automation

Back

- Our framework nests the concept of **partial automation**
  $\rightarrow$ only a fraction $\zeta_{\tau^\star} \in [0,1]$ of task $\tau^\star$ can be automated

- **Modeling:** Equivalently, rewrite pre-automation production technology as

$$Y_{i,o,t} = \Gamma \cdot \prod_{\tau \in \mathcal{T}_m} \left(X^{\text{machines}}_{i,\tau,t}\right)^{\alpha_{o,\tau}} \cdot \prod_{\tau \in \mathcal{T}_\ell \setminus \{\tau^\star\}} \left(X^{\text{labor}}_{i,\tau,t}\right)^{\alpha_{o,\tau}} \cdot$$
$$\left((1-\zeta_{\tau^\star})X^{\text{labor}}_{i,\tau^\star,t}\right)^{(1-\zeta_{\tau^\star})\alpha_{o,\tau^\star}} \cdot \left(\zeta_{\tau^\star} X^{\text{labor}}_{i,\tau^\star,t}\right)^{\zeta_{\tau^\star}\alpha_{o,\tau^\star}}.$$

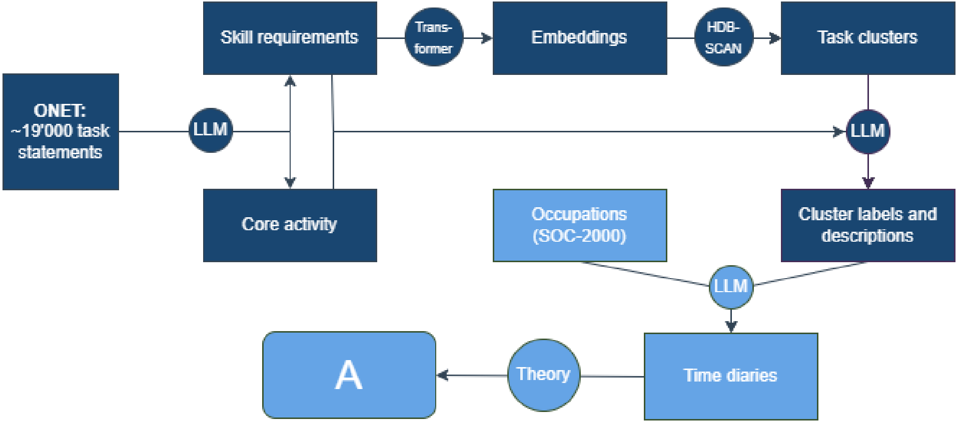
  where $\Gamma = (1-\zeta_{\tau^\star})^{-\alpha_{o,\tau^\star}(1-\zeta_{\tau^\star})}\zeta_{\tau^\star}^{-\alpha_{o,\tau^\star}\zeta_{\tau^\star}}$

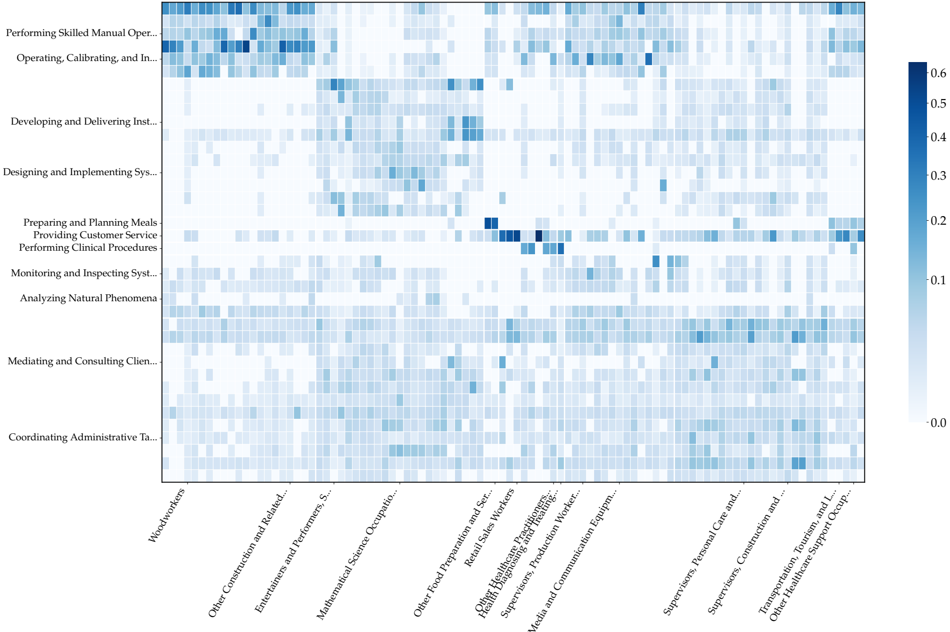
- Post-automation production technology becomes

