Federal Reserve Bank of Cleveland Working Paper Series

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Working Paper No. 26-24

September 2026

Suggested citation: Rinz, Kevin. 2026. "The Recent Evolution of AI-Related Labor Demand." Working Paper No. 26-24. Federal Reserve Bank of Cleveland. https://doi.org/10.26509/frbc-wp-202624.

Federal Reserve Bank of Cleveland Working Paper Series
ISSN: 2573-7953

The Recent Evolution of AI-Related Labor Demand*

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September 17, 2026

Abstract

AI mentions in US job advertisements have increased substantially since the beginning of 2024. The increase is concentrated in occupations more intensely exposed to the capabilities of large language models: one additional standard deviation of exposure is associated with a 3.1 percentage point increase in the rate at which job ads mention AI. Alongside this increase in AI mentions, more exposed occupations have seen job postings stabilize after a period of relative decline, posted wages rise, and hires and separations rise, all relative to less exposed occupations. Realized wages for new hires have risen consistent with posted wages, while wages of continuously employed workers have declined, possibly because exposed occupations have seen labor markets become less tight.

Keywords: artificial intelligence, labor demand, skills, job postings
JEL codes: J23, J24, O33.

*Any views, opinions, and conclusions expressed herein are those of the author and do not necessarily reflect the views of the Federal Reserve Bank of Cleveland or the Federal Reserve System. I thank Kevin Jacobson and Carol Moseley for helpful research assistance and seminar participants at the Federal Reserve Bank of Cleveland and Carnegie Mellon University for useful feedback. The analysis underlying this paper was conducted with the help of artificial intelligence, specifically Claude Opus 4.8, Claude Opus 5, and Claude Fable 5. Contact: kevin.rinz@clev.frb.org

Artificial intelligence (AI) capabilities are expanding rapidly, raising questions about potential labor market consequences. Prior work suggests that aggregate labor demand has largely held up (Alekseeva et al., 2021; Acemoglu et al., 2022; Hampole et al., 2025; Humlum and Vestergaard, 2025), though estimated effects on employment and earnings sometimes conflict (Johnston and Makridis, 2026; Azar et al., 2025) and much of this work considers a period when frontier models were meaningfully less capable than they are today.[1] Other work points to possible exceptions for narrower groups, like early career workers (Brynjolfsson et al., 2025; Hosseini and Lichtinger, 2025; Tucker, 2026; Orr et al., 2026) or freelancers (Hui et al., 2024). In this paper, I examine how occupation-level AI exposure relates to job ad content, posted wages, realized wages, and worker flows through 2026Q2.[2] Job ads alone point to stable to strengthening labor demand alongside growing employer interest in AI; however, incorporating worker flows suggests labor markets have become less tight in more exposed occupations.

Evidence from Job Ads

After gradually trending up for years, mentions of AI-related terms in online advertisements for full-time jobs collected by Lightcast spiked in 2024Q3 (Figure 1a). This spike consisted almost entirely of mentions of the term "artificial intelligence" (shown in green) and occurred mostly in ads for jobs in computer and mathematical occupations (light green) like software developers, data scientists, and computer and information research scientists.[3] The spike was 95 percent driven by within-employer shifts in language (Table A1), and these mentions quickly receded. In aggregate, they were replaced by mentions of the initialism "AI" in combination with terms that are more generic or suggestive of company or product branding

[1] For example, Claude Code and Codex became widely available in May 2025. Claude Fable and GPT-5.6 Sol, each of which has had access restrictions imposed by the federal government, were released in June and July 2026, respectively.

[2] Though posted wage data are subject to some practical and conceptual caveats (Batra et al., 2023), these data do track the wages of new hires in aggregate (Hazell and Taska, 2025).

[3] Figure A1 shows top occupations mentioning AI-related terms over the last year and their rates of mentioning AI during the 2024Q3 spike.

rather than tied to specific skills (shown in orange).[4] Aggregate mentions of specific AI skills have continuously evolved over this period and accelerated in 2026. Mentions of AI in the context of disclosing employer use of AI in hiring processes (shown in purple) have also increased recently.[5]

Employer-occupations that adopted the term "artificial intelligence" in 2024Q3 largely stopped using it in subsequent quarters, and few of them moved on to more specific AI language. Of those that posted ads again the next quarter, about a third no longer mentioned "artificial intelligence" or any other term related to AI (Figure 1b). The shares of employer-occupations posting ads mentioning "artificial intelligence" declined further in subsequent quarters, and only about 2 percent of them mention a more specific AI-related term in a job ad six quarters later.

