

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

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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



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Sarah O'Connor and John Burn-Murdoch

Published DEC 18 2025



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

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- ⇒ **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 framework to quantify 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

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 - 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 raises the return to social non-routine manual skills, reduces the return to analytical skills**
- ③ Distribution: **AI is progressive**—low-earners benefit more than high-earners

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**Job transformation
drives each one of
these results**

What's new? Position in the literature.

We develop a framework to quantify job transformation effects and demonstrate their central role in shaping the labor market consequences of AI.

- **Job transformation** [Autor et al., 2003; Spitz-Oener, 2006; Autor and Handel, 2013; Atalay et al., 2020; Autor et al., 2024; Gathmann et al., 2024]
 - ⇒ **formalize & link with skills** → 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]
 - ⇒ introduce jobs and task bundling → 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]
 - ⇒ directly estimate granular skills → **demonstrate key role of JT**
- **Multi-dimensional skills** [Lindenlaub, 2017; Lise-Postel-Vinay, 2021; Deming, 2023; Grigsby, 2023]
 - ⇒ **estimate** distribution of task-specific skills → **tie skill returns to automation**

Theory

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 $M_{i,\tau,t}$
 $\rightarrow X_{i,\tau,t}^{\text{machines}} = \exp(z_\tau) M_{i,\tau,t}$

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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

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

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Markets

Labor: Competitive

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

Occupational output: Competitive

Final good: Competitively traded numeraire

Firm's profit maximization problem yields:

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

The **occupational task-weight matrix A** summarizes relative weights attached to tasks $\tau \in \mathcal{T}_l$ across occupations $o \in \mathcal{O}$:

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

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

Model yields a tractable and intuitive log-linear wage equation

▶ Intercept term

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

$$\begin{aligned}
 \underbrace{\text{log wage of } i}_{w_{i,o,t}} \text{ if choose } o \text{ in } t &= \underbrace{\text{occ.-specific intercept (incl. prices)}}_{\mu_o} + \underbrace{\sum_{\tau_l} \frac{\alpha_{o,\tau}}{LS_o} \cdot s_{i,\tau}}_{\text{weighted skills}} + \underbrace{\text{idiosyncratic productivity shock (not crucial)}}_{\varepsilon_{i,t}} \\
 &= \mu_o + \underbrace{\frac{1}{n_{\text{skill}}} \sum_{\tau_l} s_{i,\tau}}_{\text{scalar absolute advantage}} + \text{Cov} \left(n_{\text{skill}} \cdot \frac{\alpha_{o,\cdot}}{LS_o}, \underbrace{s_{i,\cdot} - \frac{1}{n_{\text{skill}}} \sum_{\tau_l} s_{i,\tau}}_{\text{specialization vector}} \right) + \varepsilon_{i,t}
 \end{aligned}$$

Automation leads to job transformation *given* task bundling

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

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

- **Job transformation:** weight on $\tau^* \downarrow$ & weight on other entries \uparrow proportional to their occupation-specific weight, i.e. $A'_o - A_o = \frac{\alpha_{o,\tau^*}}{LS_o} \times \left(\frac{\alpha_{o,1}}{LS'_o} \quad \frac{\alpha_{o,2}}{LS'_o} \quad \dots \quad -1 \quad \dots \right)$

	τ^*	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

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- We nest “**partial automation**”: only a fraction $\zeta_{\tau^*} \in [0, 1]$ 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

$$\underbrace{\mathbb{E} [W_{i,o,t+1} - W_{i,o,t}]}_{\Delta \text{ potential log wage for } i \text{ in } o} = \underbrace{\Delta \mu_o + (A'_o - A_o)}_{\Delta \text{ task weights in } o} \cdot \underbrace{s_i}_{\text{individual skill vector}}$$

1 Occupation-level effects:

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

2 Job transformation effects:

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

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

$$l_{i,\tau,t} = \frac{\alpha_{0,\tau}}{\sum_{\tau \in \mathcal{T}_i} \alpha_{0,\tau}} := A_{0,\tau}$$

- robustness: aggregated O*NET weights
- time-varying (pre-2000, post-2000)

- **Step 2: *estimate skill distribution* (\bar{s}, Σ_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](#)

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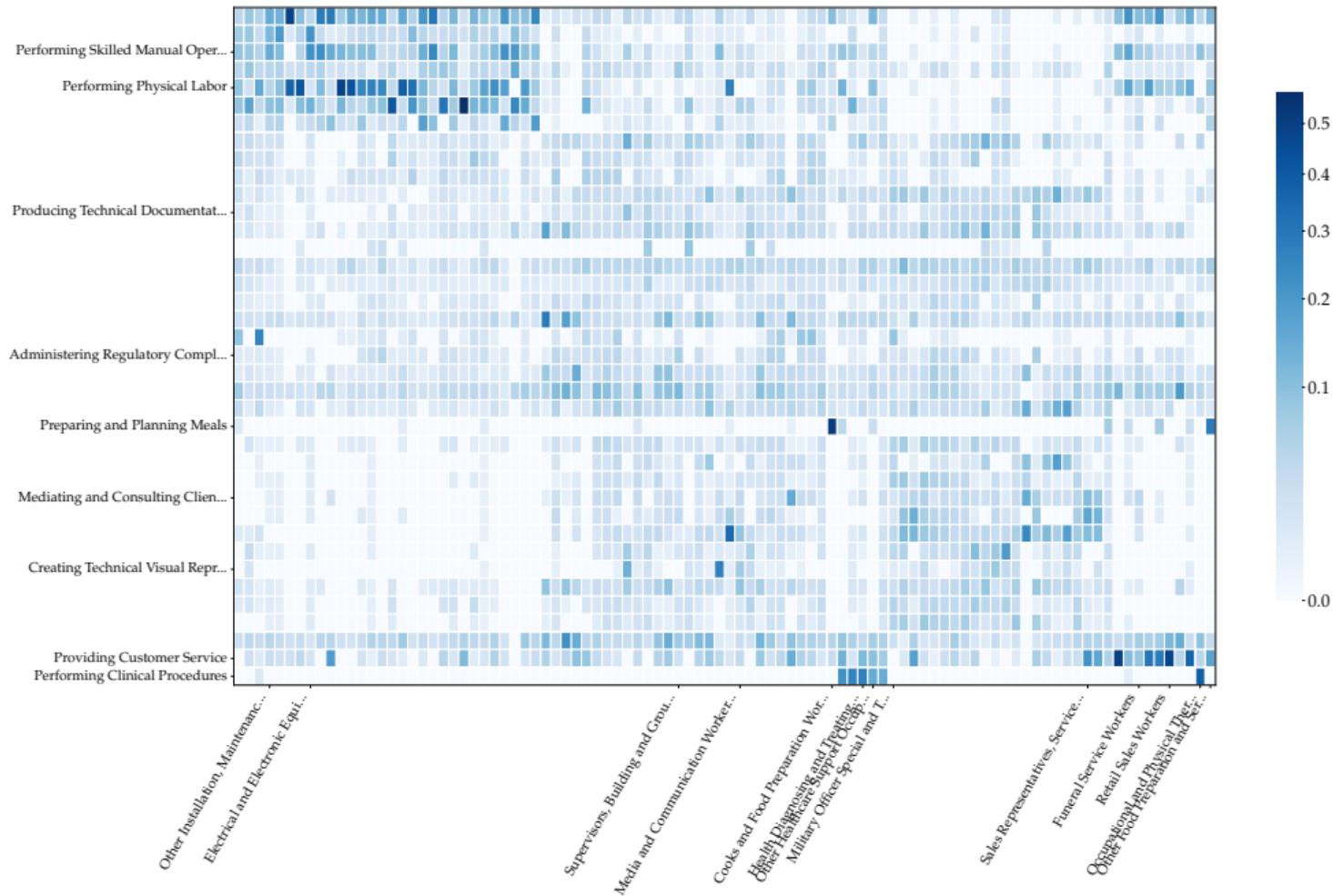
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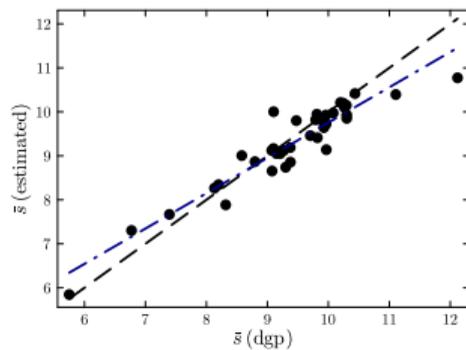
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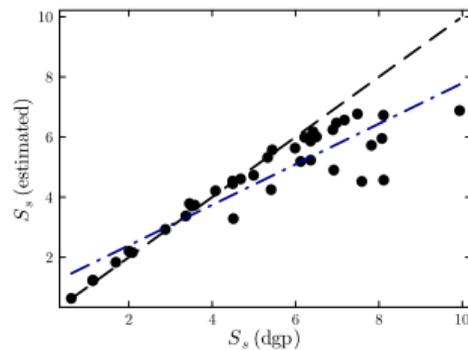
► Graphs

Validation: Monte-Carlo study

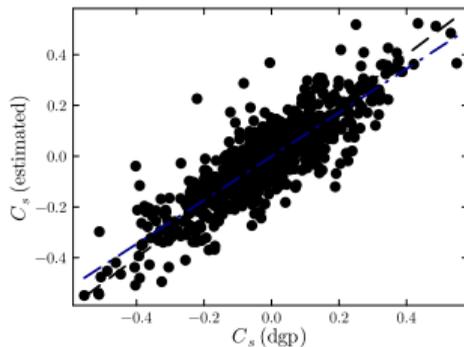
(a) Means



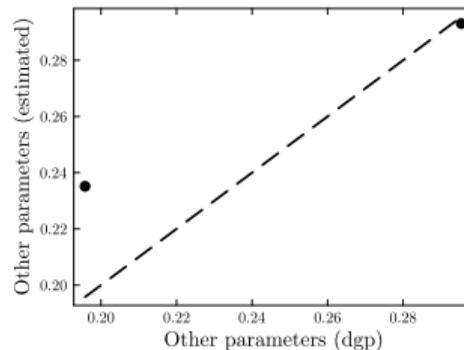
(b) Standard deviation



(c) Correlation



(d) Other parameters



- Parameter estimates

- Skill correlations vs. literature
- Skills along the wage distribution vs. literature

[▶ Details](#)[▶ Details](#)

- Steady state

- Occ. employment shares
- Wages
 - Occ. level averages
 - Between-within occ. variance decomposition
- Occ. transitions:
 - Staying and switching probabilities
 - Switches explained by task distances
 - Individual switching frequency shaped by specialization

[▶ Details](#)[▶ Details](#)[▶ Details](#)[▶ Details](#)[▶ Details](#)

- Historical: RBTC

- Skill returns: ↑ return to social skills [Deming, 2017]
- Employment: polarization [Autor & Dorn, 2013]

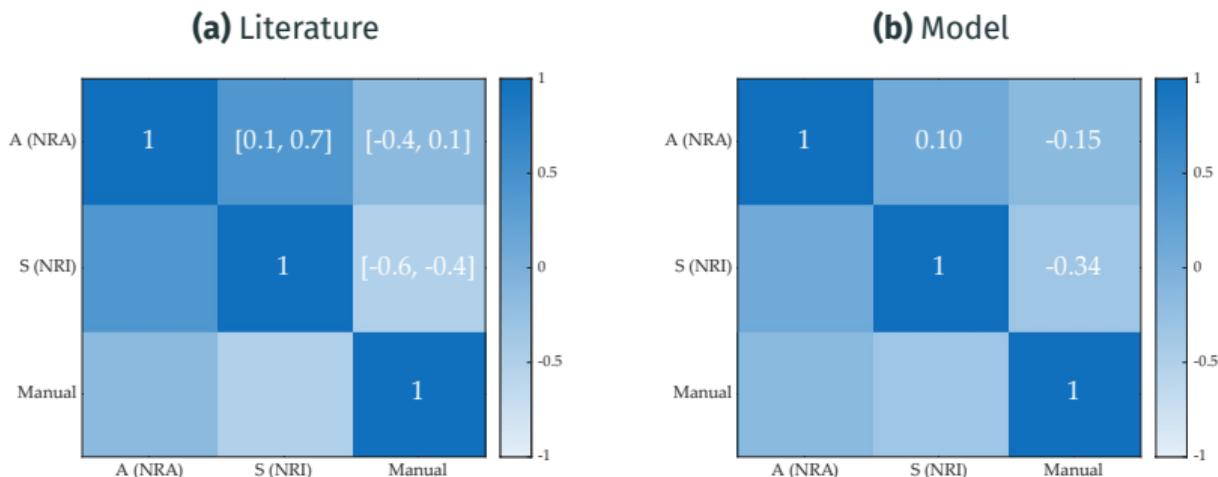
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Estimated skill correlations match empirical literature