$$Y_{i,o,t} = \Gamma \cdot \prod_{\tau \in \mathcal{T}_\ell \setminus \{\tau^\star\}} \left(X^{\text{labor}}_{i,\tau,t}\right)^{\alpha_{o,\tau}} \cdot \left(X^{\text{labor}}_{i,\tau^\star,t}\right)^{(1-\zeta_{\tau^\star})\alpha_{o,\tau^\star}} \cdot \left(X^{\text{machines}}_{i,\tau^\star,t}\right)^{\zeta_{\tau^\star}\alpha_{o,\tau^\star}} \cdot \prod_{\tau \in \mathcal{T}_m} \left(X^{\text{machines}}_{i,\tau,t}\right)^{\alpha_{o,\tau}}.$$

Summary of step 1 pipeline

Back




Performing Skilled Manual Oper...
Operating, Calibrating, and In...
Developing and Delivering Inst...
Designing and Implementing Sys...
Preparing and Planning Meals
Providing Customer Service
Performing Clinical Procedures
Monitoring and Inspecting Syst...
Analyzing Natural Phenomena
Mediating and Consulting Clien...
Coordinating Administrative Ta...
Woodworkers
Other Construction and Related...
Entertainers and Performers, S...
Mathematical Science Occupatio...
Other Food Preparation and Ser...
Retail Sales Workers
Other Healthcare Practitioners...
Health Diagnosing and Treating...
Supervisors, Production Worker...
Media and Communication Equipm...
Supervisors, Personal Care and...
Supervisors, Construction and ...
Transportation, Tourism, and L...
Other Healthcare Support Occup...
0.6
0.5
0.4
0.3
0.2
0.1
0.0

