

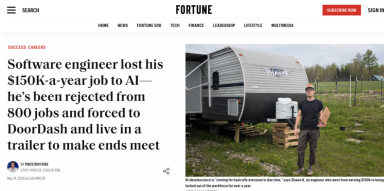
Canaries in the Coal Mine? Six Facts About the Recent Employment Impacts of Artificial Intelligence

Erik Brynjolfsson, Bharat Chandar, and Ruyu Chen

Stanford University

October 7, 2025

Lots of discussion about AI's impact on the entry-level labor market



The New York Times

Opinion | A 'White-Collar Blood Bath' Doesn't Have to Be Our Fate

Instead of asking which future is coming, we should be asking which future we want.
2 days ago



Axios

Behind the Curtain: Top AI CEO foresees white-collar bloodbath

Dario Amodei — CEO of Anthropic, one of the world's most powerful creators of artificial intelligence — has a blunt, scary warning for the...

1 month ago



Business Insider

The AI coding apocalypse

In the age of artificial intelligence, entry-level coders are doomed. But some engineers are thriving.

Feb 25, 2025



The New York Times

For Some Recent Graduates, the A.I. Job Apocalypse May Already Be Here

The unemployment rate for recent college graduates has jumped as companies try to replace entry-level workers with artificial intelligence.

4 weeks ago



The New York Times

Opinion | I'm a LinkedIn Executive. I See the Bottom Rung of the Career Ladder Breaking.

Eventually, A.I. will create plenty of jobs. The World Economic Forum predicts that number could be as high as 78 million more jobs, even after...

1 month ago



“Canaries in the coal mine” for AI’s impact

Are we already seeing changes in the labor market driven by AI? Particularly for entry-level workers?

- ▶ **ADP:** monthly payroll records through July 2025 for millions of workers

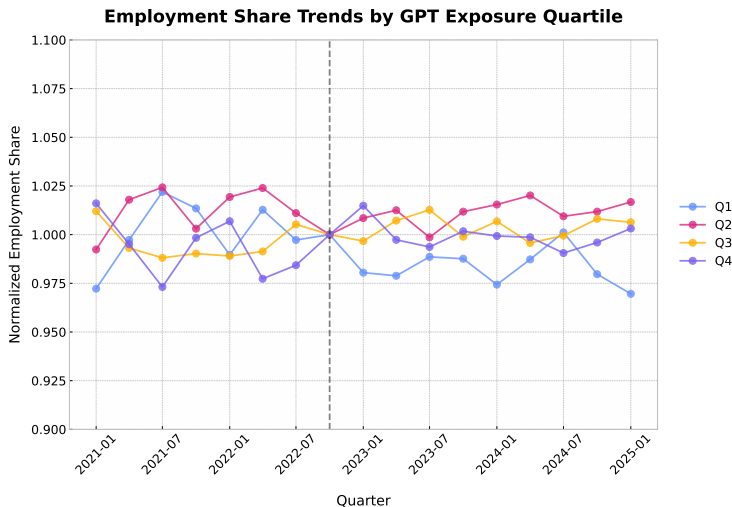
Preview of results

- ▶ ↓ in employment for 22-25 y/o AI-exposed workers
 - 13% ↓ with firm-time effects
- ▶ No employment decline for unexposed or experienced workers
- ▶ ↓ entry-level employment for *automotive* but not *augmentative* work
- ▶ Limited change in annual salary
- ▶ Robust across alternative samples (w/o tech sector, non-teleworkable, etc.)

Compared to prior work, use large-scale, real-time data

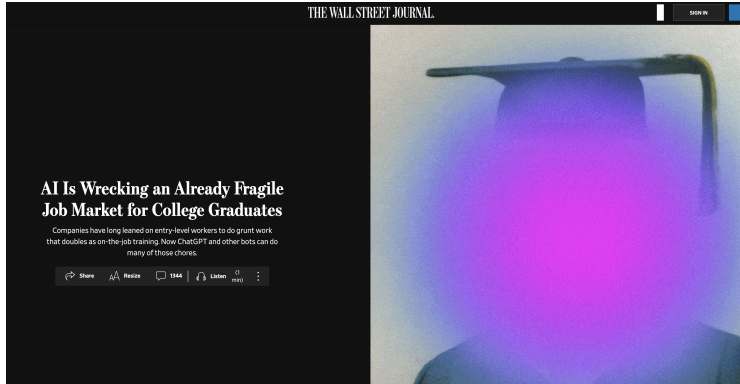
- ▶ **CPS data:** Chandar (2025); Dominski and Lee (2025); Lim et al. (2025); Eckhardt and Goldschlag (2025); Gimbel et al. (2025)
 - Not much evidence of widespread labor market disruption
 - Very small samples for individual age-occupation cells
- ▶ **Other work:** Humlum and Vestergaard (2025); Hampole et al. (2025); Johnston and Makridis (2025)
 - Possibly increased overall hiring in exposed industries
 - Cannot look at time series for age-occupation in recent periods
- ▶ **ADP data real-time, large-scale, worker-firm panel**
 - Doshay and Bantock (2025); Hosseini and Lichtinger (2025); Klein Teeselink (2025)

Not seeing widespread job displacement in government data



Chandar (2025); Eckhardt and Goldschlag (2025); Gimbel et al. (2025)

