Ahn & Carollo:
“AI and Labor-Market Reallocation”

Discussion by Lukas Freund

Boston College

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Rapid progress in AI calls for improved measurement infrastructure

We Must Act Now

A Statement on AI's Transformation of the Economy

1. **AI may become radically more powerful over the next 10 years.**
2. **This could drive an unprecedented transformation of our economy, larger than the Industrial Revolution, but unfolding over a vastly shorter time frame. It could bring risks, including large-scale job displacement, as well as opportunities such as major gains in living standards.**
3. **Economists, policymakers and technology leaders must act now to understand the economics of transformative AI and to build the incentives, guardrails, and institutions needed to steer AI in a direction that complements humans and benefits society.**

July 13, 2026

Nearly 200 Economists and Tech Leaders Warn of A.I. Threats

A letter calls for policymakers to do more to understand and respond to potential disruptions from artificial intelligence.

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Jack Clark, a co-founder of Anthropic, is among the signers of a statement warning that A.I. could transform the economy faster than previous technologies. Saul Loeb/Agence France-Presse — Getty Images

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Measurement is urgent: Infrastructure to detect *when* and *where* disruption appears.

Theory of automation suggests we need to track multiple margins of change

- **Possibility of large-scale disruption is real...**
  - automation $\rightarrow$ few people left working as weaver, elevator operator, typist, ...
  - task-based models: machines *displace* labor ($\neq$ factor-augmenting)

  [Acemoglu-Autor, 2011; Acemoglu-Restrepo, 2018; ...]

- **...but neither inevitable nor reducible to job loss**

  [Autor, 2015; Acemoglu-Restrepo, 2019; Adao et al., 2024; Hampole et al., 2025; Freund-Mann, 2025]

  1. **Exposure** to AI does not necessarily translate into *job loss*
     - substitution effect: does AI automate *all* or *part* of the tasks in the job?
     - scale effect: are productivity gains large enough and demand sufficiently elastic to raise (sectoral) labor demand?
  2. **Job transformation** (changing task content of work) **shifts skill returns**
  3. **New types of tasks and jobs emerge**

  $\Rightarrow$ Workers need to **reallocate** across tasks & jobs

> **Measurement needs to encompass multiple margins of labor market change.**

What do we already know from the empirical literature?

1. At the **aggregate level**, despite rapid adoption, no flashing warning lights

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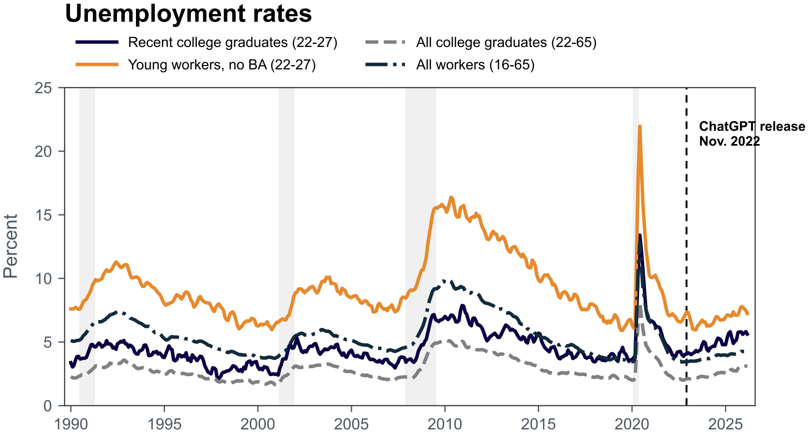


Notes. Fed New York, "The Labor Market for Recent College Graduates" - updated through March 2026; CPS (IPUMS). Rates are seasonally adjusted and smoothed with a 3m-MA.

What do we already know from the empirical literature?

▸ Data on software developers

1. At the **aggregate level**, despite rapid adoption, no flashing warning lights

2. **It's very hard to identify the *causal* effect of AI** given concurrent tech boom-bust hiring cycle, interest rate hikes, remote work, etc.
   $\rightarrow$ focus of literature is to try resolve this identification challenge

3. **Micro evidence** points to AI-induced disruption in narrow slices of the labor market
   - careful studies: (modestly-sized) **relative declines in hiring but not separations for junior workers** in exposed occupations *[e.g., Brynjolfsson-Chandar-Chen, 2025]* and at adopting firms *[e.g., Hosseini-Lichtinger, 2025; Klein Teeselink, 2025]*
   - questions remain around timing *[Frank et al., 2025]*, external validity *[Humlum-Vestergaard, 2026]*, driver *[Lambert-Schindler, 2026]*

This paper & my discussion

- **This paper:** Combine standard occupational AI exposure measures & an “adoption” proxy with CPS microdata
  $\rightarrow$ document labor market flows across worker groups
  1. Job finding rates fall for most-exposed occupations, separations don’t rise
  2. Within-job activity switching rises
  3. AI is putting upward pressure on the natural unemployment rate

> **Main contribution:** systematic measurement of AI-era labor market, along several margins, with accounting discipline that ensures “adding up” to aggregates.