Validation of LLM-generated time shares: overview

Back

1. LLM-generated task weights for (o, τ) 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? ✓

Alternative A matrix: O*NET bottom-up

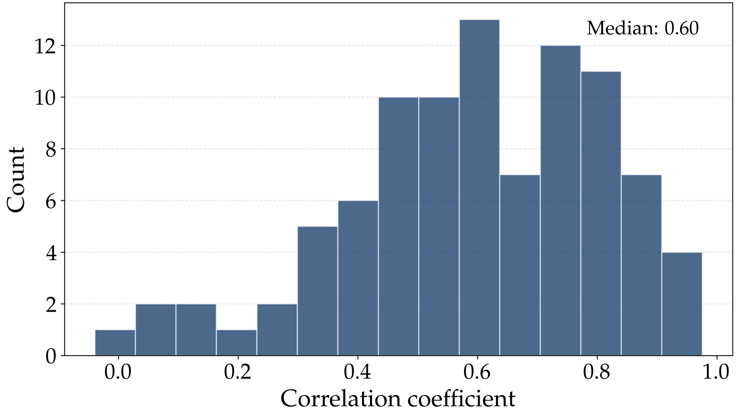
Back

- ONET contains (Likert scale) “task ratings” indicating the importance of detailed tasks i for o
- Create occupational task-weight matrices A_p (for $p \in \{2000s, 2010s, 2020s\}$, where each cell (o, τ) contains the average importance of task τ for occupation o
  - Notation
    - o' = detailed ONET occupation (8-digit), i = detailed ONET task, τ = cluster (model task)
    - $v \in V_p$ = ONET versions in period p
    - $r_{o',i,v} \in 1, 2, 3, 4, 5$ = raw importance rating of task i for occupation o' in version v; normalized to [0, 1]: $\tilde{r}_{o',i,v} = \frac{r_{o',i,v}-1}{4}$
    - $\mathcal{D}_{o,\tau,v}$ = set of (o', i) pairs in version v where o' maps to o and i maps to τ
  - Steps
    1. Sum weights across all (detailed occupation, detailed task) pairs: $S_{o,\tau,v} = \sum_{(o',i)\in\mathcal{D}_{o,\tau,v}} \tilde{r}_{o',i,v}$
    2. Average across versions within the period: $S_{o,\tau} = \frac{1}{|V_p|} \sum_{v\in V_p} S_{o,\tau,v}$
    3. Normalize to task shares within each occupation:

$$A_p(o, \tau) = \frac{S_{o,\tau}}{\sum_{\tau'} S_{o,\tau'}}$$

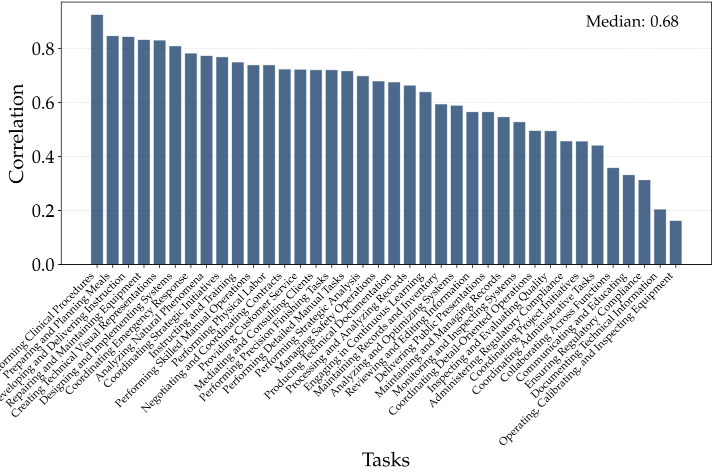
Validation: LLM task weights vs. ONET bottom-up – occupation level

Back



Validation: LLM task weights vs. ONET bottom-up – task-level

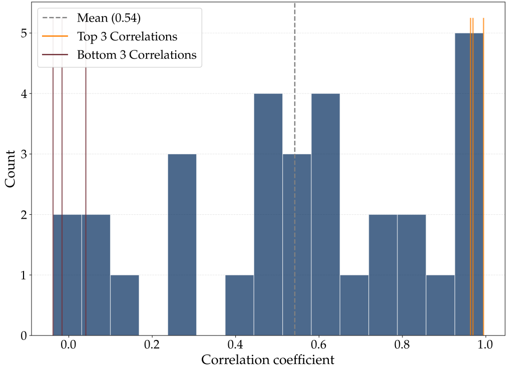
Back



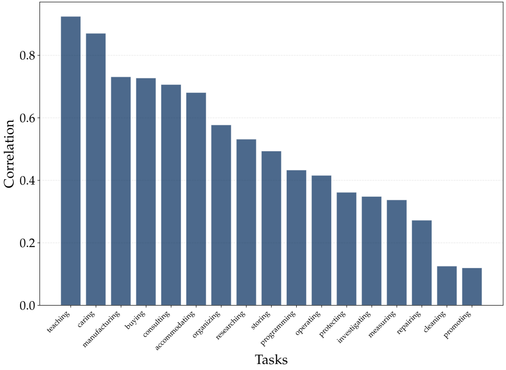
Validation: LLM-generated task shares vs. BIBB

Back

(a) Occupation-level correlations



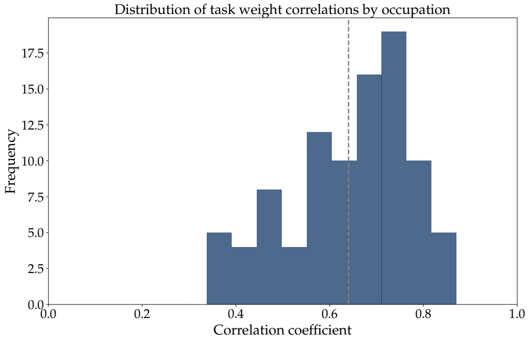
(b) Task-level correlations



Validation: O*NET GWAs (1)