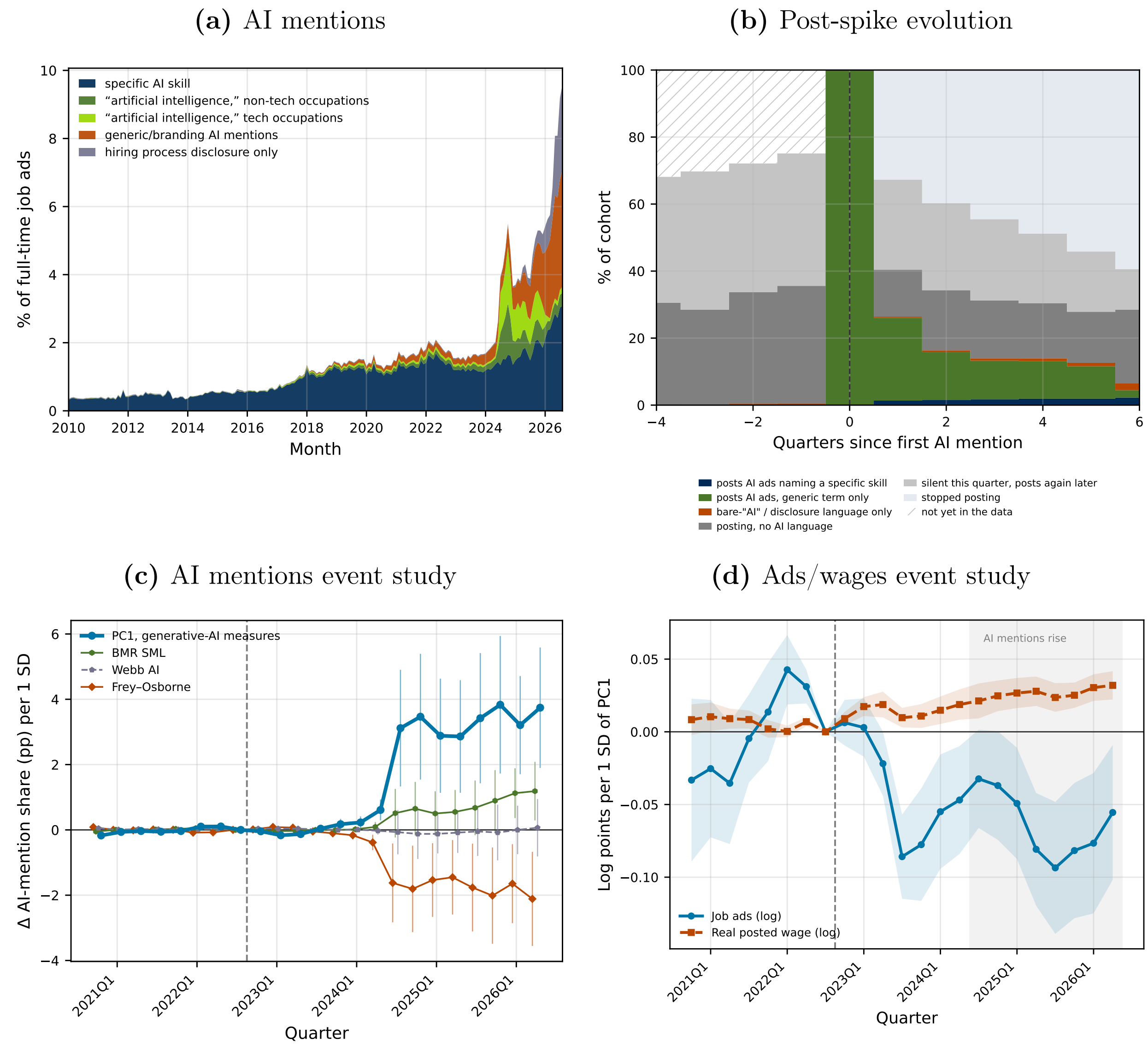
The short-lived nature of the spike in "artificial intelligence" mentions and its concentration within tech occupations suggest that the spike represented a temporary shift in how employers describe jobs rather than temporary interest in AI skills. Language reverts even within employer-occupation cells, while survey-measured AI adoption has grown faster than AI mentions since the spike (Figure A2). Employers may have learned that AI skills are becoming table stakes, thus making it unnecessary to discuss them explicitly in ads. Why did the spike happen in 2024Q3? That timing aligns with the May 2024 release of GPT-4o, which put frontier capabilities in free products. This could have increased awareness and understanding of their value or the appeal to employers of emphasizing AI. OpenAI released its first reasoning model, o1, in September 2024, but that was already at the peak of the spike, too late to have driven it.

Increased mentions of AI-related terms tend to appear in ads for jobs that are more exposed to AI via large language models (LLMs). Recent work has quantified occupational

[4] Examples include terms like AI company, AI-native, predictive AI, harness AI, AI products, and similar constructions.

[5] See Appendix B for discussion of how these different types of mentions are identified. That appendix also discusses analysis comparing the content of AI and non-AI ads over time, which shows modest shifts alongside the spike in AI mentions that subsequently revert.

Figure 1: AI Exposure and Job Ads



Source: Lightcast and author's calculations.

Notes: Panel (a) plots the monthly share of ads for full-time jobs containing each type of AI reference: a skill drawn from a list of AI-related terms provided by Lightcast; the phrase "artificial intelligence" as the only such term, shown separately for computer and mathematical occupations; uses of the initialism "AI" in combination with various words suggesting branding, generic, or non-technical uses; and language disclosing an employer's use of AI in hiring. The categories are mutually exclusive, so the bands sum to the overall mention rate. Panel (b) follows the employer-occupation pairs whose first AI mention was the phrase "artificial intelligence" in 2024Q3 and classifies what each posted in the quarters around it. Panels (c) and (d) report β_t from Equation 1 and 95 percent confidence intervals with 2022Q3 omitted and exposure measured in standard deviations; standard errors are clustered on occupation. Panel (c) compares the first principal component of the exposure measures based on LLMs with the three measures not based on LLMs. Monthly data in panel (a) end August 2026; quarterly data in other panels end 2026Q2.

exposure to AI based on the ability of LLMs to perform relevant skills or tasks (Felten et al., 2021, 2023; Eloundou et al., 2024; Handa et al., 2025; Eisfeldt et al., 2025; I focus on the first principal component of these measures); uses described in AI patents (Webb, 2020); and the probability that pre-LLM machine learning tools could fully automate jobs (Frey and Osborne, 2017) or automate constituent tasks (Brynjolfsson et al., 2018).[6] I incorporate these exposure measures into descriptive event-study regressions of the form

$$y_{ot} = \sum_{t \neq 2022q3} \beta_t \left(\text{Exposure}_o \times 1[\text{Quarter=t}]\right) + \alpha_o + \delta_t + \epsilon_{ot} \tag{1}$$

where outcomes y_{ot} include the share of job ads mentioning AI-related terms, the total number of job ads posted, and posted wages; $Exposure_o$ is a demeaned exposure measure in standard deviation units; α_o represents occupation fixed effects; and δ_t represents quarter fixed effects.[7] The coefficients β_t represent the change in outcome y_{ot} from the quarter before ChatGPT's release (2022Q3) to quarter t for each standard deviation of AI exposure in occupation o.[8] Figure 1c shows that the share of job ads mentioning AI-related terms increased by about 3 percentage points per standard deviation of occupational exposure to LLM capabilities in 2024Q3, rising to nearly 4 percentage points in subsequent quarters, suggesting that LLM exposure measures dynamics that employers are responding to now.[9] Other exposure measures have more muted or even negative correlations with AI mentions in job ads.