- **Discussion:** 2 comments on what the approach can (and cannot) tell us about AI.

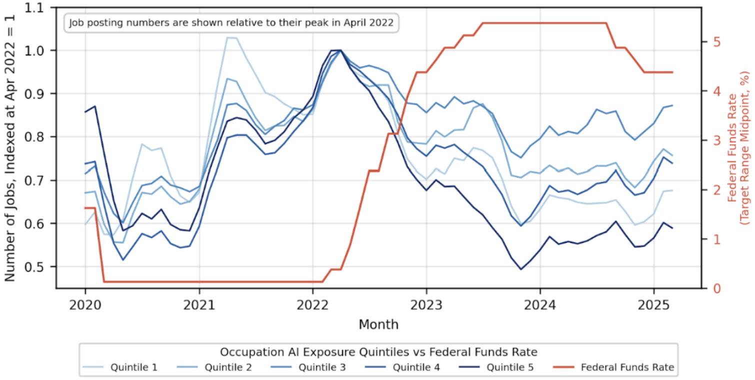
Comment #1: Causal language in the paper should be tempered

- **Every headline in the paper is causal in form**
  - unemployment gaps “driven by” exposure, dispersion “owing to AI,” a natural rate raised “by AI,” etc.

- **But there are many things happening in the economy aside from AI**
  - tech hiring boom-bust cycle, rapid rate-hiking cycle, remote work, etc.

One example: rate hike cycle started just before ChatGPT release

Chart 3: Federal Funds Rate vs. Job Postings by AI Exposure Quintile (Jan 2022 - Oct 2023)



Sources: Lightcast, Eloundou et al. (2024), FRED

Notes. Iscenko-Millet (2026).

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  - unemployment gaps "driven by" exposure, dispersion "owing to AI," a natural rate raised "by AI," etc.
- **But there are many things happening in the economy aside from AI**
  - tech hiring boom-bust cycle, rapid rate-hiking cycle, remote work, etc.
- **The paper does little to justify that causal reading**
  - very limited discussion of threats to causality & few attempts to address them (e.g., time and industry FEs in two regressions, but even those only absorb common shocks)
  - trying to isolate *effects* of AI is focus of peer papers: firm and time FEs, within-firm within-occupation seniority comparisons, pre-2022 placebos, statistical horse-races, etc.
- Language we employ matters: AI's labor market impact is a very salient topic

> **The paper measures the AI era (not the *effect* of AI).**

Comment #2: Adjust natural-unemp.-rate "counterfactual" for common trends

Paper's exercise & interpretation

Four groups: exposure L/H × adoption L/H

ESTIMATE

Smooth trend rates of job loss, $s_{g,t}$, & job finding, $f_{g,t}$

→

CONSTRUCT

Group natural rates

$$u^*_{g,t} = \frac{s_{g,t}}{s_{g,t} + f_{g,t}}$$

Aggregate: $\approx$ +20bps

→

ACCOUNTING

Sequentially freeze each group's $u^*_{g,t}$ at its Dec. 2022 value

$\rightarrow$ **High-exposure workers raise the natural rate by about +17bps**

Interpretation: upside pressure on the natural rate driven by LLMs

Alternative

Data: much of post-2022 job-finding decline is *common* across groups

Exercise: replace the high-exposure groups' job-finding decline with the *low-exposure decline*

$\rightarrow$ **About +6bps reflects faster deterioration in high-exposure job finding**

Interpretation: captures anything causing differential decline in high-exposure job finding

Summary

▸ Additional comments

Valuable analysis that systematically tracks the AI-era labor market.

- **Suggestions for paper:**
  1. Embrace that the analysis is not causal – systematic tracking of flows for differentially exposed groups is a useful descriptive
  2. Account for common trends when constructing accounting-style natural rate counterfactuals

Thank You!

Extra Slides

Some further suggestions (free disposal!)

- De-emphasize claims à la “exposed workers look better — lower unemployment and separations, higher attachment.” This is just the well-known skill gradient.
- The activity-switch measure is very interesting – worth investing in improved (understanding of) measurement, e.g.:
  - what’s the threshold for “yes”? starting to use ChatGPT? return-to-office schedule? promotion?
  - around half of CPS interviews are proxy responses - is the increase robust if those are excluded?
- Stress test the trend-cycle filter: robustness exercises suggest that the filter tends to over-attribute cyclical variation to trend
- To speak to age-gradient finding in the literature, can use CPS demographics data to add age split within exposure groups

Job postings for software developers are recovering