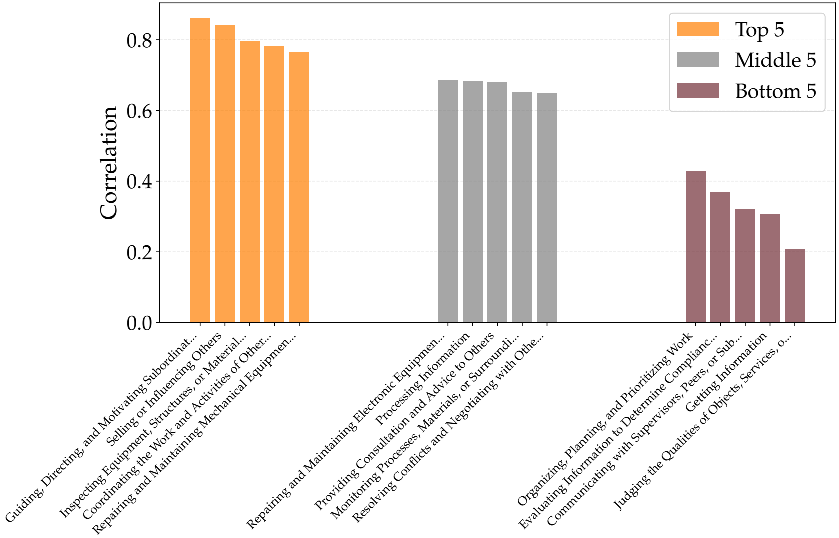
Back

- 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



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

Details on the estimation strategy I

Back

- We consider two separate A-regimes (and occupational price vectors $(\vec{p}, \vec{p}'))$
- We assume that regimes change in the year $t^* = 2000$
- Exact likelihood:

$$\prod_i \int_s \left[\left(\int_{w_{i,\cdot,-\omega.}} \prod_t P(\hat{o}_{i,t} = \omega_{i,t} | w_{i,\cdot,\cdot}, \nu) \cdot f(w_{i,t,-\omega_t} | s, w_{i,\cdot,\omega.}, \varsigma, \vec{p}, \vec{p}') \right) \right.$$

$$\left. \cdot f(s | w_{i,\cdot,\omega.}, \varsigma, \bar{s}, \Sigma_s, \vec{p}, \vec{p}') \right] \cdot f(w_{i,\cdot,\omega.} | \varsigma, \bar{s}, \Sigma_s, \vec{p}, \vec{p}')$$

- We maximize this likelihood while imposing that prices satisfy

$$H(\vec{p}, \vec{p}') = \Delta \log p_o + \frac{1}{\sigma} \left(\Delta \log Y_o(\vec{p}, \vec{p}') - \Delta \log Y(\vec{p}, \vec{p}') \right) = 0$$

Details on the estimation strategy II

Back

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

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

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

$$\hat{\mathcal{L}}_i(w_{i,t,\omega},\nu,\varsigma,\bar{s},\Sigma_s,\vec{p},\vec{p}') = \left(\frac{1}{n_o}\sum_j\prod_t P(\hat{o}_{i,t}=\omega_{i,t}|w_{j,t,\cdot},\nu)\right)\cdot f(w_{i,\cdot,\omega.}|\varsigma,\bar{s},\Sigma_s,\vec{p},\vec{p}')$$

- We use the implicit function theorem to compute an augmented gradient that accounts for the GE restriction:

$$\bar{D}_x\mathcal{L} = D_x\mathcal{L} + D_{\vec{p}'}\mathcal{L}\cdot(-D_{\vec{p}'}H)^{-1}\cdot D_xH \quad \forall x\in\{\nu,\varsigma,\bar{s},\Sigma_s,\vec{p}\}$$