► Classification

► Skill indices

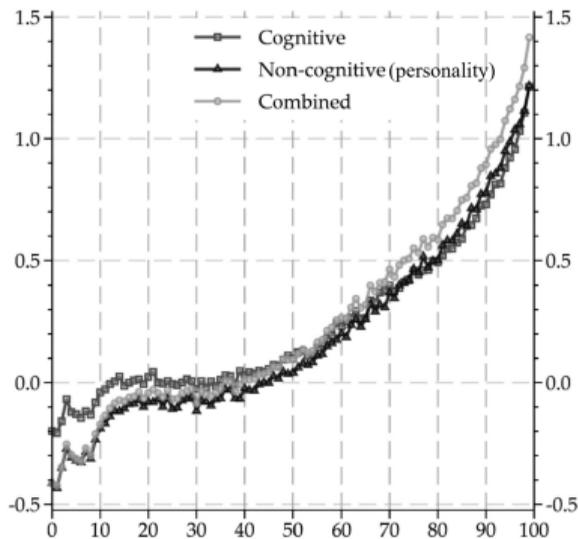
- Literature often studies coarser task classification, esp. NRA/NRI/NRM/RC/RM [e.g., *Autor et al., 2003*] → map our granular tasks to this classification & create skill indices
- → Estimated correlations match empirical ranges for aggregated skills [*Deming, 2017*; *Guvenen et al., 2020*; *Lise & Postel-Vinay,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



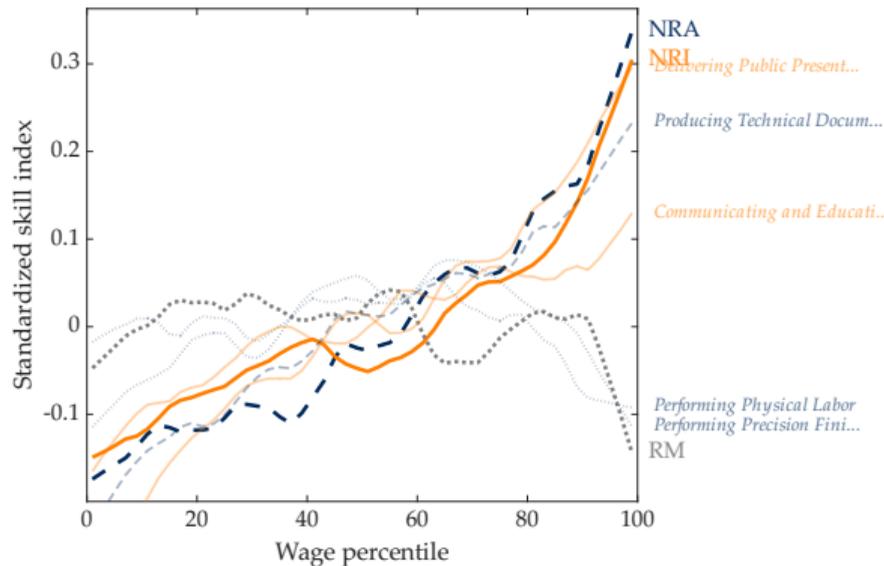
Skills vary along the wage distribution in line with data

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

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

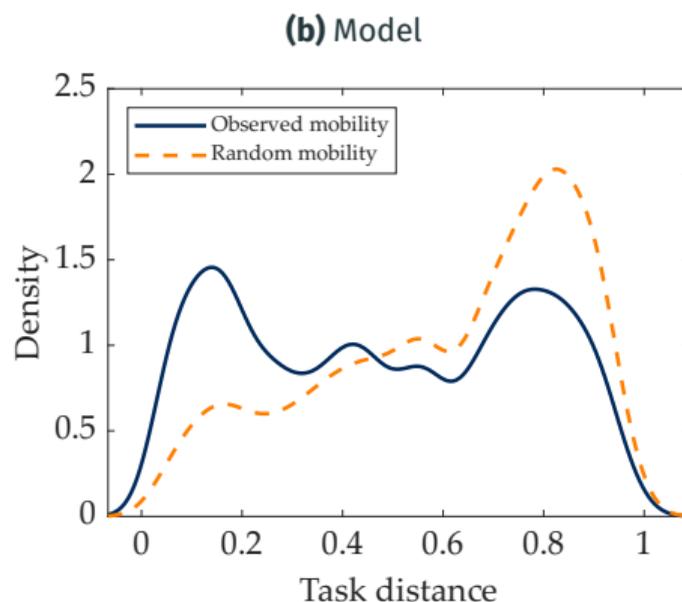
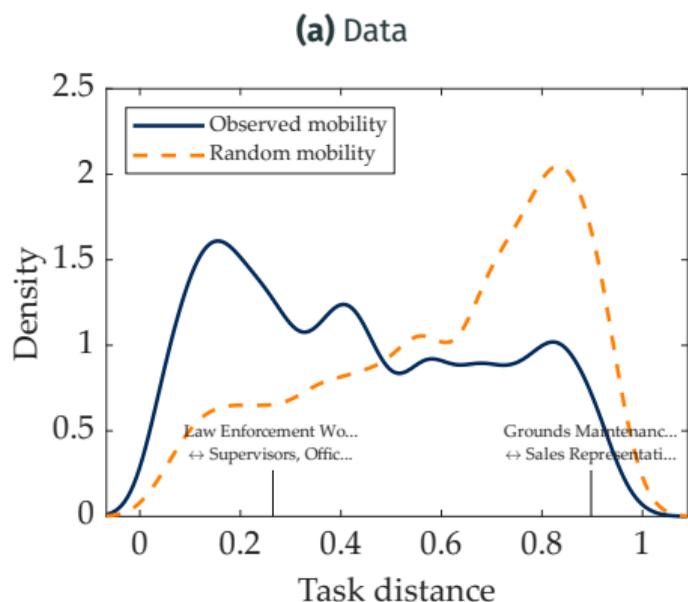


(b) Model



Task requirements explain switching in model and data

→ In model & data, workers move to occupations with similar task requirements—strong evidence for relevance of task-specific skills [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

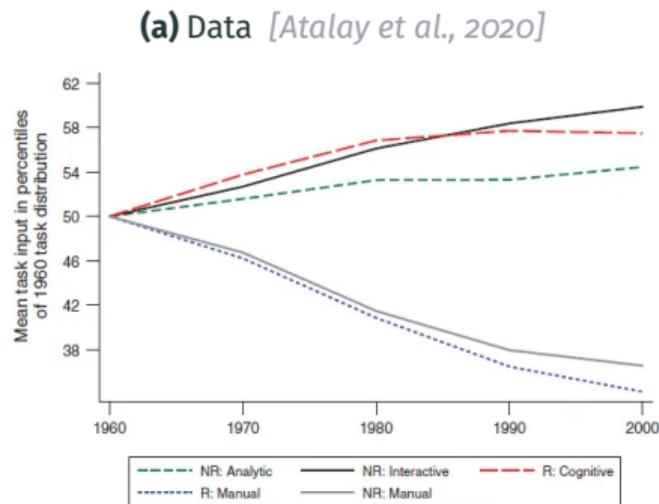
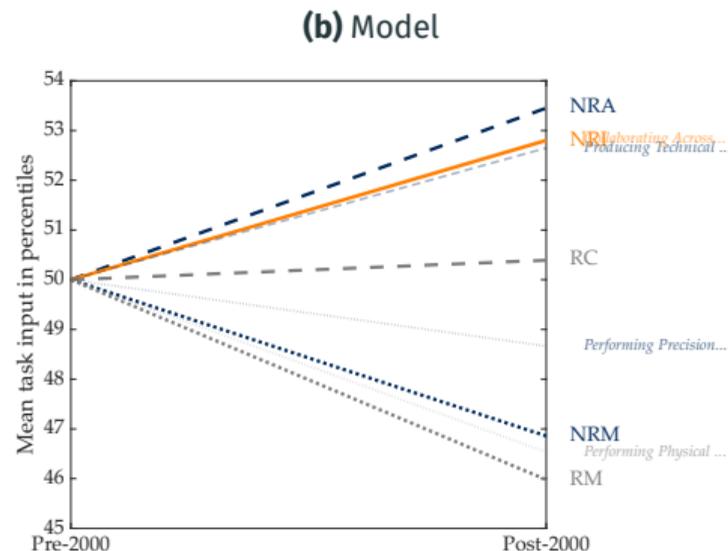


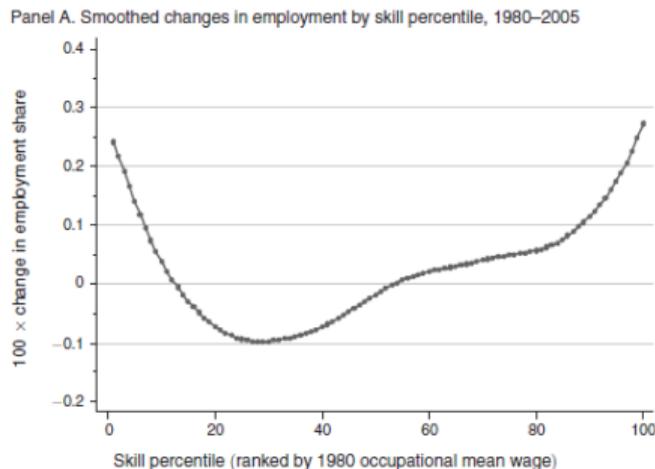
FIGURE 3. COMPARISON TO AUTOR, LEVY, AND MURNANE (2003, FIGURE 1)



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]

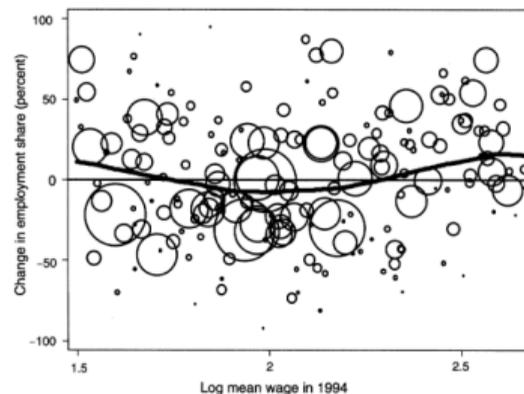


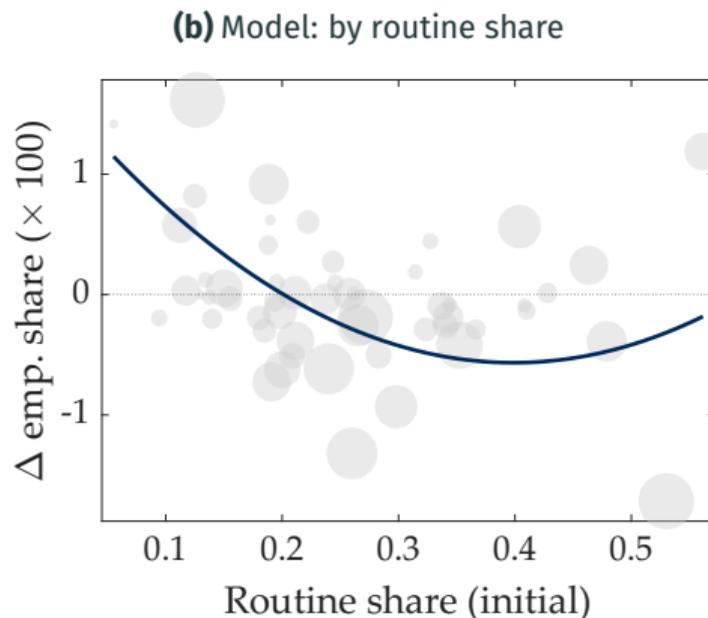
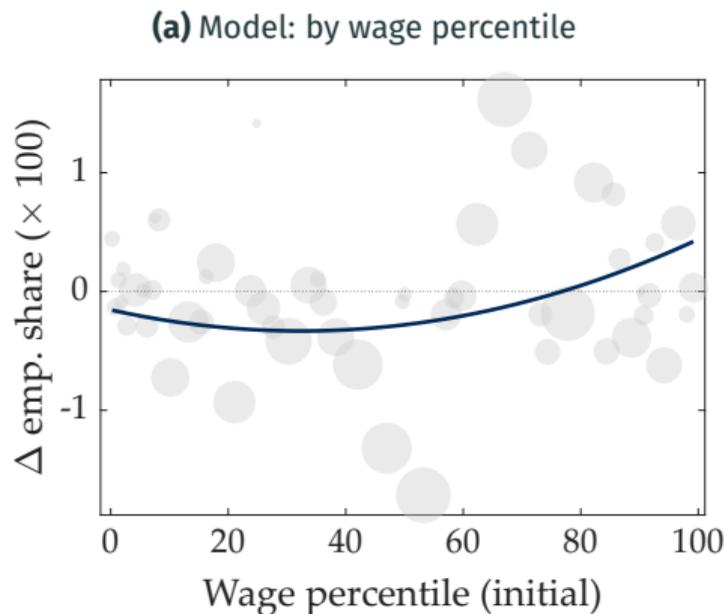
FIGURE 1. PERCENTAGE CHANGES IN EMPLOYMENT SHARES OVER 1993–2006 FOR JOBS RANKED BY THEIR 1994 LOG WAGE