But what about young workers? Not enough data



Despite warnings in business in media

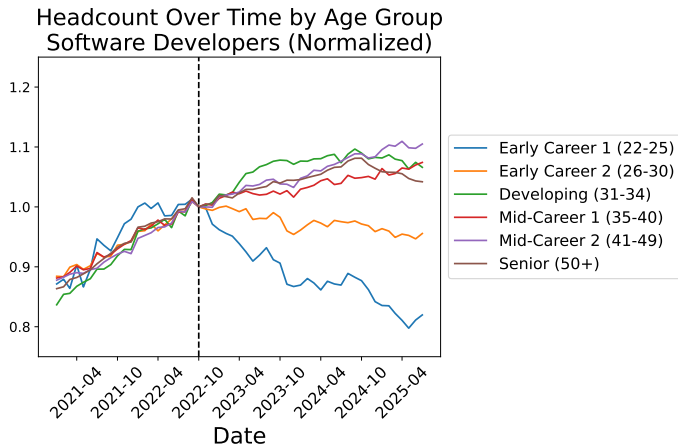


“AI could wipe out half of all entry-level white-collar jobs — and spike unemployment to 10-20% in the next one to five years”

How we study this

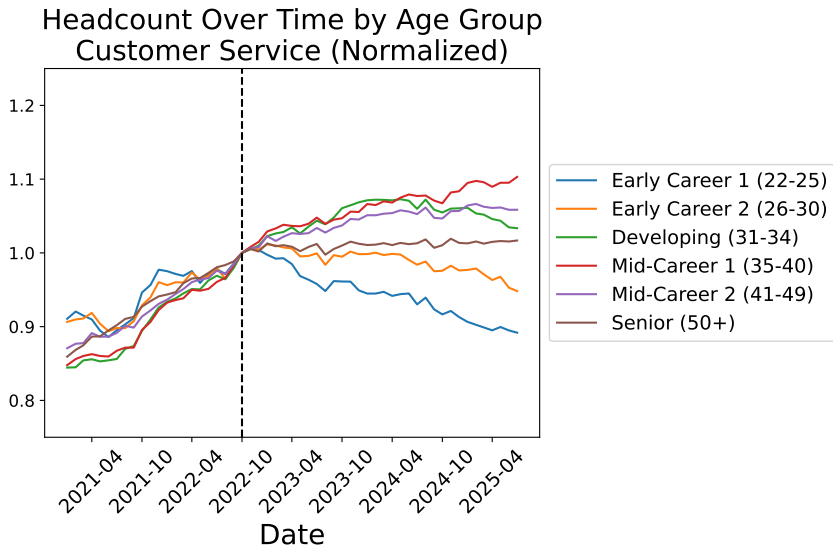
- ▶ ADP
 - Full-time, regular workers 22-70
 - Balanced sample of firms 2021-2025 (remove companies entering and leaving)
 - 3.5-5 million workers observed per month
- ▶ AI exposure measures
 - GPT-4 β from Eloundou et al. (2024)
 - Overall, automation, and augmentation measures from Anthropic Economic Index (Handa et al., 2025)