Details on the estimation strategy III

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

Brief summary of NLSY '79 data

Back

- 6,033 workers, 1979-2018, 110,618 total observations
  - drop individuals in the military sample and the minority oversample
- Construct annual panel comprising each individual's primary job (if any)
  - we focus on full time jobs only
- Harmonized occupational classification at SOC-2000 "minor groups" level (# 93)
  - we drop very small occupations (<¡0.3% employment share)
- Average st. dev. of log wages: 0.60
- Average annual moving probability $\sim$ 37%

Parameter values

Back

- We calibrate the cross-occupation EoS $\sigma = 2$ following Burstein-Morales-Vogel (2019) who estimate $\sigma \in \{1.81, 2.10\}$.
- For the scalar parameters, we estimate $\nu = 0.20$ and $\varrho = 0.30$.
- $\nu = 0.20$ implies that reducing prospective wages in a given occupation by 1% lowers the odds of choosing this occupation by about 5%
- $\varrho = 0.30$ indicates that a one-standard-deviation occupation-specific random productivity shock can raise or lower wages by about 30% in a given year.

Task categorization following Autor et al. (2003)

Back

- **Mapping to conventional task categories:** Following ALM2003 and others, let category $c \in \{NRA, NRI, NRM, RC, RM, U\}$, where "U" stands for "unclassified"
  - We use an LLM pipeline to map each model task τ to categories c.

- **Individual-level task shares:** Define the task share of task τ for worker i in year t as $\tilde{\alpha}_{o(i,t),\tau} = \frac{\alpha_{o(i,t),\tau}}{\sum_{\tau \in \mathcal{T}_l} \alpha_{o(i,t),\tau}}$, where $o(i,t)$ is the occupation chosen by i in year τ. Define individual-year specific task indices that measure the "intensity" of category c in worker i's job in year t, consistent with to surveys [Spitz-Oener, 2006; Antonczyk et al., 2006]
  - $\text{Taskindex-unweighted}_{ict} = \frac{\sum_{\tau \in \mathcal{T}} \mathbf{1}\{\tau \in c\} \cdot \mathbf{1}\{\tilde{\alpha}_{o(i,t),\tau} \geq \text{threshold}\}}{\sum_{\tau \in \mathcal{T}} \mathbf{1}\{\tilde{\alpha}_{o(i,t),\tau} \geq \text{threshold}\}}$, where "threshold" is a minimum time-share requirement (default: 0.1).
  - $\text{Taskindex-weighted}_{ict} = \frac{\sum_{\tau \in \mathcal{T}} \mathbf{1}\{\tau \in c\} \cdot \tilde{\alpha}_{o(i,t),\tau}}{\sum_{\tau \in \mathcal{T}} \tilde{\alpha}_{o(i,t),\tau}}$.

Skill indices and regressions

Back

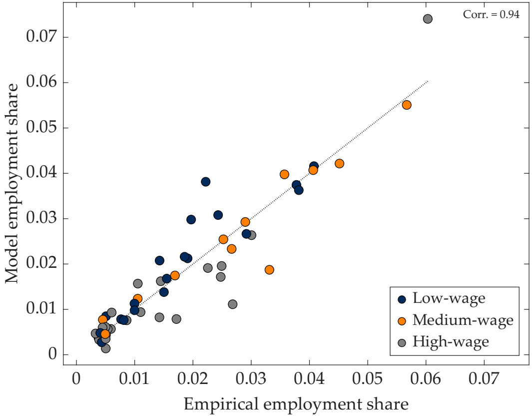
- **Construction of skill measures:** For each worker i, we construct aggregate skill measures in three steps, aligned with literature *[Deming, 2017; Edin et al., 2022]*
  1. Standardize each task-specific log skill $s_{i\tau}$ in the population: $\tilde{s}_{i\tau} = \frac{s_{i\tau} - \bar{s}_\tau}{\sigma_{s_\tau}}$
  2. Average standardized skills within category c: $\bar{s}^{raw}_{ic} = \frac{1}{|\mathcal{T}_c|} \sum_{\tau \in \mathcal{T}_c} \tilde{s}_{i\tau}$
  3. Re-standardize the aggregate: $S_{ic} = \frac{\bar{s}^{raw}_{ic} - \overline{\bar{s}^{raw}_c}}{\sigma_{\bar{s}^{raw}_c}}$
- **Wage regression:** straightforward pooled OLS wage regression

$$\log w_{it} = \delta_t + \sum_{c \in \mathcal{C}} \beta_c S_{ic} + \varepsilon_{it} \tag{1}$$