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

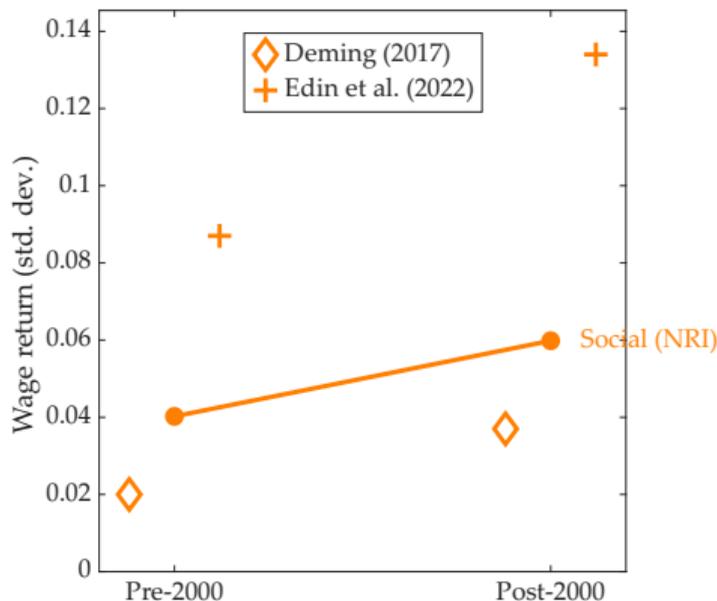
→ Model matches this U-shaped change in employment and the role of declining routine jobs



Model matches evidence on rising return to social skills

→ 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

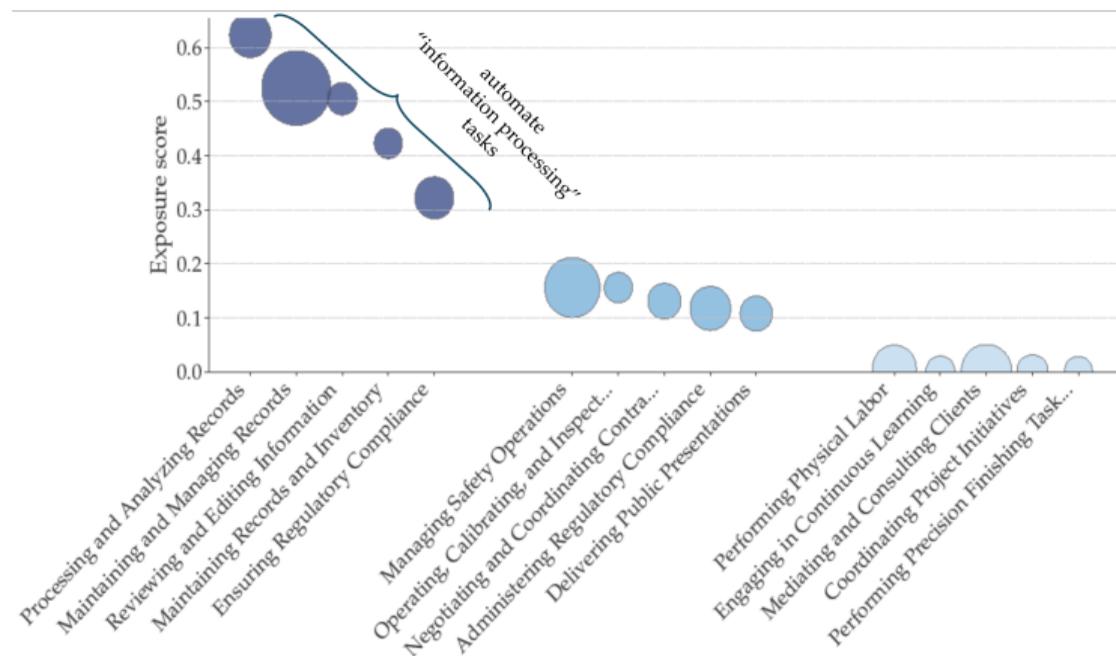


We use the model to project the wage effects due to LLM automation

- **Scenario:** What are effects for individual workers if LLMs automate certain tasks?
- **Measurement challenge:** which specific tasks will be/are being automated?
- **Solution:** exploit mapping of model tasks to task exposure measures
 - framework is flexible enough to map to many exposure measures from literature [Webb, 2019; Eloundou et al., 2024; Anthropic/Handa et al., 2024; ...]
 - genAI, self-driving vehicles, humanoid robots, ...
- **Today:** focus on exposure to LLM automation
 - exposure measures from Eloundou et al. (2024)
 - scenario where z_{τ^*} is *just* high enough for a task to be automated in all occ.'s

Scenario: LLMs mostly automate information-processing tasks

→ We suppose a fraction of each task corresponding to the exposure score is automated



Share of detailed O*NET tasks within each task cluster rated as fully automatable by Eloundou et al. (2024).

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

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

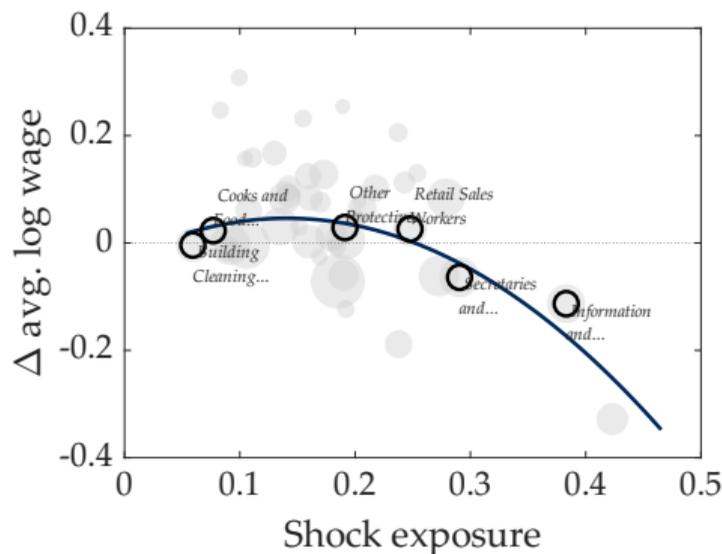
→ On average, incumbents with *some* exposure win, those heavily exposed lose
[consistent with evidence in Eisfeldt et al., 2025]

→ **Mechanism:** job transformation × selection:

[+] for low exposure (→ focus on what you're best at)

[-] for high exposure (→ machines take over what you're best at)

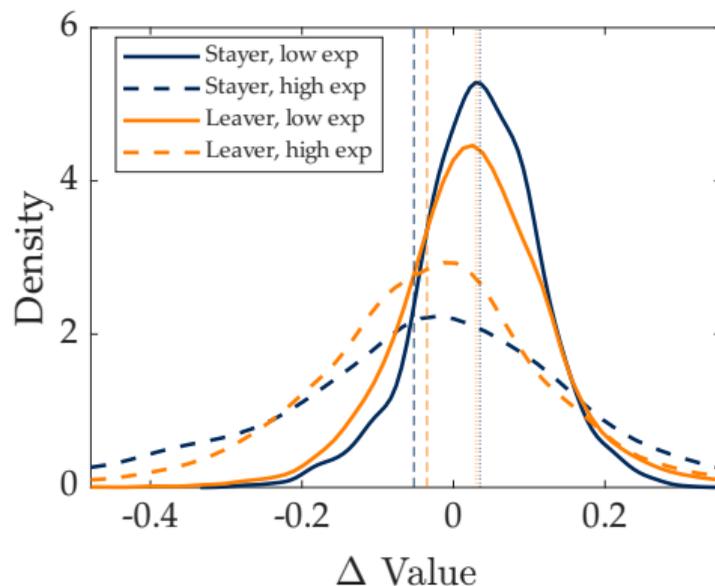
▶ Details



...but this hides heterogeneity: exposure \sim potential for change

▶ JT drives dispersion

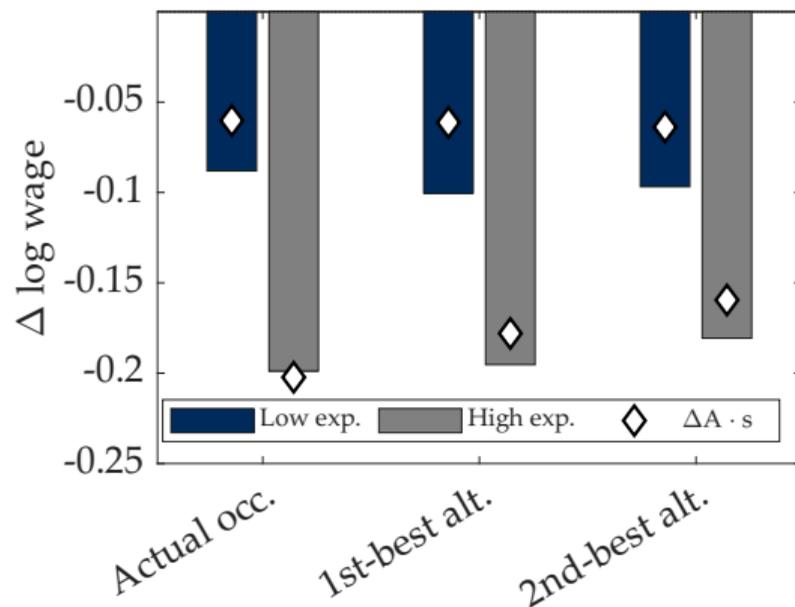
- The biggest gains & losses are among stayers in high-exposure occupations
- Winners? What's automated by AI isn't what selected them into exposed occupations.