Fact 1: Employment Declines for Young, Exposed Workers

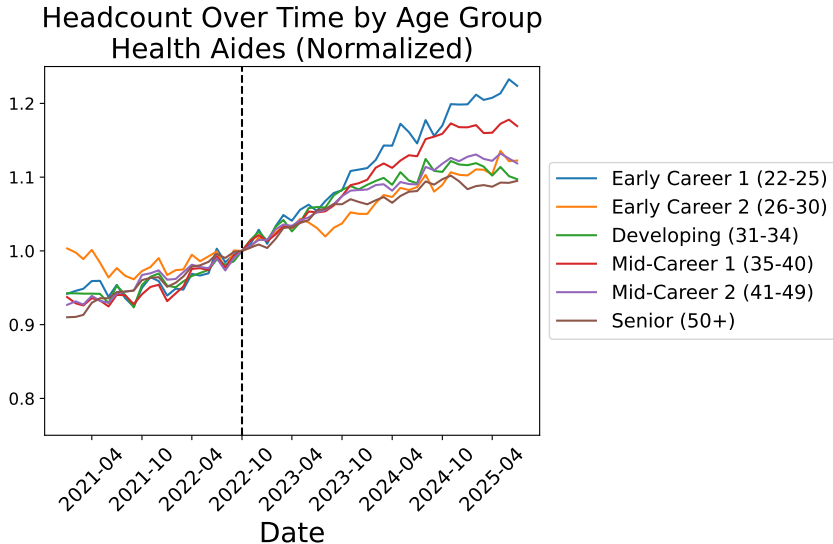


20% ↓ for 22-25 y/o software developers since late 2022

Similar findings for customer service

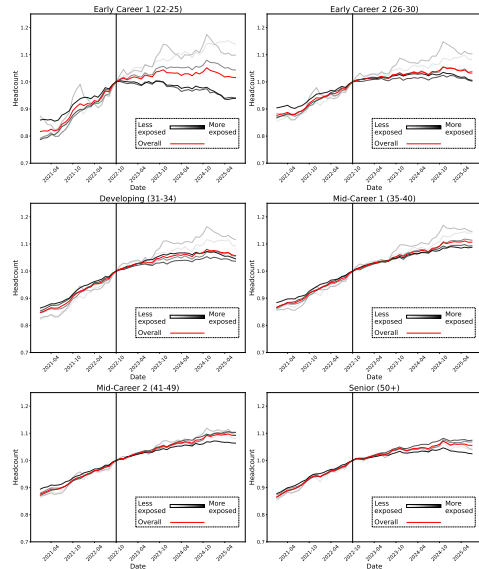


Opposite patterns for health aides

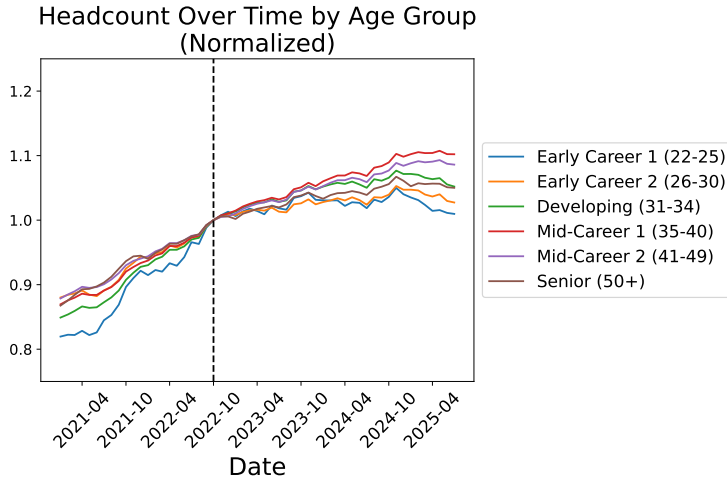


Findings hold more generally across exposure levels

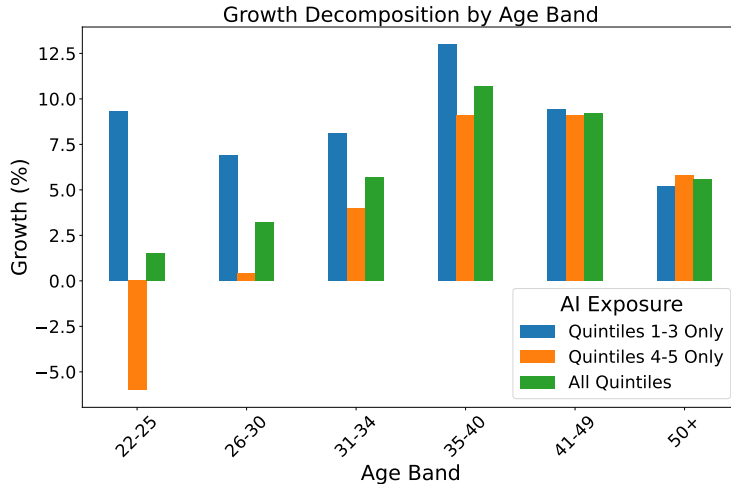
- Exposure from Eloundou et al. (2024)
- **Darker lines more exposed**



Fact 2: Overall a relative slowdown in entry-level hiring



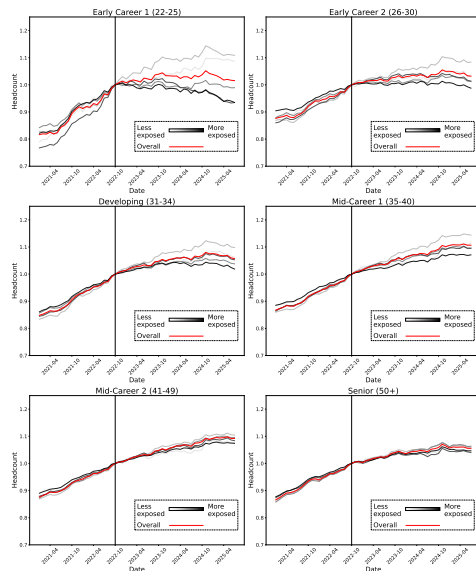
Slowdown driven by jobs exposed to AI



Could be driven by other changes in US economy. **Test alternatives.**

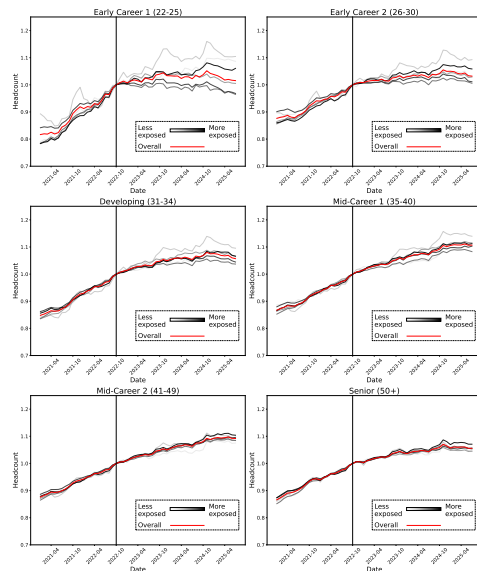
Fact 3: Employment $\downarrow$ in jobs where AI automates work

- ▶ By occupational **automation exposure** from Claude
- ▶ Ex: Software, accounting and auditing, information clerks



Fact 3: Employment $\uparrow$ in jobs where AI augments work

- By occupational **augmentation exposure**
- Ex: Management, nursing, maintenance and repair



Automation vs augmentation classification

Automotive Behaviors

AI directly executes tasks with minimal human involvement

Directive: Complete task delegation with minimal interaction

Illustrative Example: "Format this technical documentation in Markdown"

Feedback Loop: Task completion guided by environmental feedback

Illustrative Example: "Here's my Python script for data analysis – it's giving an IndexError. Can you help fix it? ... Now I'm getting a different error..."