[6] Appendix C describes each measure (Table C1), reports their pairwise correlations and most exposed occupations (Table C2), and reproduces the Figure 1 event studies measure by measure (Figure C1). Felten et al. (2021) is formulated based on more general "AI applications" rather than LLM capabilities specifically, but the applications align closely with LLM capabilities and the exposure measure is highly correlated with the other LLM-based exposure measures.

[7] I use a balanced panel of occupations, and standard errors are clustered at the occupation level. I include occupations with at least 125 job ads (or 25 ads with wage information when analyzing posted wages) every quarter.

[8] Controls for stated education and experience requirements, which are potentially endogenous to exposure, change the estimates very little (Figure A3) and are omitted from the baseline; state-quarter fixed effects also have little effect.

[9] All LLM-exposure results are robust to excluding skilled trades occupations, which have low exposure to AI in terms of its ability to perform their tasks but high exposure in terms of increased demand amid the buildout of AI-related infrastructure.

Alongside increased mentions of AI, the relative quantity of ads in more vs. less LLM-exposed occupations roughly stabilized, following a period of decline that began prior to ChatGPT's release (Figure 1d). Since 2024Q3, real posted wages continued rising on a trajectory that began right after ChatGPT's release: posted wages were 1.7 percent higher per standard deviation of exposure by 2023Q1, reaching 3.2 percent by 2026Q2.[10] The increases in AI mentions and posted wages, in particular, appear to be driven by the highest-exposure occupations (Figure A4); excluding tech occupations from the analysis does not meaningfully alter the pattern of estimates reported here. While there is an ad-level AI posted wage premium (Figure A5), the wage increase in more LLM-exposed occupations is, if anything, clearer for ads not mentioning AI (Figure A6).

Job ads show increased discussion of AI alongside stable quantities of ads and rising posted wages. Together, these do not suggest collapsing labor demand, consistent with prior work. However, posting ads is not the same as hiring, wage posting can be strategic and does not necessarily translate cleanly into realized wages, and tracking ads does not account for potential changes in separations or employers' desire to replace departed employees. These are all important considerations for understanding potential shifts in labor demand, and I turn to the Current Population Survey (CPS) to explore them further.

Evidence from the CPS

Following the introduction of ChatGPT, more LLM-exposed occupations saw modest increases in both employment outflows (Figure 2a) and inflows (Figure 2b) on the order of 3–5 percent of pre-period averages.[11] Outflows have been largely to non-employment, with

[10]The share of job ads posting a wage increases substantially over this period, raising potential concerns about changing selection into wage posting. Appendix D shows that these wage estimates survive sample restrictions, reweighting, and bounding designed to address it.

[11]Due to smaller sample sizes, I use fewer and longer time periods in the CPS analysis: 2020Q4–2022Q3 (pre-ChatGPT), 2022Q4–2024Q2 (post-ChatGPT, pre-AI mention spike), and 2024Q3–2026Q2 (since AI mentions spiked). Regressions with labor flows as outcomes are estimated at the occupation-quarter level with flows expressed per 100 employed and cells weighted by pre-period employment. Estimates change little when controls for workers' outside options (Borusyak et al., 2023) are included (Figure A7), though high

most to non-participation. Among transitions to unemployment, almost all have been due to layoffs; there is no evidence of increased quits to unemployment. Inflows are also primarily from non-employment, though most are from unemployment rather than non-participation. Point estimates for outflows are slightly larger than for inflows, suggesting net flows out of more exposed occupations, but the difference is not statistically significant. The churn (gross flow) rate is over 0.4 percentage points higher after the introduction of ChatGPT and nearly 0.6 percentage points higher during the period in which AI mentions in job ads rise.[12]

Estimated changes in the realized real wages of new hires are not distinguishable from zero, but point estimates are positive, reaching about 1 percent since AI mentions spiked. The confidence intervals for changes in realized wages generally contain the point estimates for changes in posted wages (Figure 2c). Wage changes for workers making job-to-job transitions are closer to zero. Wages of continuously employed workers not changing jobs fall by about 0.9 percent in the later post period, a statistically significant change. Their wages may have fallen because more LLM-exposed occupations saw labor market tightness decline over the same period, with unemployed workers per new job ad rising by about 9 percent per standard deviation of exposure (Figure 2d); more competition for fewer opportunities to change jobs translates into less upward pressure on wages for workers who stay in their jobs.[13]

Conclusion

Measures of occupational exposure to the capabilities of LLMs are capturing dynamics that employers are responding to now, as evidenced by increased mentions of AI in ads for jobs in more exposed occupations. On balance, the employer adjustments that this shift in job ad language represents have been associated with labor markets in which demand is modestly

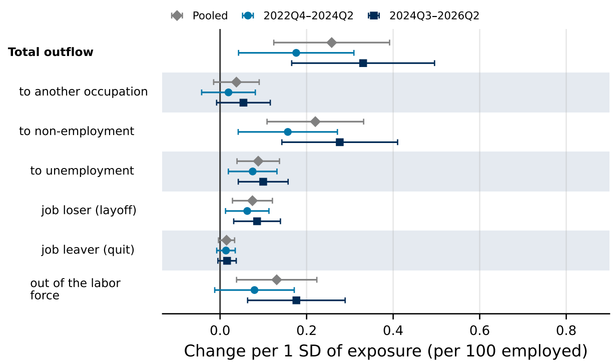
correlations between exposure and some outside option measures (Table A2) can make estimates less precise.