- **Interpretation:** Coefficients represent the change in log wage associated with a one standard deviation increase in the respective skill measure

Occupational employment shares

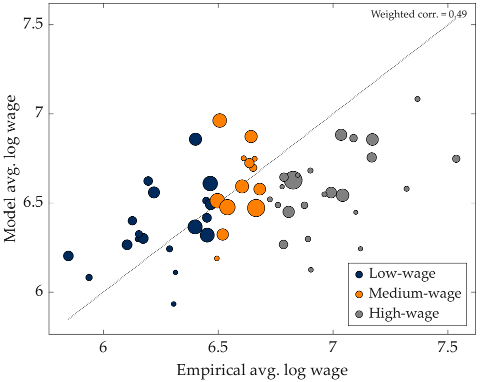
Back



Wages: dispersion & occ. level averages

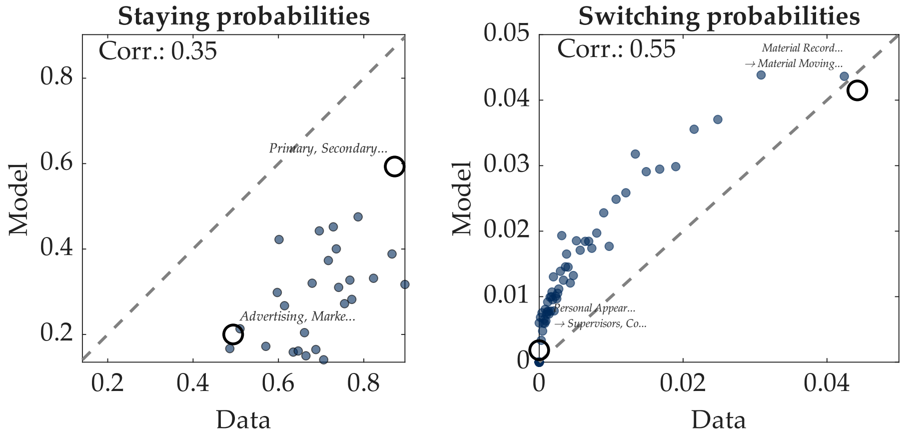
Back

- Wage variance decomposition: model moments reasonably aligned with data
  - data: std. dev. 0.54, 30% between-occ. share
  - model: std. dev 0.57, 13% between-occ. share



Model endogenously generates plausibe occupational transitions

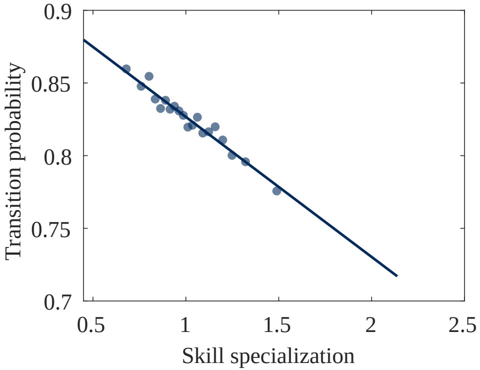
→ Model endogenously generates persistence (though not quite enough, as we include no exogenous switching costs) & directionally tracks switching patterns



Model properties: specialization shapes switching frequency

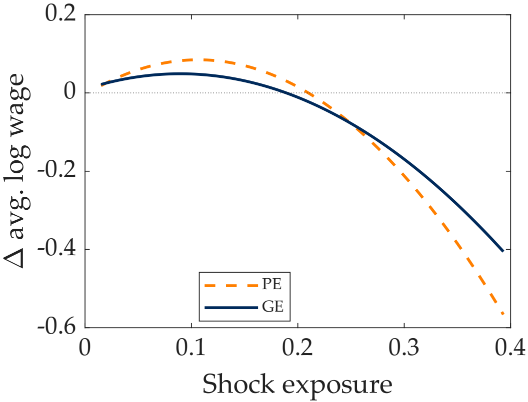
Back

→ Skill specialization tends to generate persistence in occupational choice *[Kambourov and Manovskii, 2008; Geel et al., 2011]*