Augmentative Behaviors

AI enhances human capabilities through collaboration

Task Iteration: Collaborative refinement process

Illustrative Example: "Let's draft a marketing strategy for our new product. ... Good start, but can we add some concrete metrics?"

Learning: Knowledge acquisition and understanding

Illustrative Example: "Can you explain how neural networks work?"

Validation: Work verification and improvement

Illustrative Example: "I've written this SQL query to find duplicate customer records. Can you check if my logic is correct and suggest any improvements?"

Fact 4: Robustness to Firm-Level Shocks

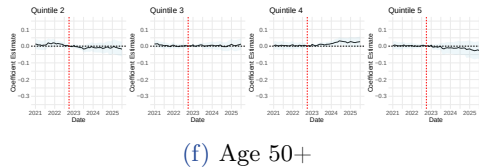
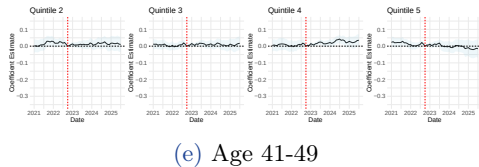
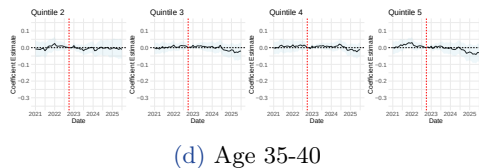
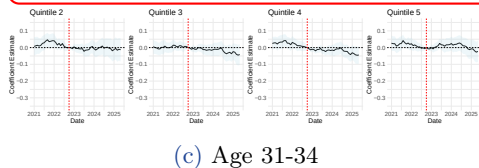
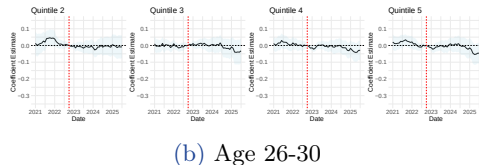
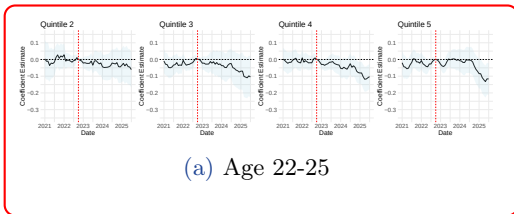
- ▶ Alternative explanation: industry- or firm-level shocks correlated with occupational sorting (e.g., interest rate changes).
- ▶ Event study Poisson regression with firm-time and firm-quintile fixed effects

$$\log(E[y_{f,q,t}]) = \sum_{q' \neq 1} \sum_{j \neq -1} \gamma_{q',j} 1\{t = j\} 1\{q' = q\} + \alpha_{f,q} + \beta_{f,t} + \epsilon_{f,q,t} \quad (1)$$

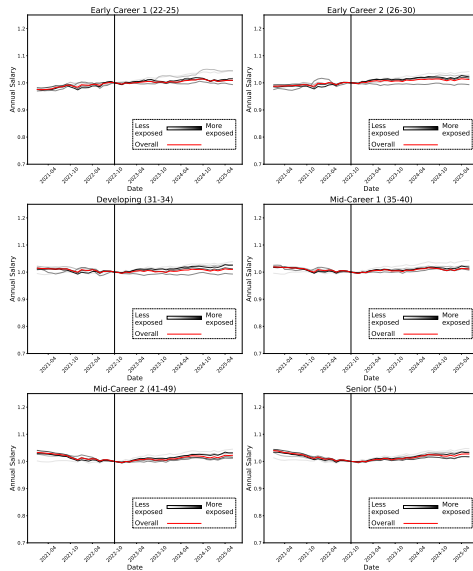
Run separately for each age group

- ▶ Absorbs shocks that affect *all workers* in a firm
 - Relative hiring changes for more- and less- exposed workers

Fact 4: 13% relative $\downarrow$ in employment for exposed young workers



Fact 5: No clear divergence in compensation



Fact 6: Trends hold under alternative analyses

1. Excluding tech sector [▶ 1](#) [▶ 2](#)
2. Teleworkable vs non-teleworkable jobs [▶ 1](#) [▶ 2](#)
3. College vs non-college workers [▶ 1](#) [▶ 2](#)
4. Men and women [▶ M](#) [▶ F](#)
5. Part-time and temporary workers [▶ View](#)

And more in the paper

AI and Labor Markets:
What We Know and Don't Know

Some claims about AI and the Labor Market

- ▶ The overall impact of AI on aggregate employment is likely small right now
- ▶ AI is likely diminishing hiring for AI-exposed entry-level jobs

Next steps:

- ▶ Building employment trackers using high-quality data
- ▶ Firm AI adoption data, ideally an A/B test on adoption

AI exposure measures are better than most people think

- ▶ Tomlinson et al. (2025) find 70-90% correlation between Copilot usage and Eloundou et al. (2024) exposure
- ▶ Exposure predicts employment changes

Next steps:

- ▶ Actual large-scale data from AI labs on usage by occupation

Gathering new evidence on where we expect greatest AI progress

- ▶ Ongoing work from Brynjolfsson, Halperin, Ramani, Bommasani, others
- ▶ GDPval (Patwardhan et al., 2025), Apex from Mercor

Next steps:

- ▶ Prediction markets for future disruption by occupation?