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”

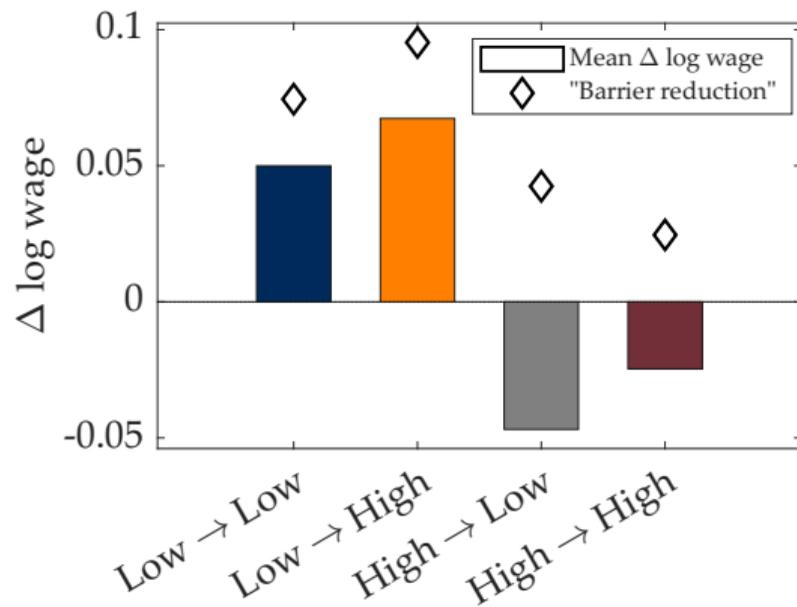
→ Job transformation leads to correlated ↓ in potential wages across likely occupations



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

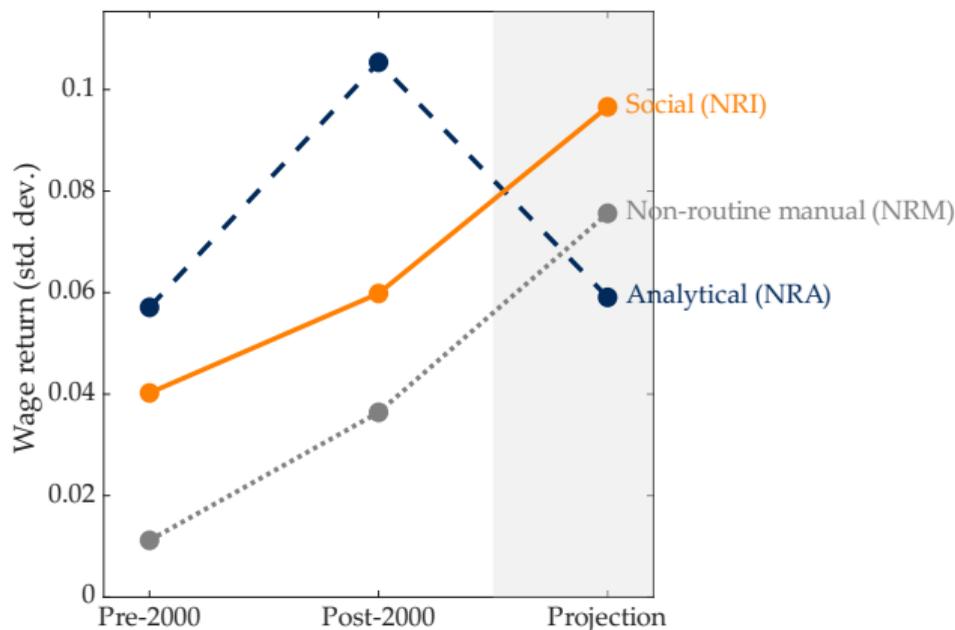


Sub-sample of occupational leavers.

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

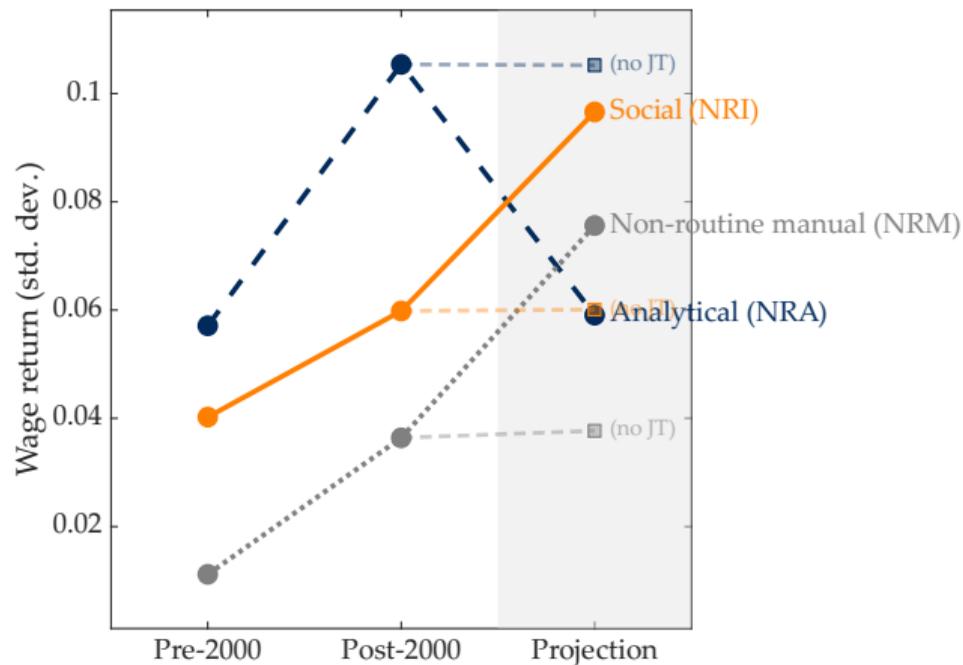
Result #2: AI raises the return to social & NRM skills

→ 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



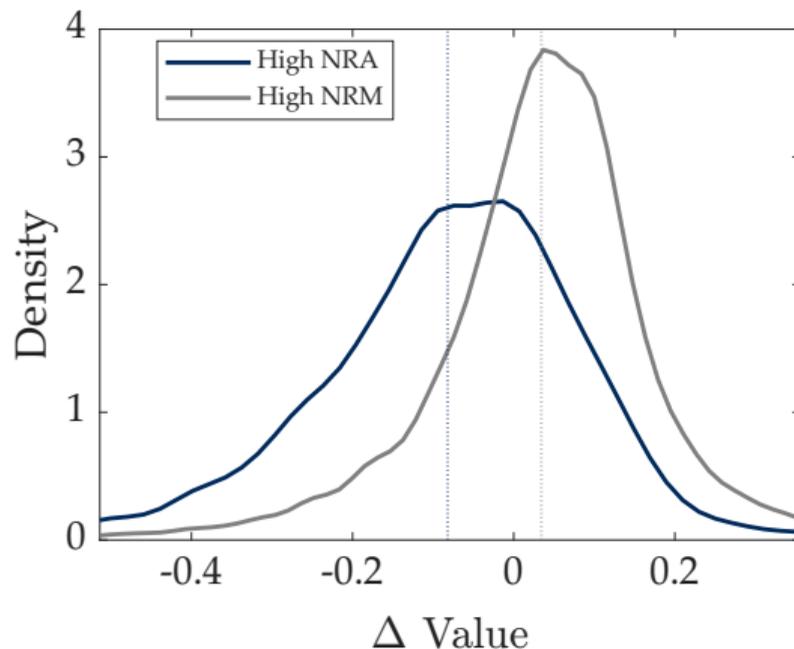
Job transformation drives these shifts in returns

→ We miss these shifts if we abstract from job transformation



These shifts help predict who the winners & losers tend to be

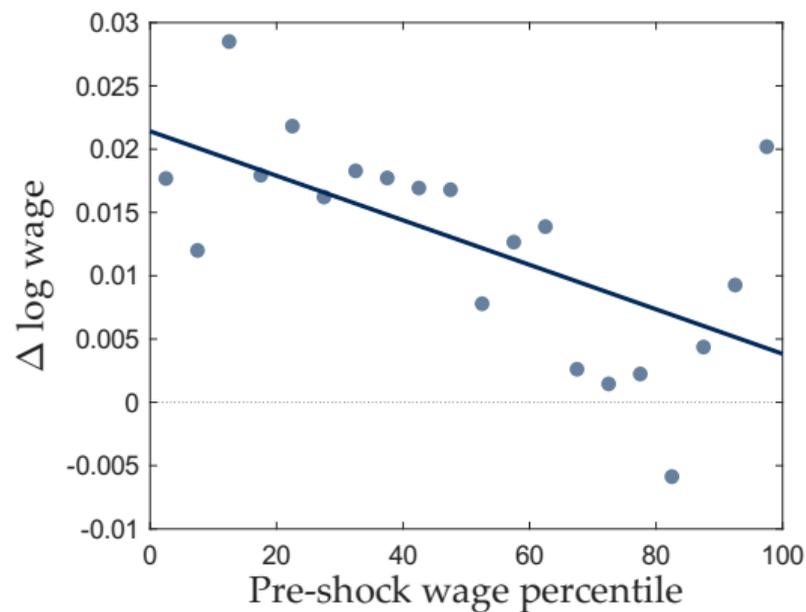
→ High-NRA workers are over-represented among losers, high-NRM workers are over-represented among winners



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

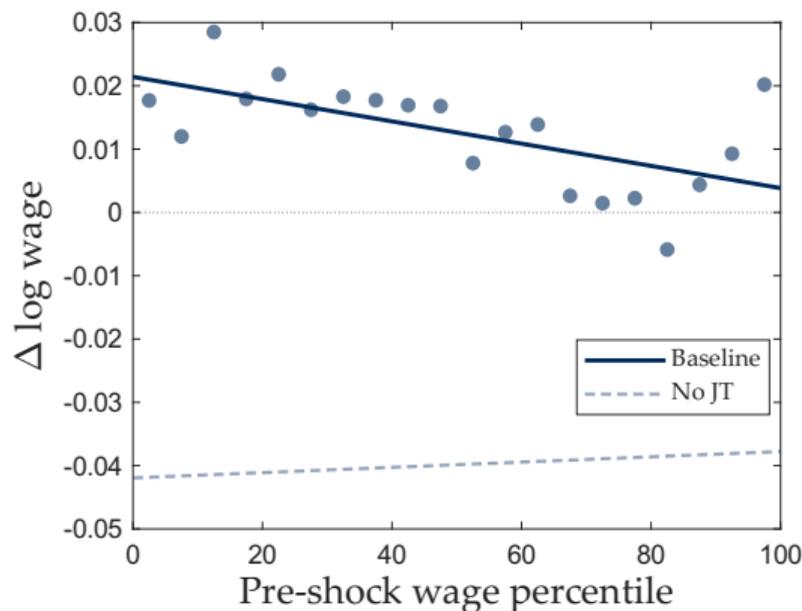
Result #3: AI shock is mildly “progressive”

→ Wage gains disproportionately accrue to low-wage earners



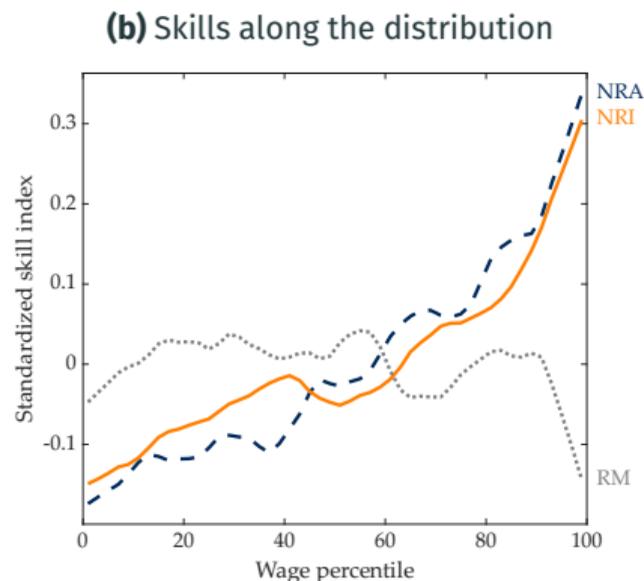
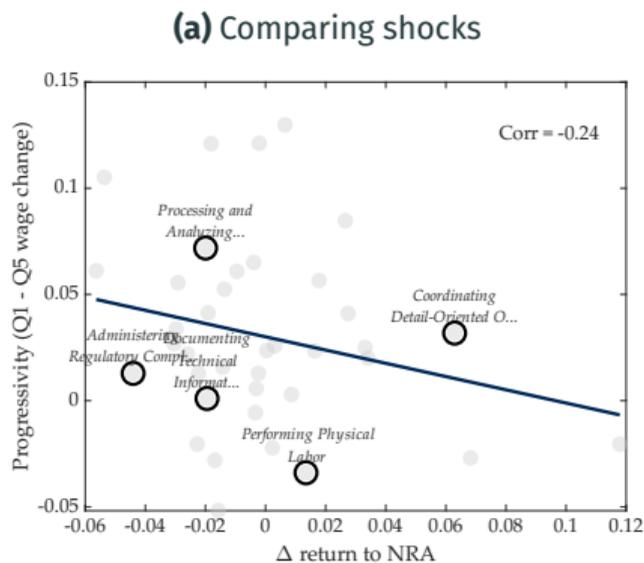
Result #3: AI shock is mildly “progressive” because of JT

- Wage gains disproportionately accrue to low-wage earners—once you account for JT
- JT also generates increase in *average* wage = productivity effect



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



Conclusion

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

We develop a framework to quantify job transformation effects and demonstrate their central role in shaping the labor market consequences of AI.