[12] Consistent with prior work (Brynjolfsson et al., 2025; Tucker, 2026), I find reduced hiring among younger workers relative to older workers, which leads to net outflows of younger workers from more exposed occupations. See Table A3. More exposed occupations also increase minimum experience requirements, but do not become more likely to list an experience requirement in their ads. See Figure A8.

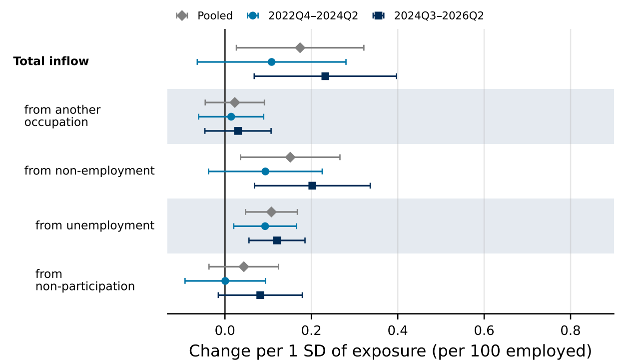
[13] Here, analysis of tightness uses new job ads posted during a period rather than the stock of current job openings, which is the concept measured by the Job Openings and Labor Turnover Survey.

Figure 2: AI Exposure, Employment Flows, and Earnings

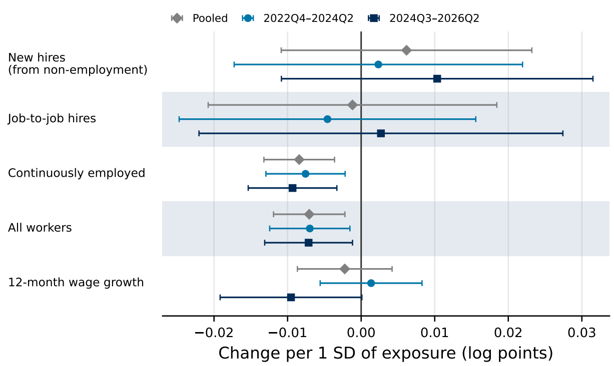
(a) Outflows



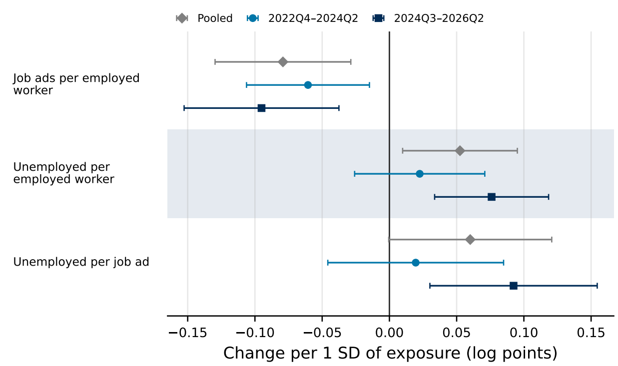
(b) Inflows



(c) log(real weekly earnings)



(d) Labor market tightness



Source: Current Population Survey, Lightcast, and author's calculations.
Notes: Plotted points are difference-in-differences estimates of the change in the dependent variable per standard deviation of AI exposure, measured relative to the pre-ChatGPT period (2020Q4–2022Q3), with 95 percent confidence intervals. Exposure is the first principal component of the exposure measures based on large language models, averaged to the Census occupation. The pooled estimate and the two post-period estimates come from separate regressions. Panels (a) and (b) use occupation-quarter cells built from month-to-month person links, expressed per 100 employed and weighted by pre-period employment; panel (c) uses individual weekly earnings records, in logs and deflated by the CPI-U; in panel (d), to avoid dropping cells with no unemployed CPS respondents, ratios of unemployed workers to job ads or to employment are instead estimated by Poisson regression of the form $E\left[y_{ot} \mid \cdot\right] = \exp\left(\sum_p \beta_p \left(\text{Exposure}_o \times 1[t \in p]\right) + \alpha_o + \delta_t + \ln D_{ot}\right)$, where y_{ot} counts unemployed workers or job ads and the denominator D_{ot} enters as an offset, so β_p is the change in the log ratio per standard deviation of exposure. All specifications include occupation and quarter fixed effects and controls for age group, sex, race and ethnicity, and education. Standard errors are clustered on occupation.

weaker relative to supply, with more LLM-exposed occupations seeing unemployment per new job ad rise by about 9 percent per standard deviation of exposure. Going forward, AI adoption by both workers and employers should be tracked alongside job ad language. In occupations like data scientists, software developers, and web developers, the typical quarter over the last year has seen AI mentioned in job ads at a lower rate than 2024Q3. AI has not become less important within these occupations since then, and it will be important to have measures available that distinguish firms' production processes from their hiring or other human resources practices.