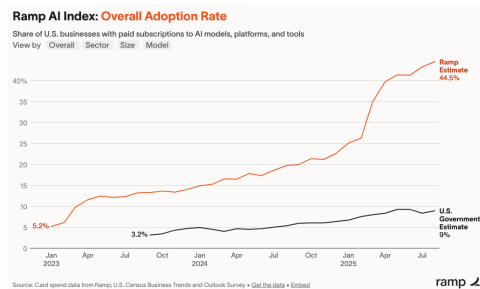


More areas for data

- ▶ Other countries?
- ▶ Firm adoption?
- ▶ Jobs with future labor demand?

Next steps:

- ▶ Better data collection and modeling



What is happening with education?

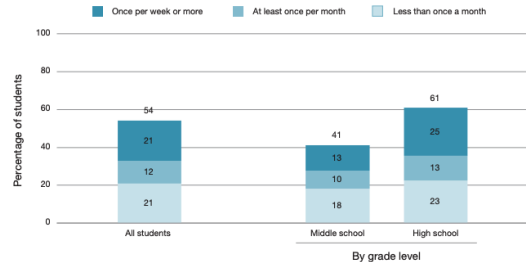
- ▶ Changing major choices? Career choices?
- ▶ Impacts on learning?
- ▶ Changes in curricula?
- ▶ Personalized learning?

Next steps:

- ▶ Need a lot more data

FIGURE 1

Student-Reported Frequency with Which They Use AI for Schoolwork

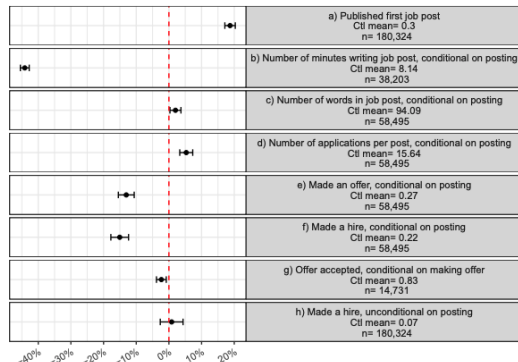


How does AI affect labor market matching?

- ▶ Reduces frictions?
- ▶ Or harms matching in equilibrium?

Next steps:

- ▶ Data on health of matching process



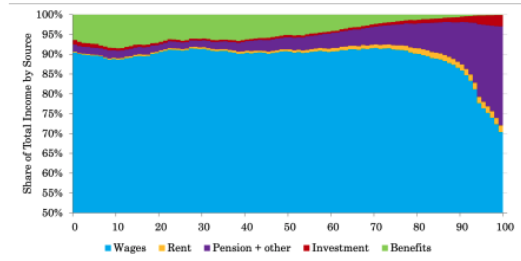
Wiles and Horton (2025)

Income and wealth inequality?

- ▶ Labor vs investment earnings (Rockall et al., 2025)

Next steps:

- ▶ Data from other countries, counterfactuals

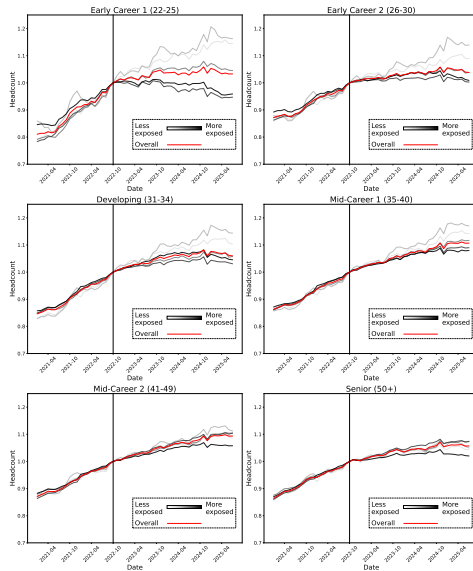


More empirically-calibrated theory and counterfactuals

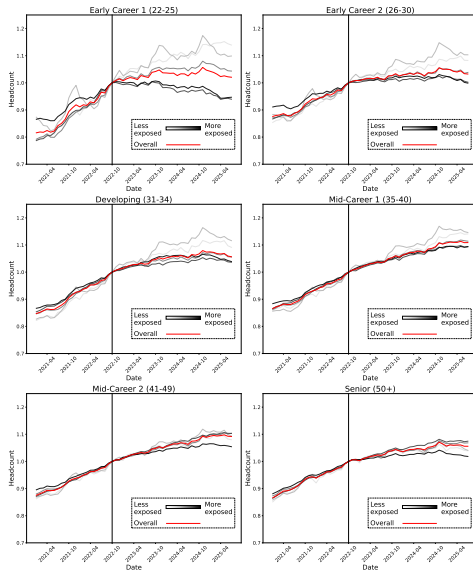
- ▶ Structural models of labor market impacts
- ▶ Policy counterfactuals
- ▶ Empirically calibrated