- ① AI **exposure** signals potential for change: large heterogeneity within occupation
- ② AI raises the return to social **skills** but lowers that of analytical skills
- ③ AI's **distributional** impact is mildly progressive

Thank You!

Extra Slides

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

[◀ Back](#)

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

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

Based on Bessen (2012)'s analysis of records of the Lawrence Company, MA.

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:**

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

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

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- **Optimality:**

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

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

- **Optimality:**

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

Capital FOC and production

- 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

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

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

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 ε ., such that:

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

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

- 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

- Intercept

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

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

- Our framework nests the concept of **partial automation**
 → only a fraction $\zeta_{\tau^*} \in [0, 1]$ of task τ^* can be automated
- **Modeling:** Equivalently, rewrite pre-automation production technology as

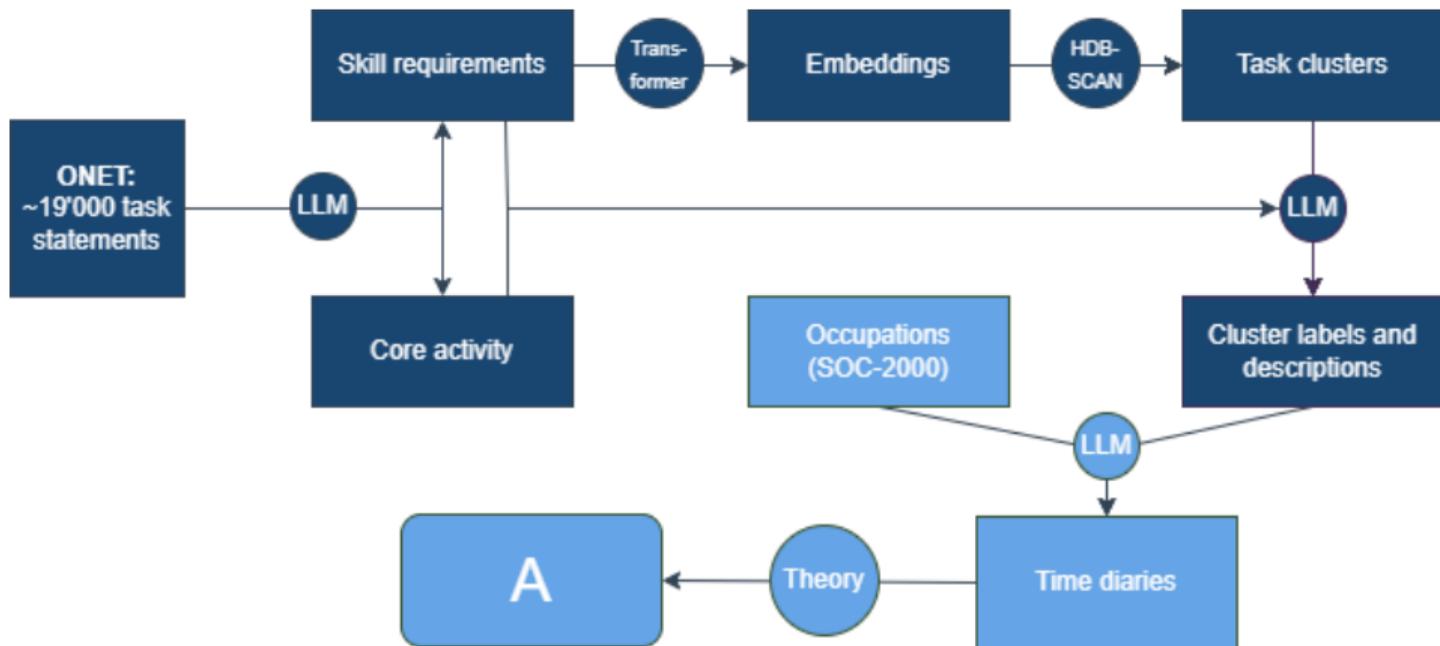
$$Y_{i,o,t} = \Gamma \cdot \prod_{\tau \in \mathcal{T}_m} (X_{i,\tau,t}^{\text{machines}})^{\alpha_{o,\tau}} \cdot \prod_{\tau \in \mathcal{T}_\ell \setminus \{\tau^*\}} (X_{i,\tau,t}^{\text{labor}})^{\alpha_{o,\tau}} \cdot ((1 - \zeta_{\tau^*}) X_{i,\tau^*,t}^{\text{labor}})^{(1-\zeta_{\tau^*})\alpha_{o,\tau^*}}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

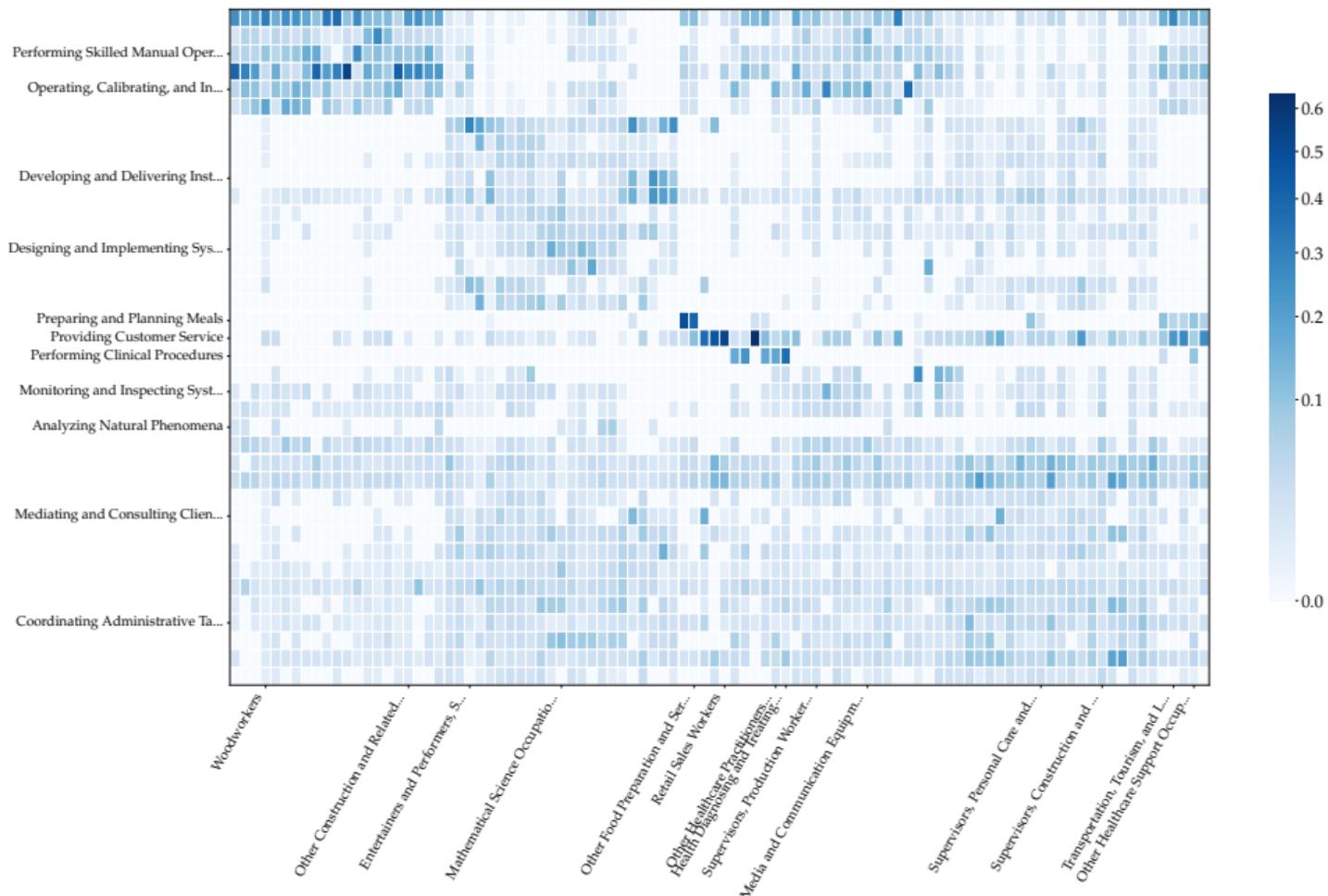
where $\Gamma = (1 - \zeta_{\tau^*})^{-\alpha_{o,\tau^*}} (1 - \zeta_{\tau^*})^{\zeta_{\tau^*}\alpha_{o,\tau^*}}$

- Post-automation production technology becomes

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

Summary of step 1 pipeline





Validation of LLM-generated time shares: overview

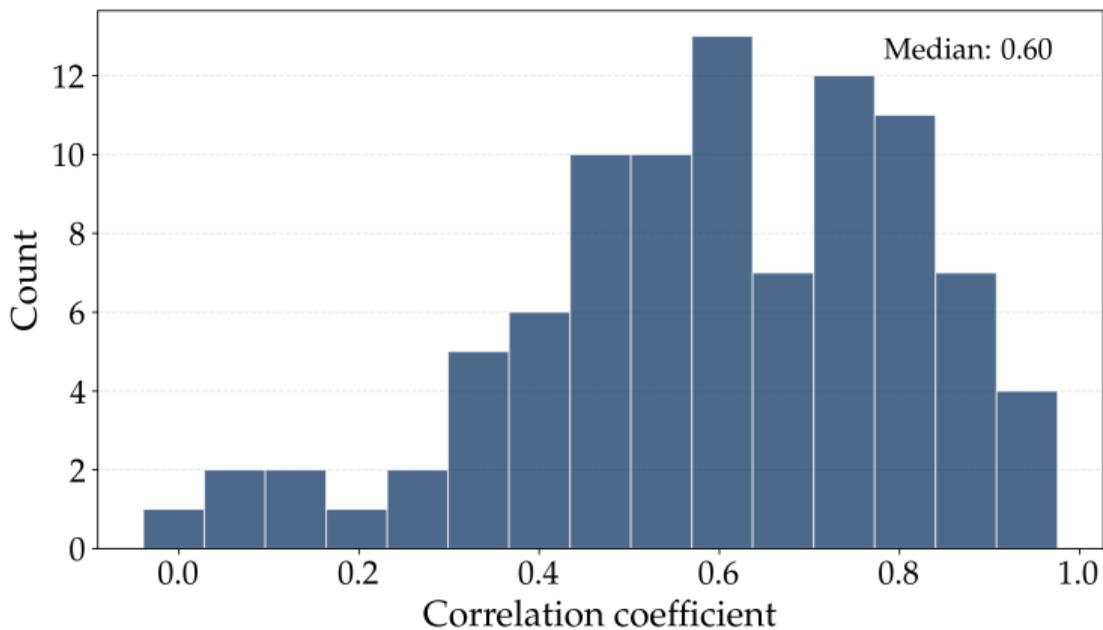
- 1 LLM-generated task weights for (o, τ) highly correlated with the average importance rating that O*NET assigns to detailed tasks within each cluster ✓
- 2 Comparison of time share measurement: LLM vs BIBB survey ✓
- 3 Comparison of LLM-generated time shares for GWAs to O*NET importance weights ✓
-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