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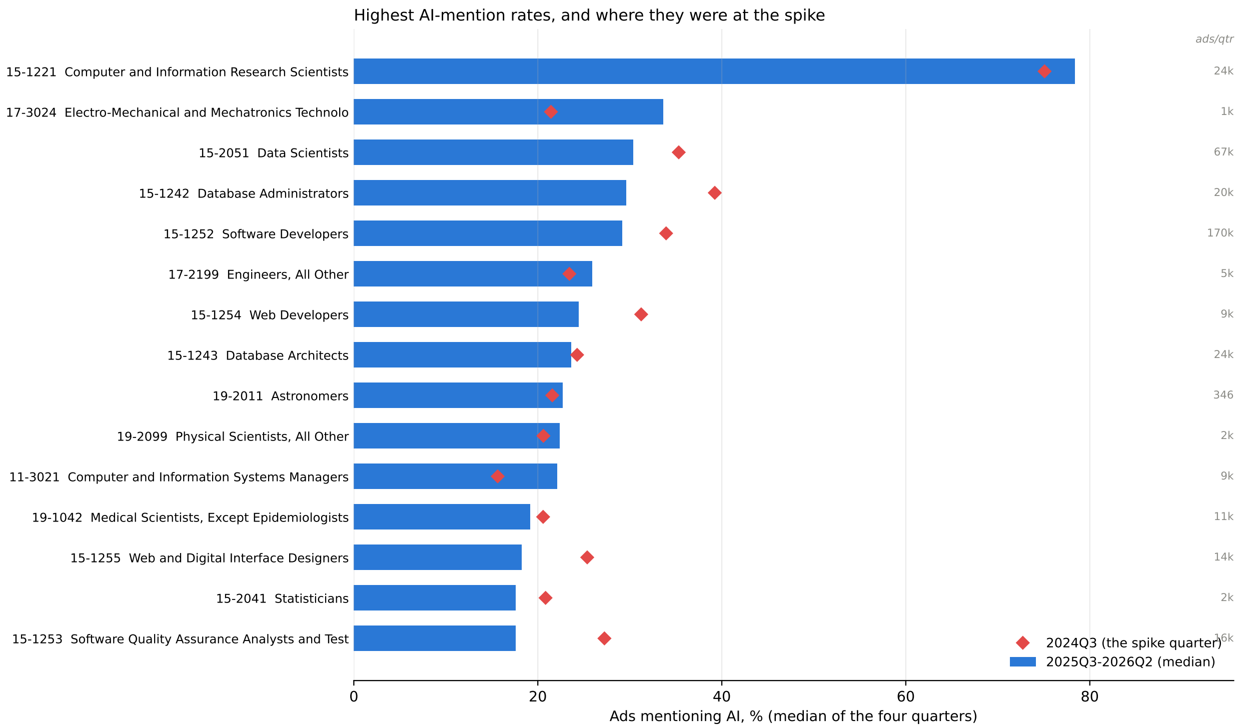
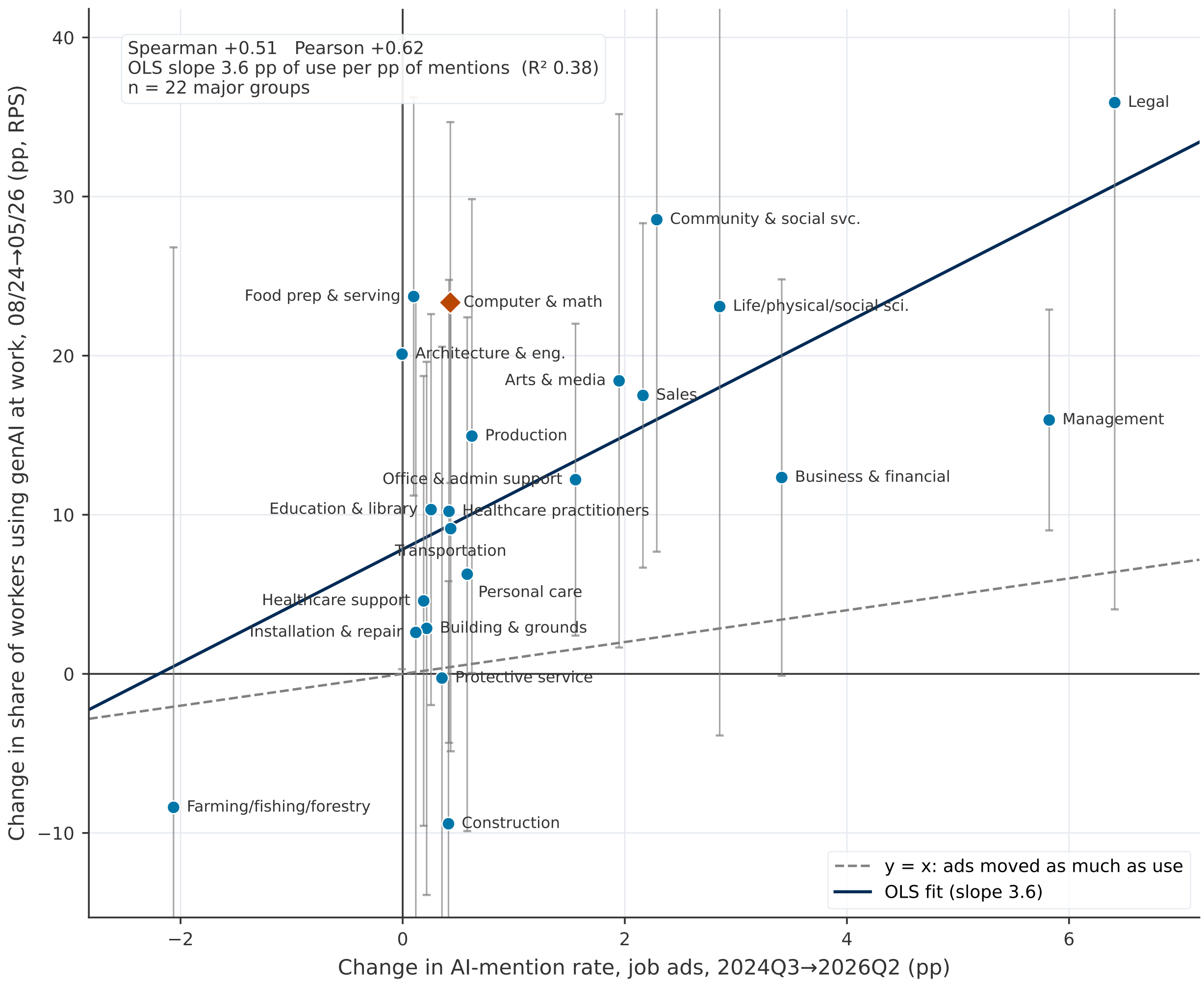
Appendix A Additional Tables and Figures