Appendix

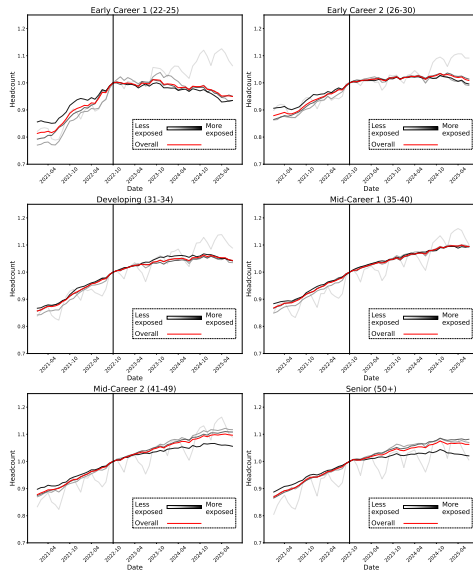
No IT sector (NAICS 51) [▶ Back](#)



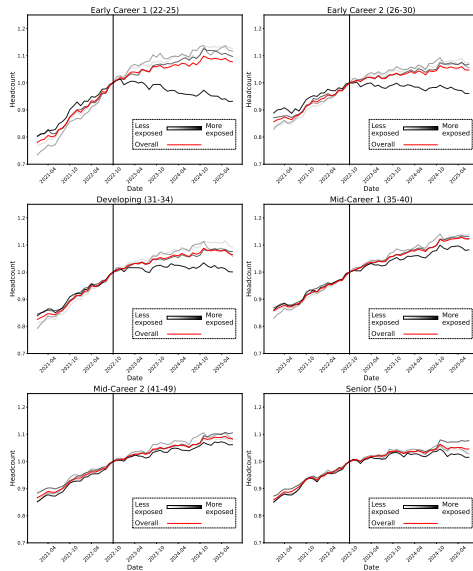
No computer occupations (SOC code 15-1) [▶ Back](#)



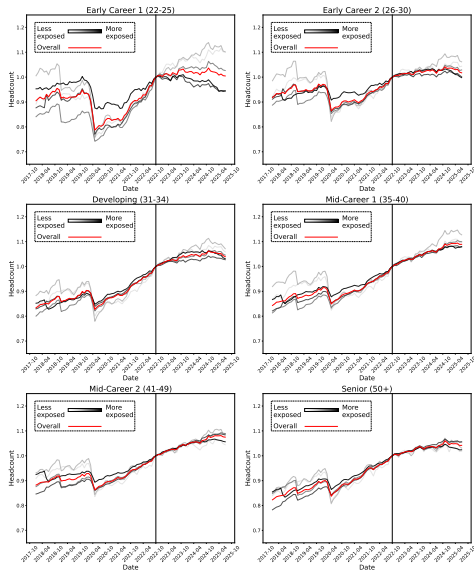
Teleworkable jobs [▶ Back](#)



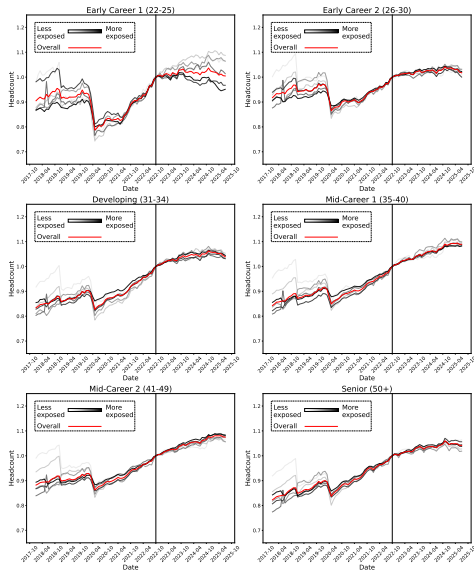
Non-teleworkable jobs [▶ Back](#)



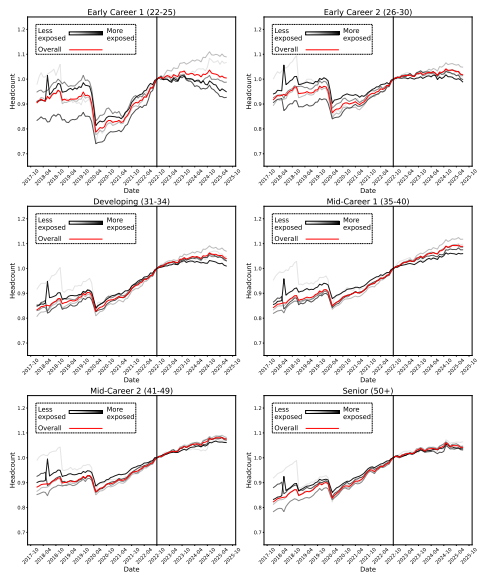
Longer horizon [▶ Back](#)



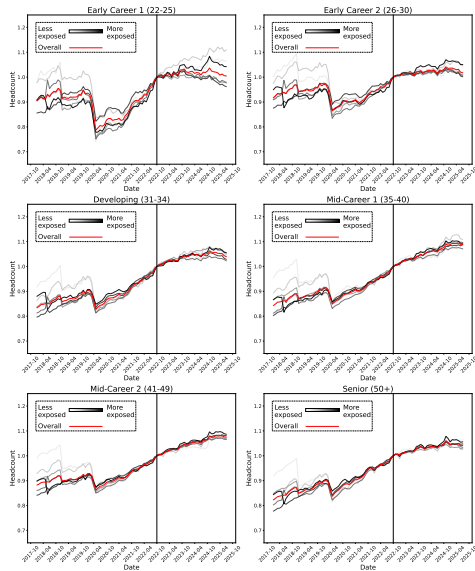
Longer horizon - Claude

[▶ Back](#)