Alternative A matrix: O*NET bottom-up

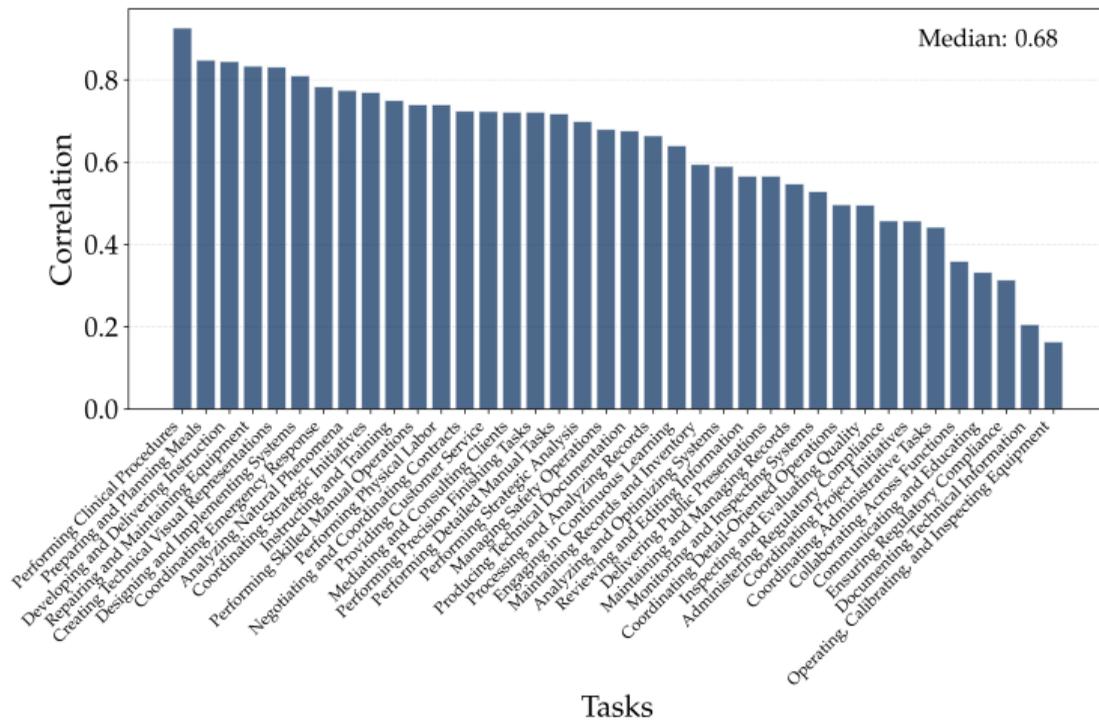
- ONET contains (Likert scale) “task ratings” indicating the importance of detailed tasks i for o
- Create occupational task-weight matrices A_p (for $p \in \{2000s, 2010s, 2020s\}$, where each cell (o, τ) contains the average importance of task τ for occupation o
 - Notation
 - o' = detailed ONET occupation (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

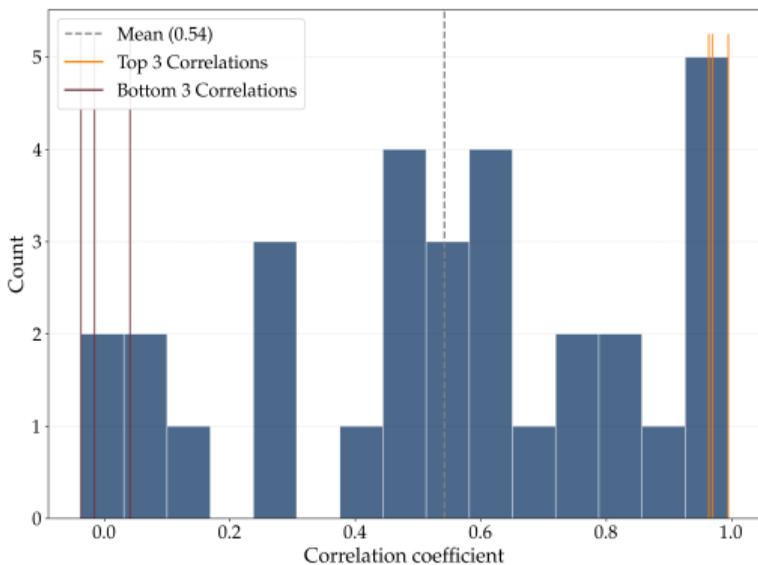


Validation: LLM task weights vs. ONET bottom-up – task-level

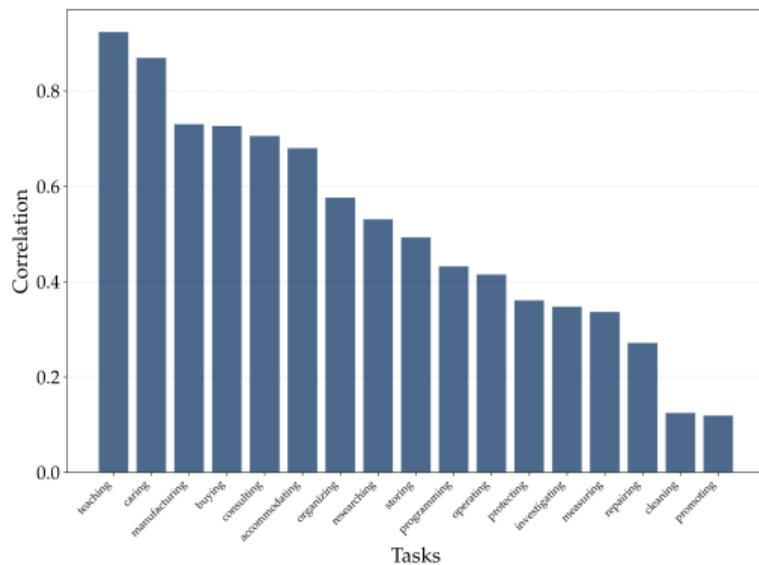


Validation: LLM-generated task shares vs. BIBB

(a) Occupation-level correlations

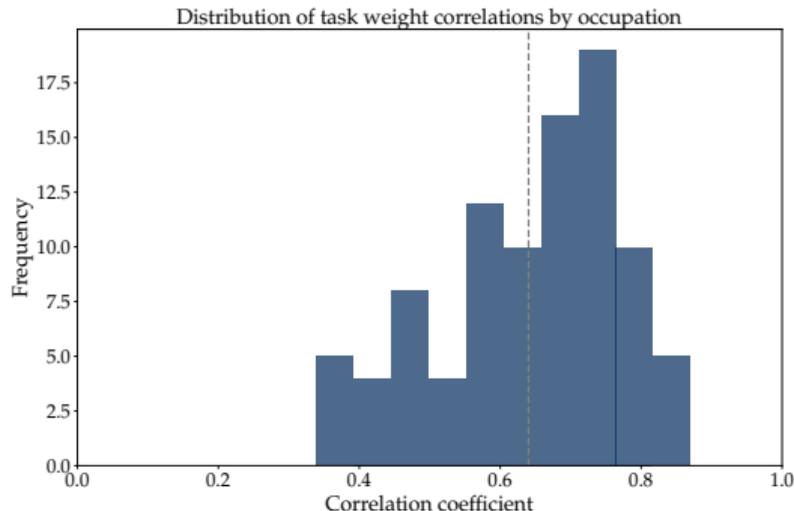


(b) Task-level correlations

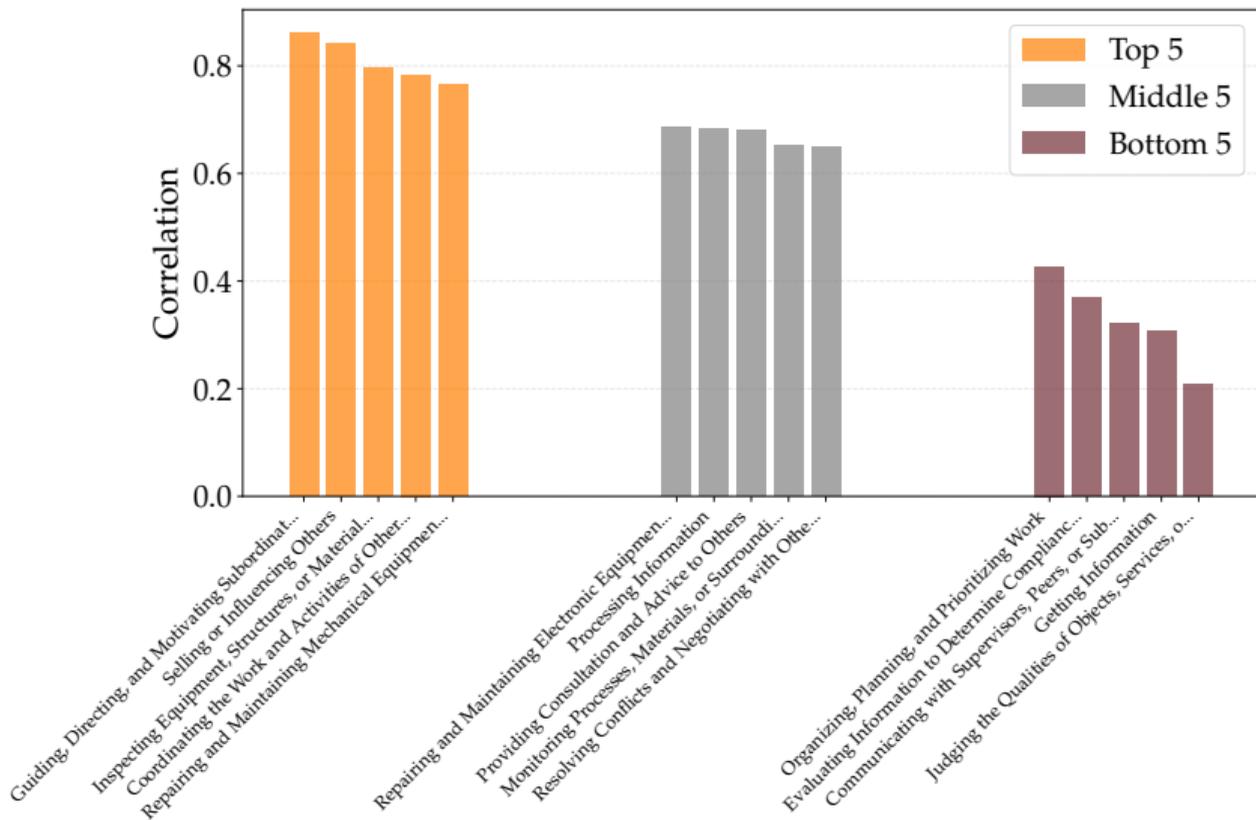


Validation: O*NET GWAs (1)

- 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?

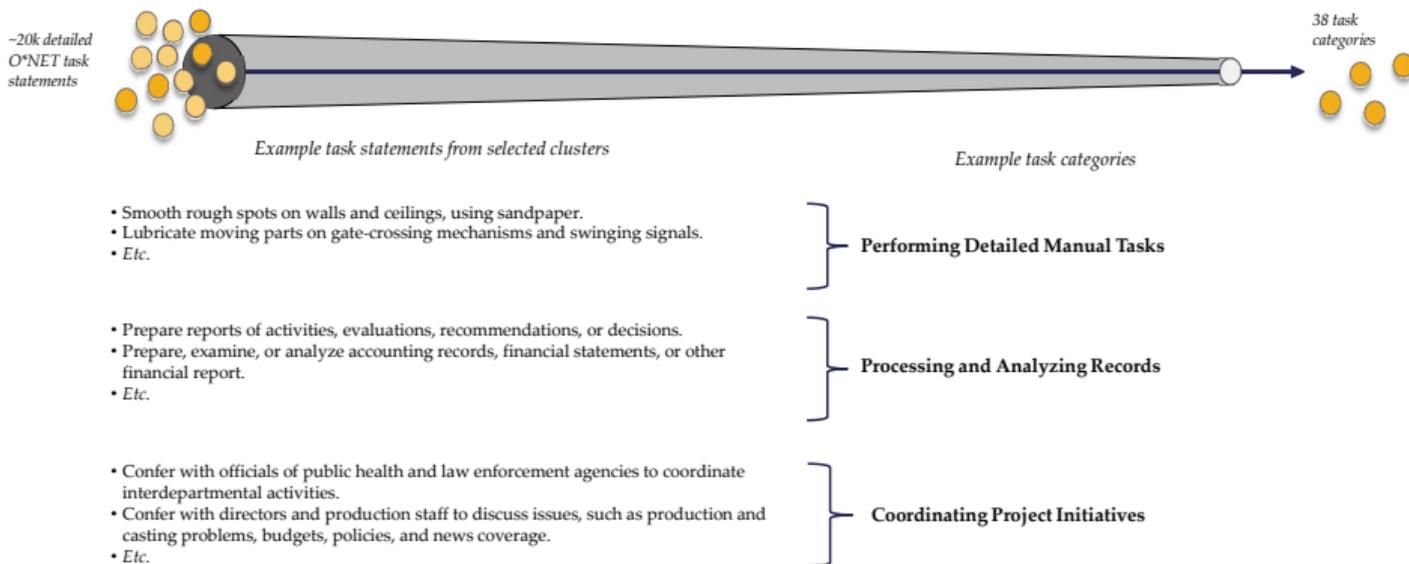


Validation: O*NET GWAs (2): correlation across occupations by task



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



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.