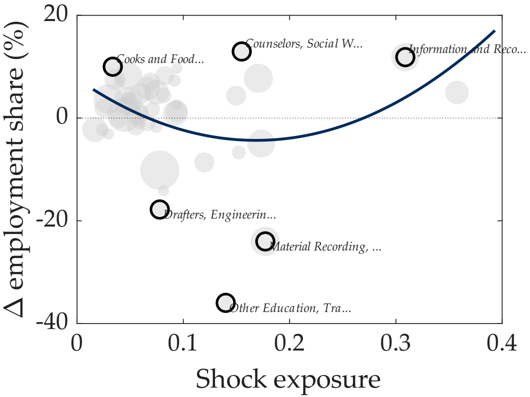


Result #1: the role of GE

Back

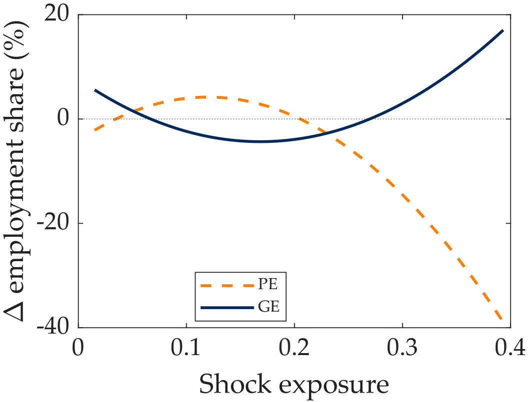


Employment effects



Employment: the role of GE

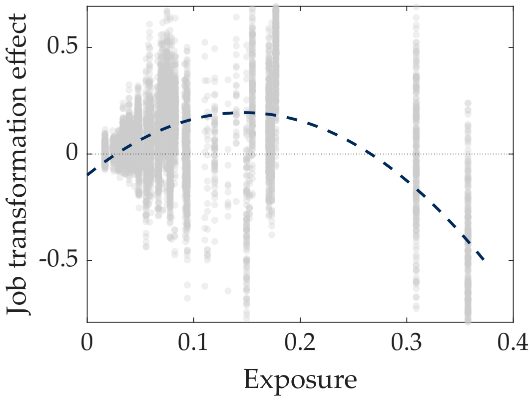
Back



Dispersion in outcomes arises from job transformation

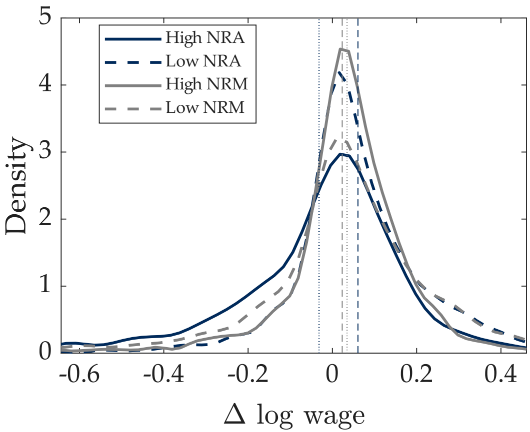
Back

→ Dispersion conditional on exposure arises from job transformation as opposed to occupation-level shifts (which ∼ by definition don't generate individual-level dispersion)



Shifts in returns explain who winners & losers are (wage version)

Back



Skilled Trades may be AI-proof

“In many of the European countries, for example, if you look at how much an electrician can make versus someone that has a professional clerical job, which can be jeopardised by AI, the electrician can make more money.” [...] “supports a view of the future where skilled trades and construction are resilient”