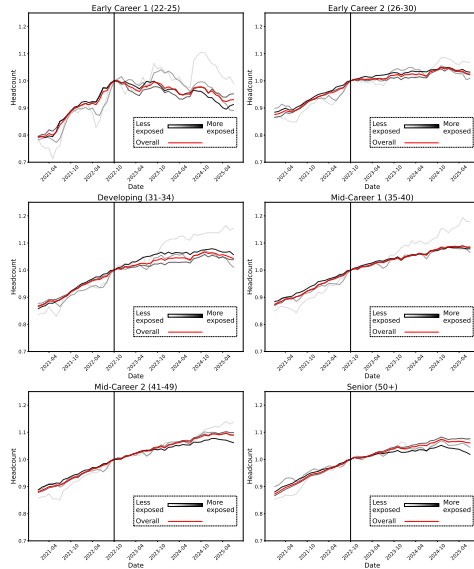
Longer horizon - Automation

[▶ Back](#)

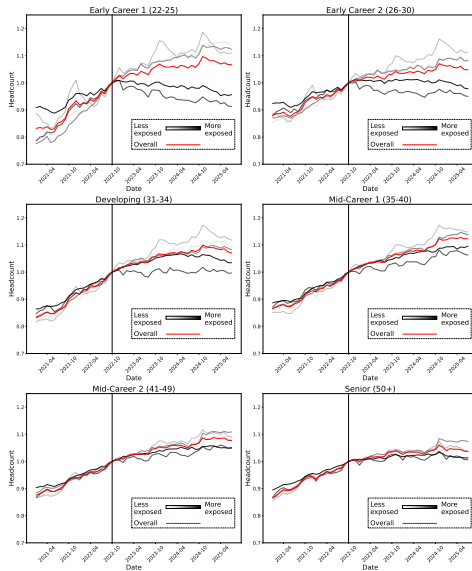
Longer horizon - Augmentation

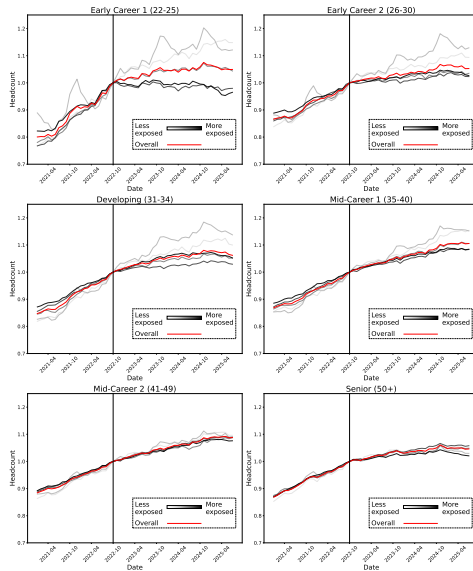
[▶ Back](#)

Greater than 70% college educated [▶ Back](#)

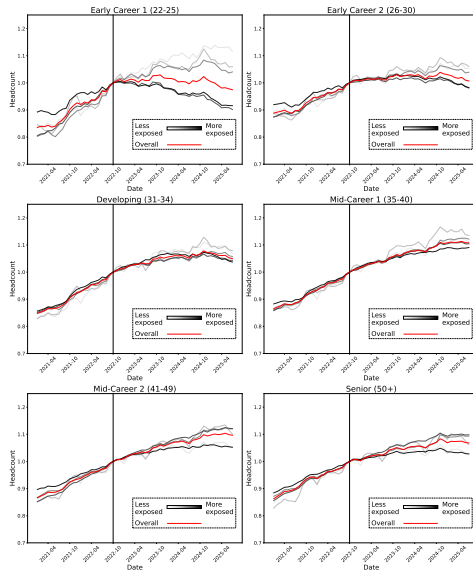


Less than 30% college educated [▶ Back](#)