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

Details on the estimation strategy I

- 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:

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

- 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

- **Strategy:** Monte Carlo integration - for all i generate n_0 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 $P(\hat{\omega}_{i,t} = \omega_{i,t} | w_{i,\cdot,t}, \nu)$ to obtain an estimator for $\mathcal{L}_i(\theta)$:

$$\hat{\mathcal{L}}_i(w_{i,t,\omega}, \nu, \varsigma, \bar{s}, \Sigma_s, \vec{p}, \vec{p}') = \left(\frac{1}{n_0} \sum_j \prod_t P(\hat{\omega}_{i,t} = \omega_{i,t} | w_{j,t,\cdot}, \nu) \right) \cdot f(w_{i,\cdot,\omega} | \varsigma, \bar{s}, \Sigma_s, \vec{p}, \vec{p}')$$

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

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

Details on the estimation strategy III

- 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

Brief summary of NLSY '79 data

- 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

- 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)

- **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 $\tilde{\alpha}_{o(i,t),\tau} = \frac{\alpha_{o(i,t),\tau}}{\sum_{\tau \in \mathcal{T}_t} \alpha_{o(i,t),\tau}}$, where $o(i, t)$ is the occupation chosen by i in year t . 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]
 - 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).
 - 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

- **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]

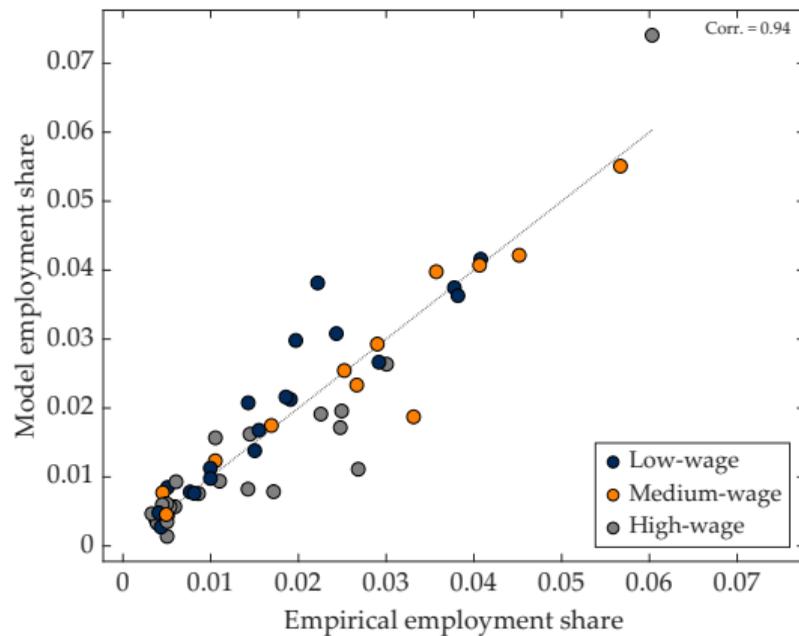
- 1 Standardize each task-specific log skill $s_{i\tau}$ in the population: $\tilde{s}_{i\tau} = \frac{s_{i\tau} - \bar{s}_\tau}{\sigma_{s_\tau}}$
- 2 Average standardized skills within category c : $\bar{s}_{ic}^{\text{raw}} = \frac{1}{|\mathcal{T}_c|} \sum_{\tau \in \mathcal{T}_c} \tilde{s}_{i\tau}$
- 3 Re-standardize the aggregate: $S_{ic} = \frac{\bar{s}_{ic}^{\text{raw}} - \bar{\bar{s}}_c^{\text{raw}}}{\sigma_{\bar{s}_c^{\text{raw}}}}$

- **Wage regression:** straightforward pooled OLS wage regression

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

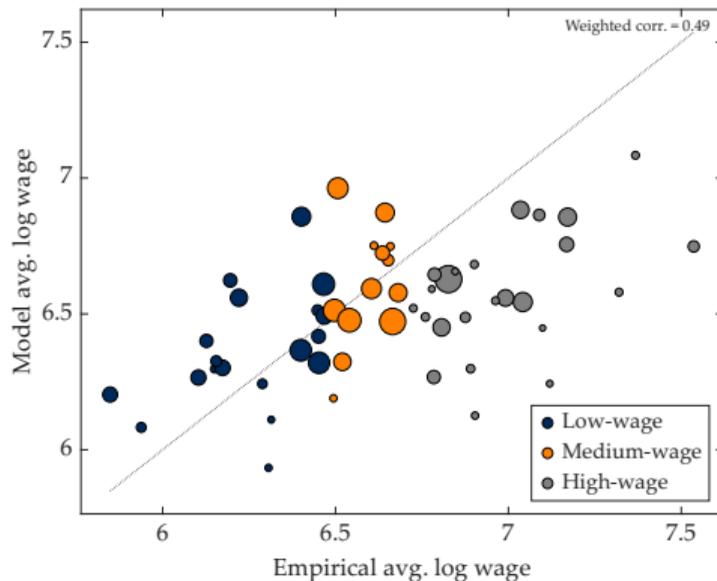
- **Interpretation:** Coefficients represent the change in log wage associated with a one standard deviation increase in the respective skill measure

Occupational employment shares



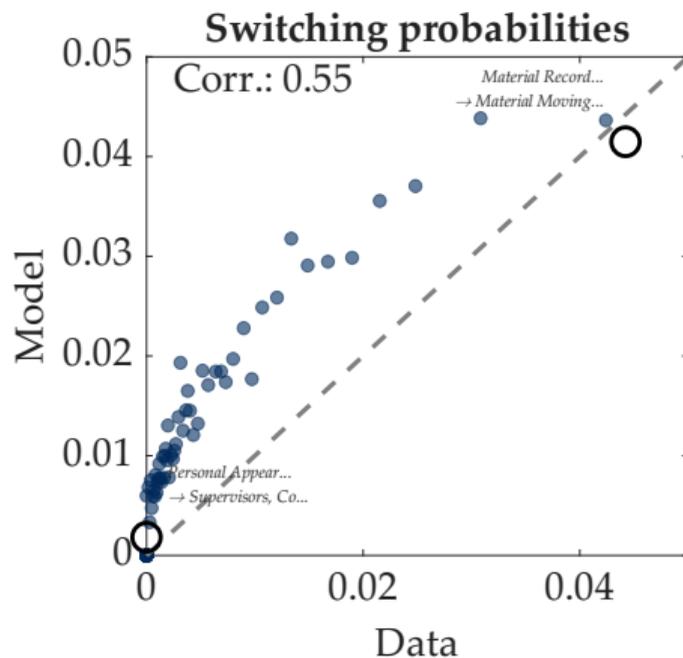
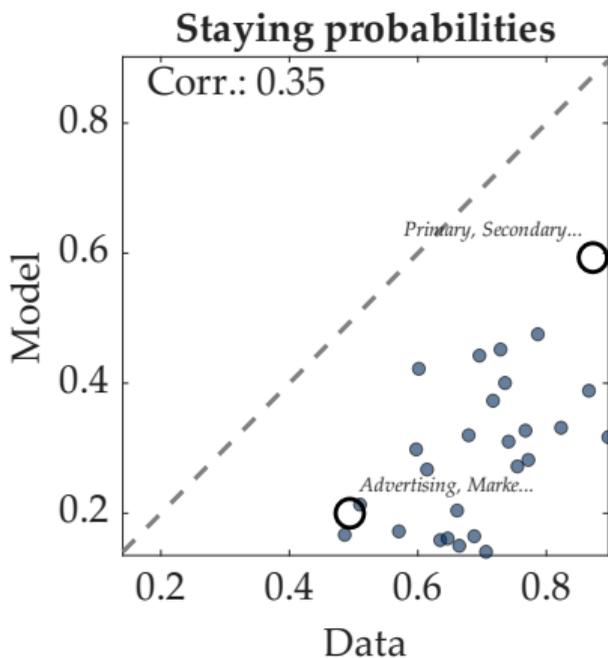
Wages: dispersion & occ. level averages

- 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



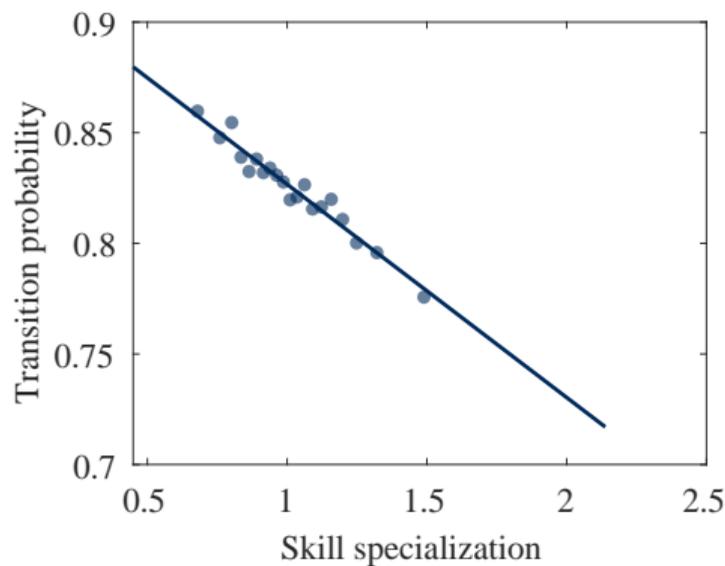
Model endogenously generates plausible occupational transitions

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

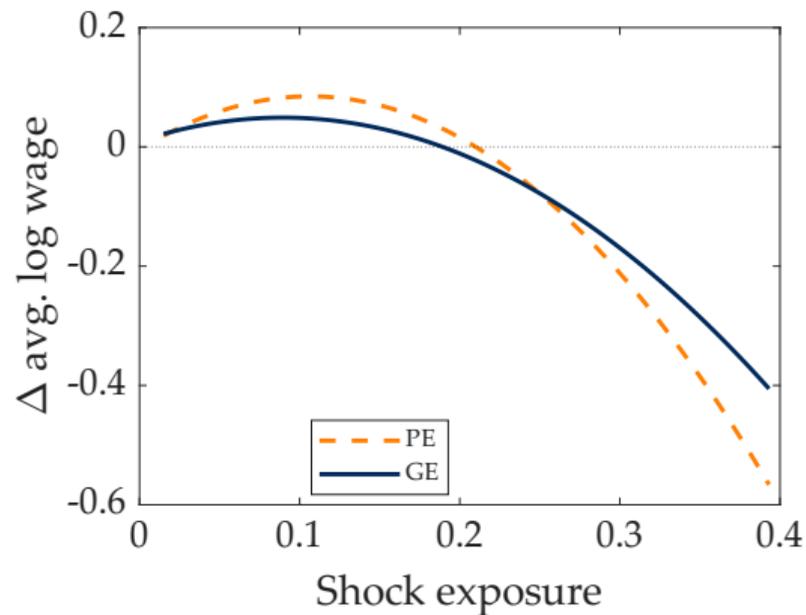


Model properties: specialization shapes switching frequency

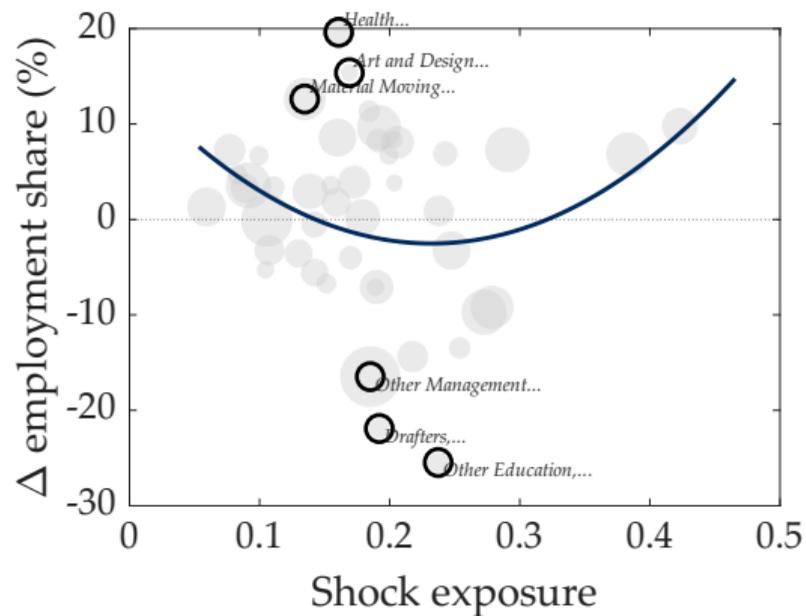
→ Skill specialization tends to generate persistence in occupational choice [*Kambourov and Manovskii, 2008; Geel et al., 2011*]