Figure A1: Top Occupations Mentioning AI-Related Terms



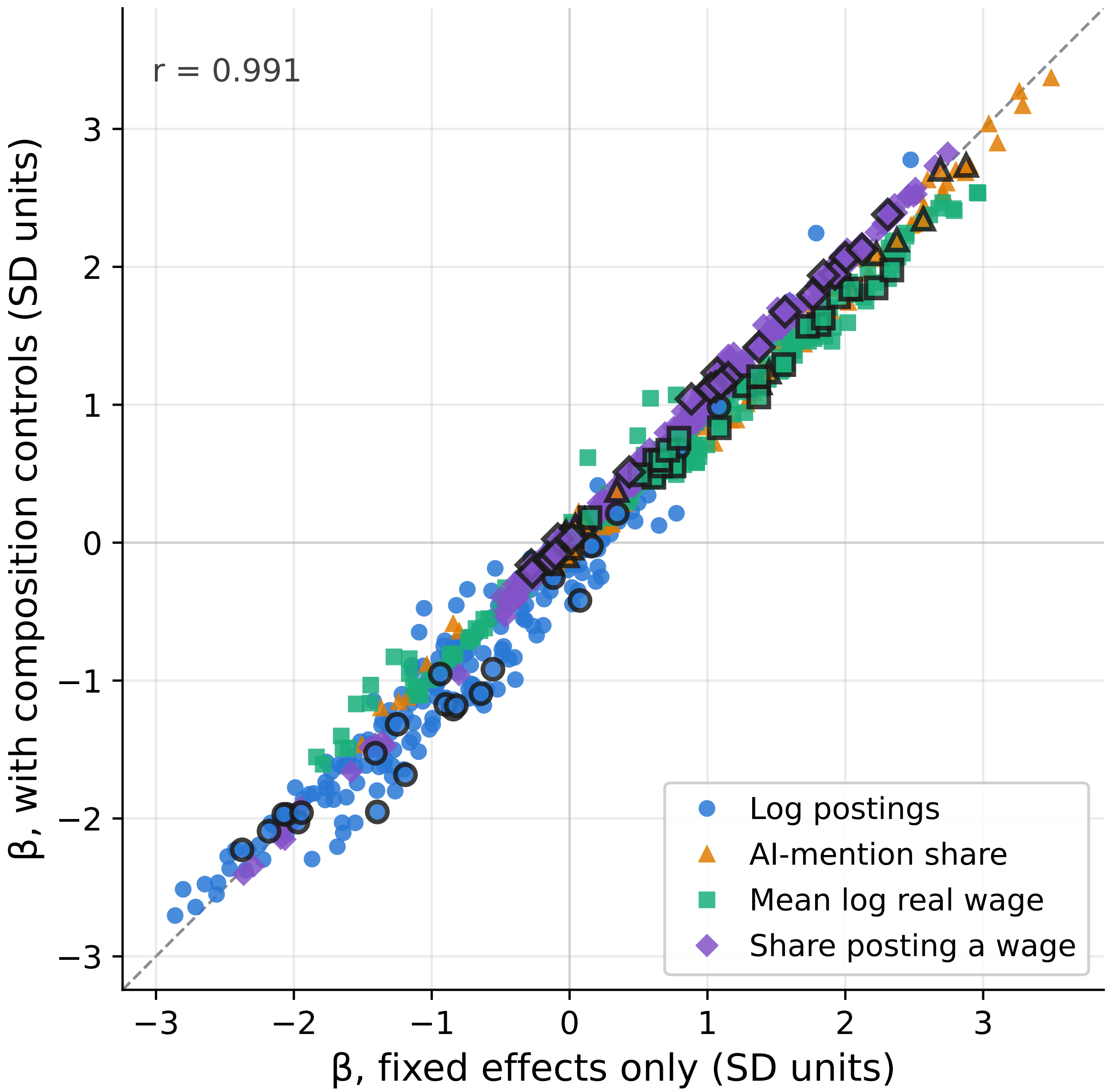
Source: Lightcast and author's calculations.
Notes: Occupations ranked by the median of their AI-mention shares over the last four quarters. Bars give that median and markers give the same occupation's share in 2024Q3; ads per quarter are reported beside each bar so that the size of each occupation is visible.

Figure A2: Change in AI Mentions in Job Ads vs. Change in Survey-Reported AI Use



Source: Lightcast, Real-Time Population Survey, and author's calculations.
Notes: Change from 2024Q3 to 2026Q2 in the share of employed workers reporting generative-AI use at work, from the Real-Time Population Survey of Bick et al. (2024), against the change in the share of job ads mentioning AI, by major occupation group. Whiskers are 95 percent confidence intervals on the survey change and are clipped where they run past the plotted range.