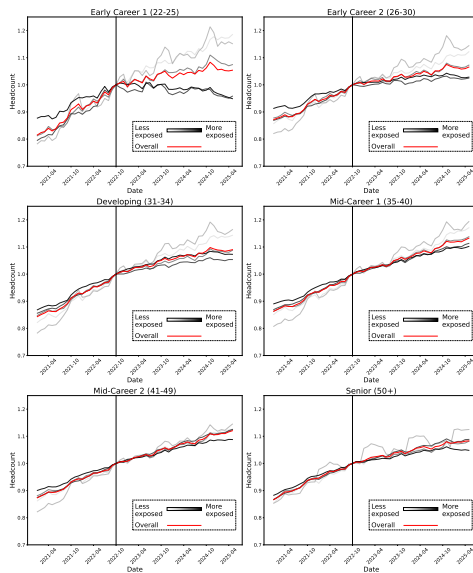




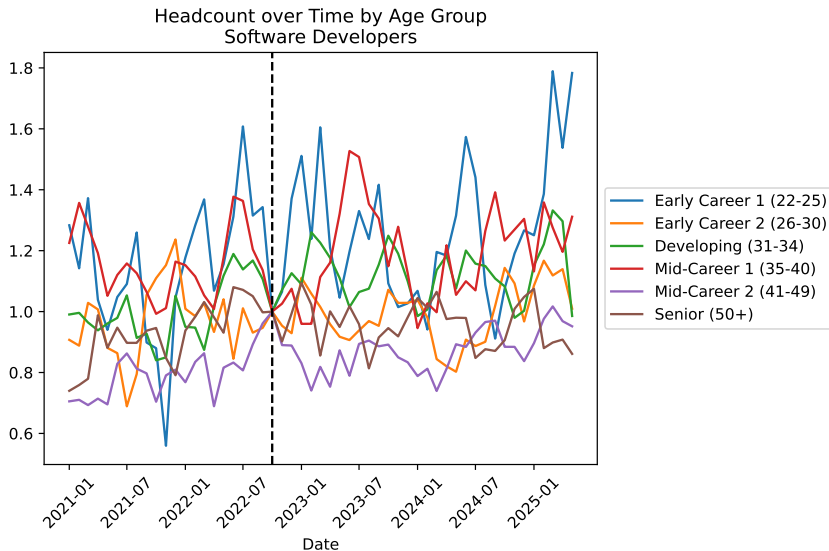
Women [▶ Back](#)



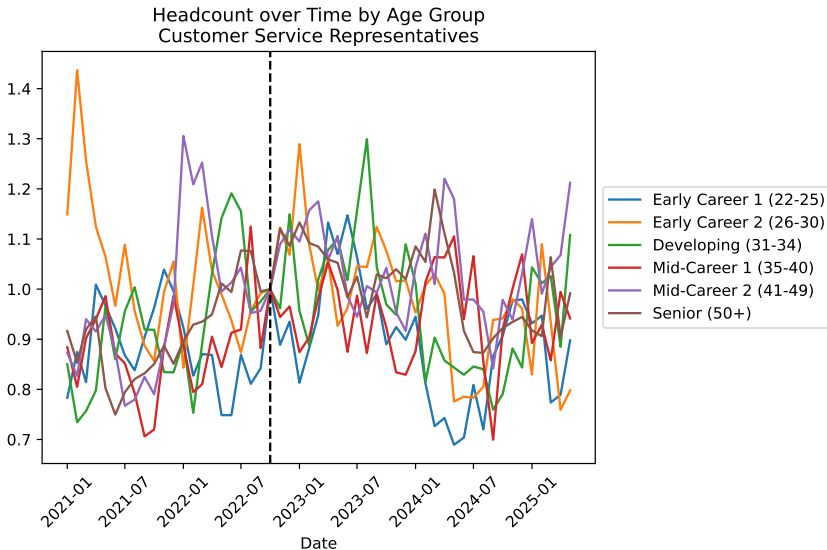
Including part-time and temporary workers [▶ Back](#)



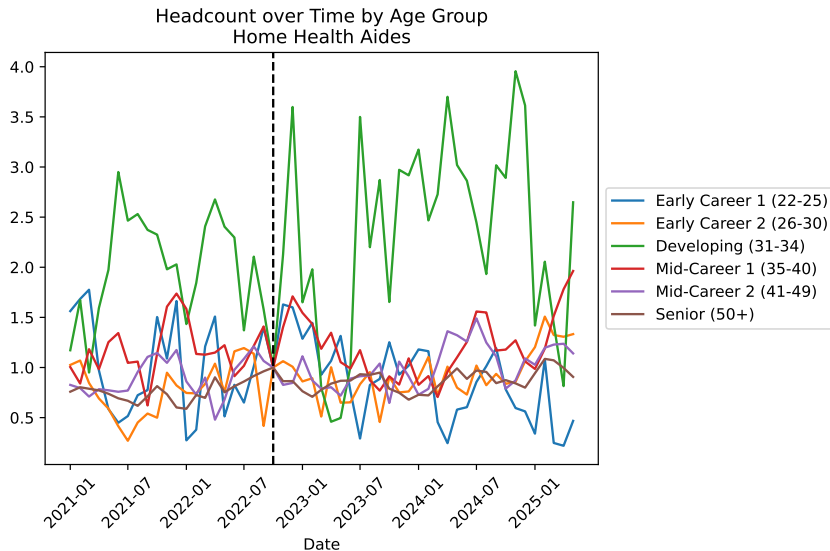
Software developers in the CPS

[▶ Back](#)

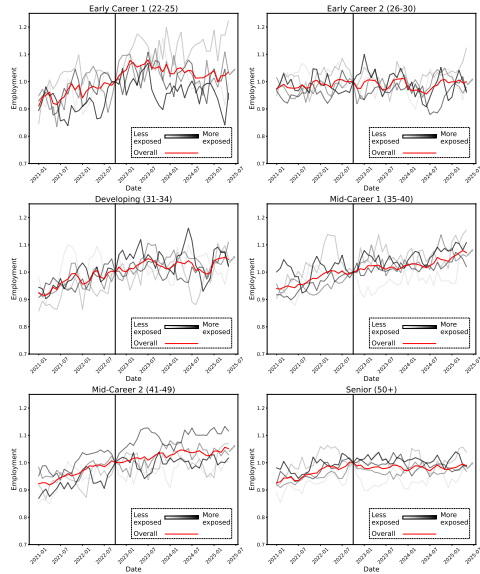
Customer service in the CPS [▶ Back](#)



Health aides in the CPS [▶ Back](#)



By exposure quintile in the CPS

[Back](#)

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