Result #1: the role of GE

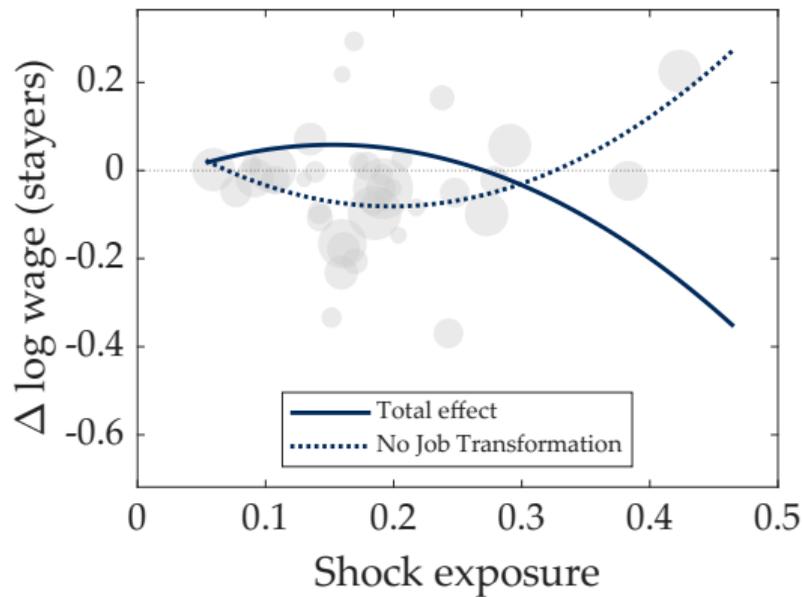


Employment effects



Job transformation drives this pattern

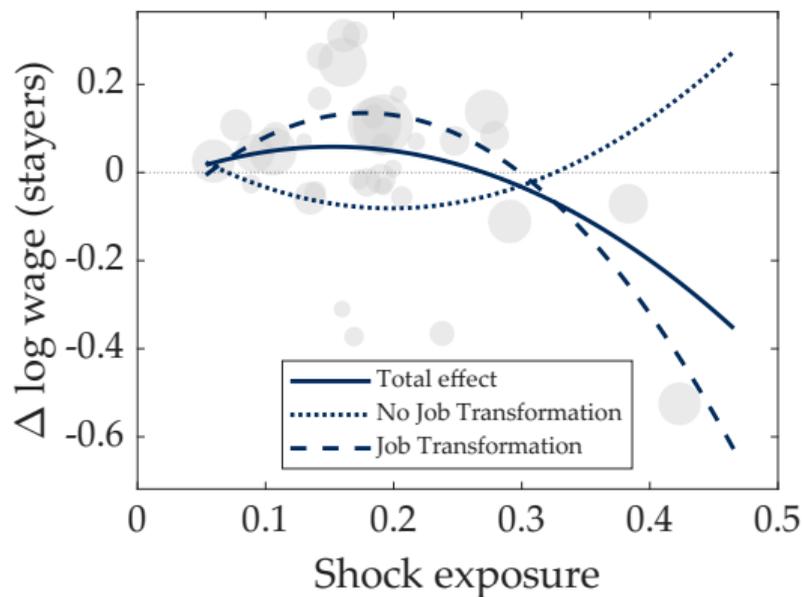
→ Holding A fixed, i.e. absent job transformation, the inverted-U shape disappears



Focusing on stayers for clarity of exposition.

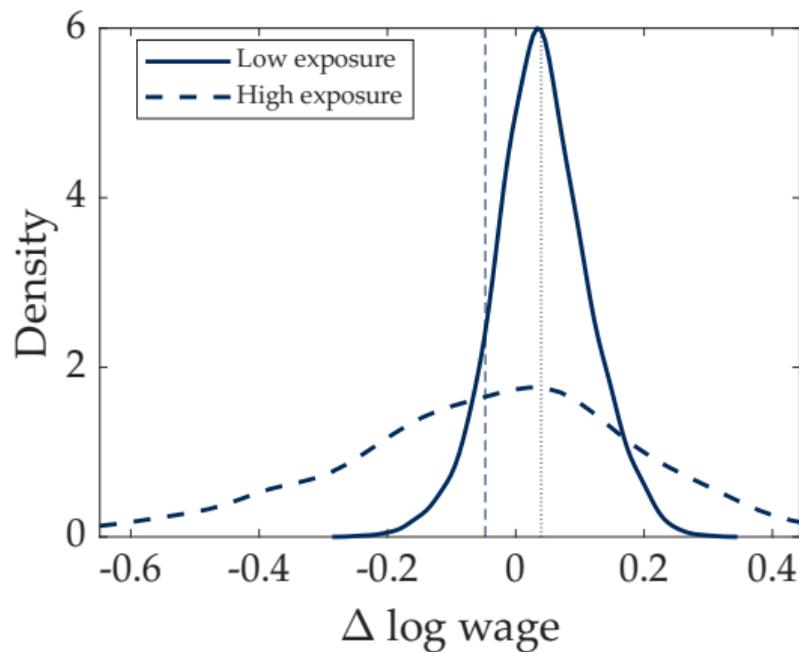
Job transformation interacts with selection

→ 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)



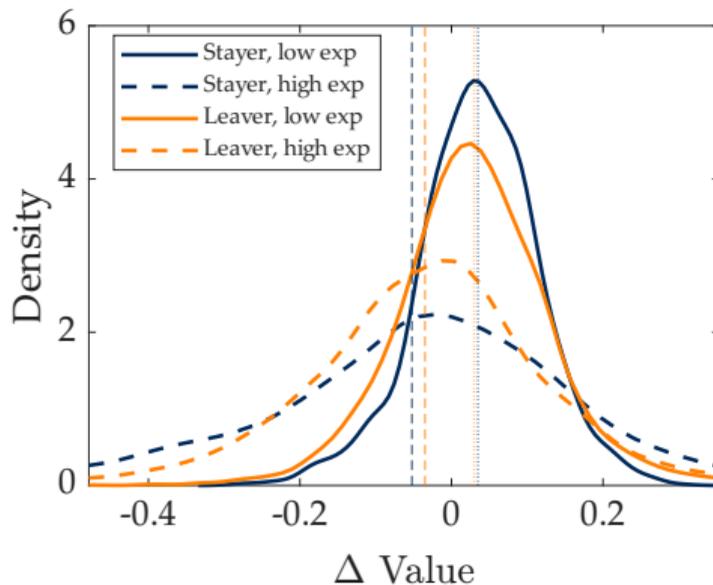
Result 1b: But the average masks large heterogeneity

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



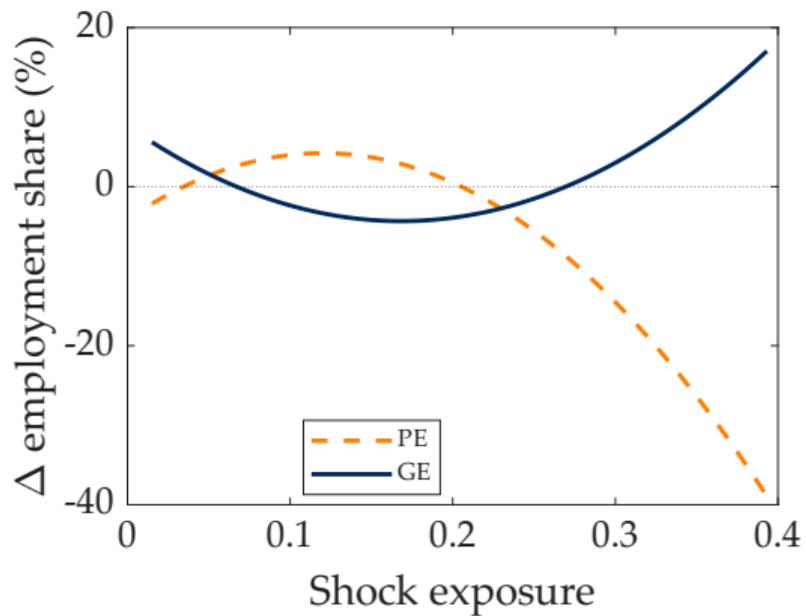
Exposure represents *potential* for change

- The biggest gains are among stayers in high-exposure occupations
- The biggest losses are among workers leaving high-exposure occupation



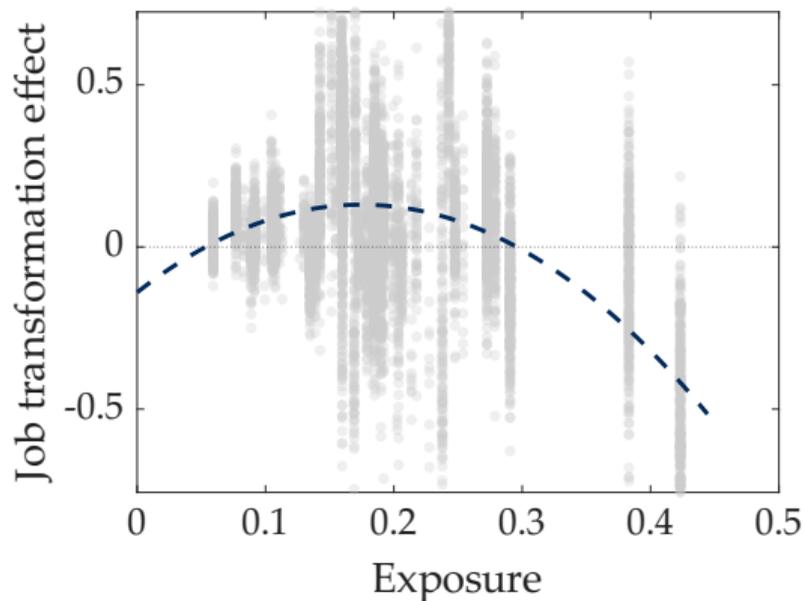
Value is defined as $V_{i,t} = \nu \log \left(\sum_{o \in \mathcal{O}} \exp \left(\frac{w_{i,o,t}}{\nu} \right) \right)$ and average out wage changes due preference-shock driven switches.

Employment: the role of GE

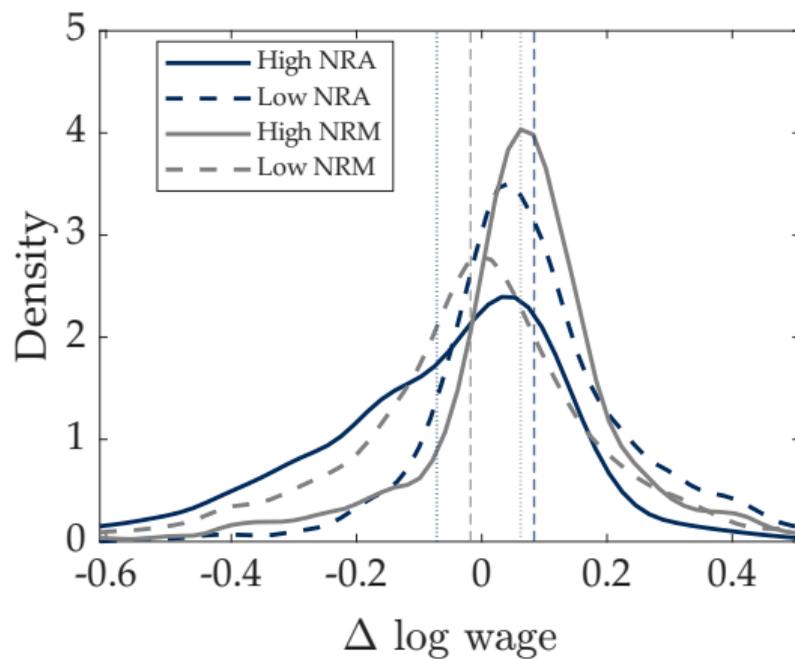


Dispersion in outcomes arises from job transformation

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



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



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

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