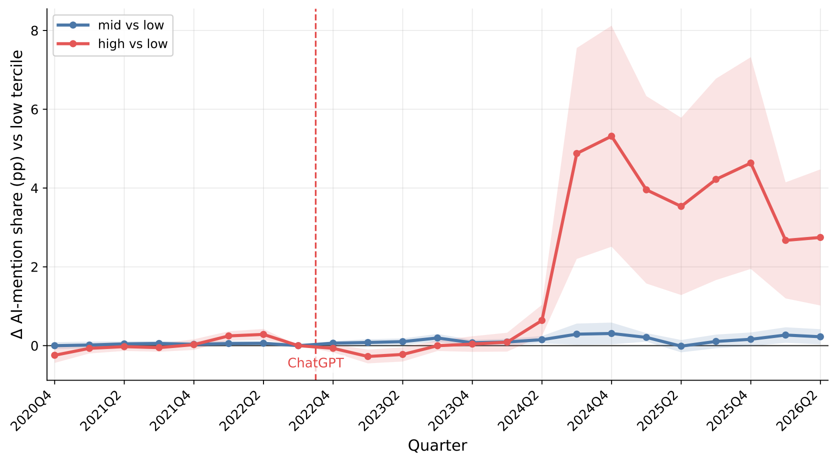
Figure A3: Event-study Coefficients With and Without Controls



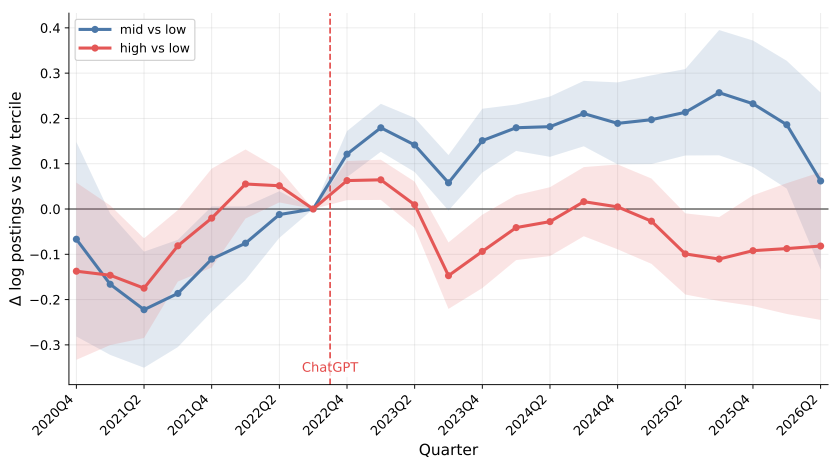
Source: Lightcast and author's calculations.
Notes: Each point is one event-study coefficient—an exposure measure in a given quarter—estimated with controls for the education and experience requirements stated in the ad, plotted against the same coefficient estimated without them. Coefficients are divided by the standard deviation of the uncontrolled estimates for their outcome so that outcomes measured in different units share an axis. Points on the 45-degree line indicate that the controls leave the estimate unchanged. Black-ringed markers are the principal-component measure.

Figure A4: Event-study Estimates, Dose-response Specification

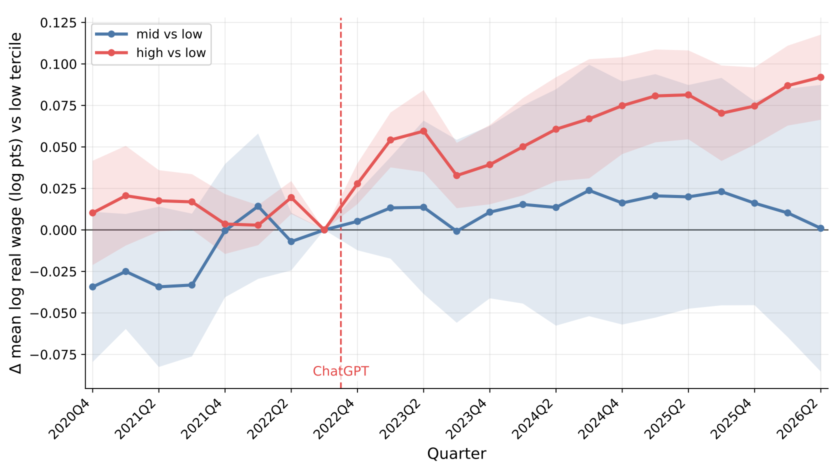
(a) AI share



(b) log(job ads)