Future-proof your career and get a blue-collar job

Plus, what to do when a popular boss moves on

Fixing up a secure future? © FT montage? Dreamstime

Isabel Berwick

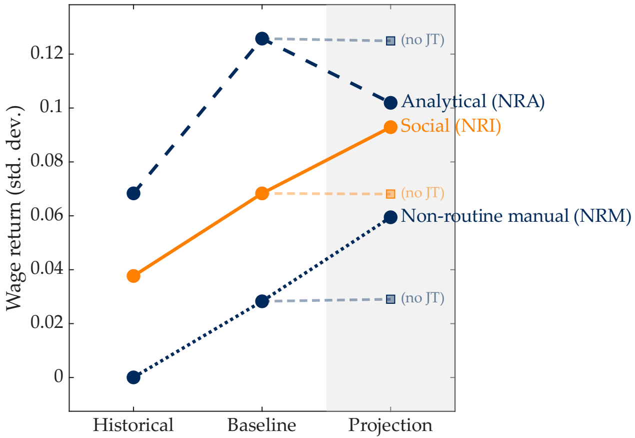
Published JAN 14 2026

0

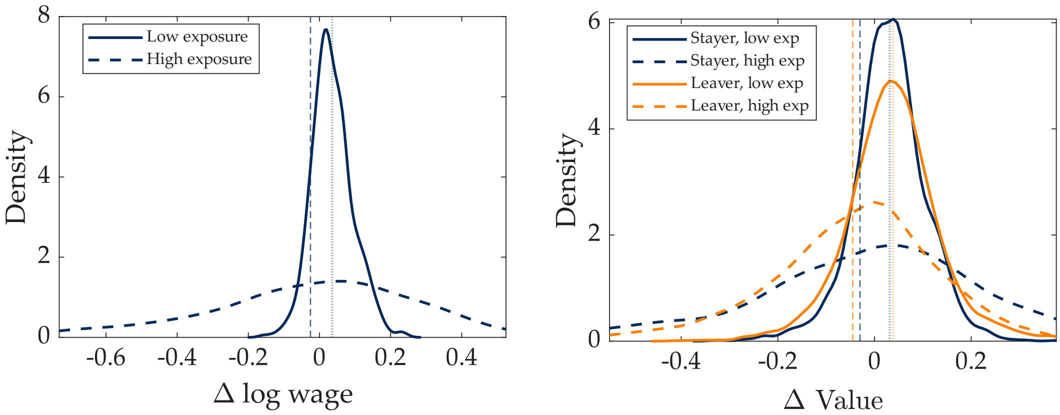
Berwick (2026, FT)

Result #2: robustness

Back



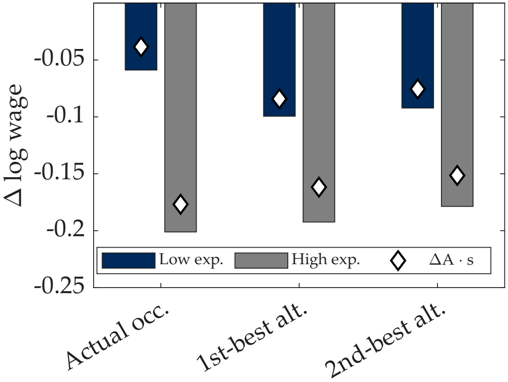
Exposure: stayers & leavers



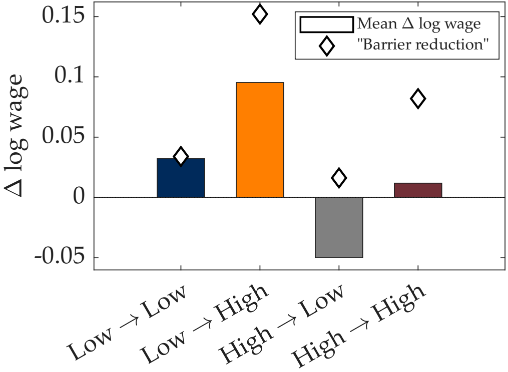
(a) Stayers by exposure

(b) Value change for stayers and leavers

A tale of tails



(a) Stayers’ deteriorating outside options



(b) Switching into high-exposure occs. yields gains