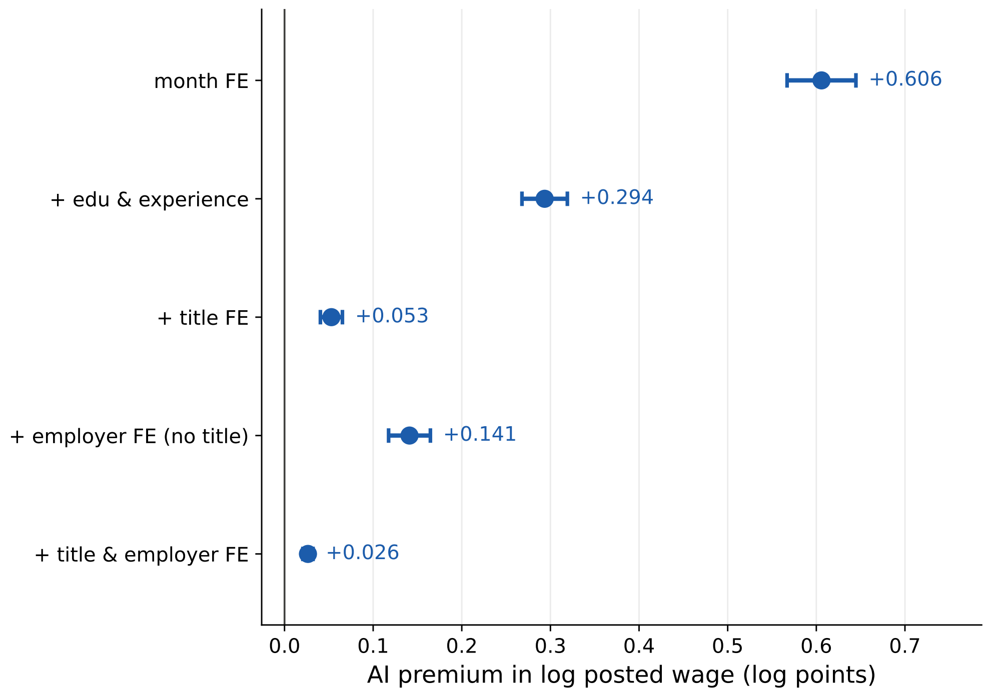
(c) Posted wages



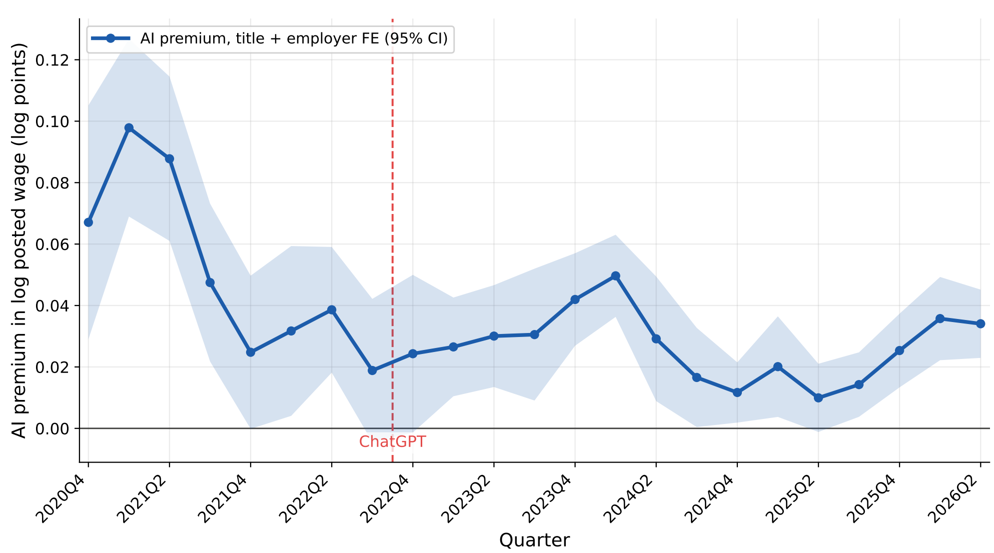
Source: Lightcast and author's calculations.
Notes: Figure reports event study estimates produced using indicators for being in the top or middle tercile of the occupational AI exposure (relative to the lowest tercile) instead of the continuous exposure measure. Terciles are determined using the first principal component of the exposure measures based on large language models. Shaded bands are 95 percent confidence intervals from standard errors clustered on occupation.

Figure A5: Ad-level AI Posted Wage Premium

(a) Pooled

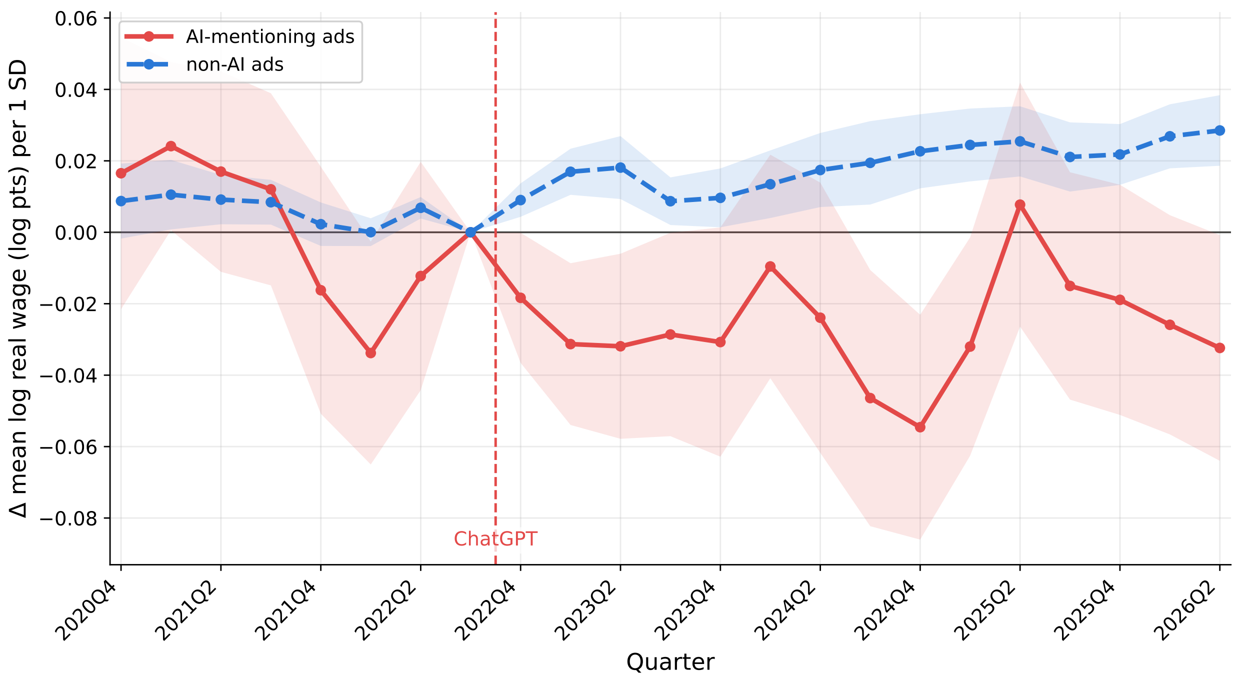


(b) Quarterly



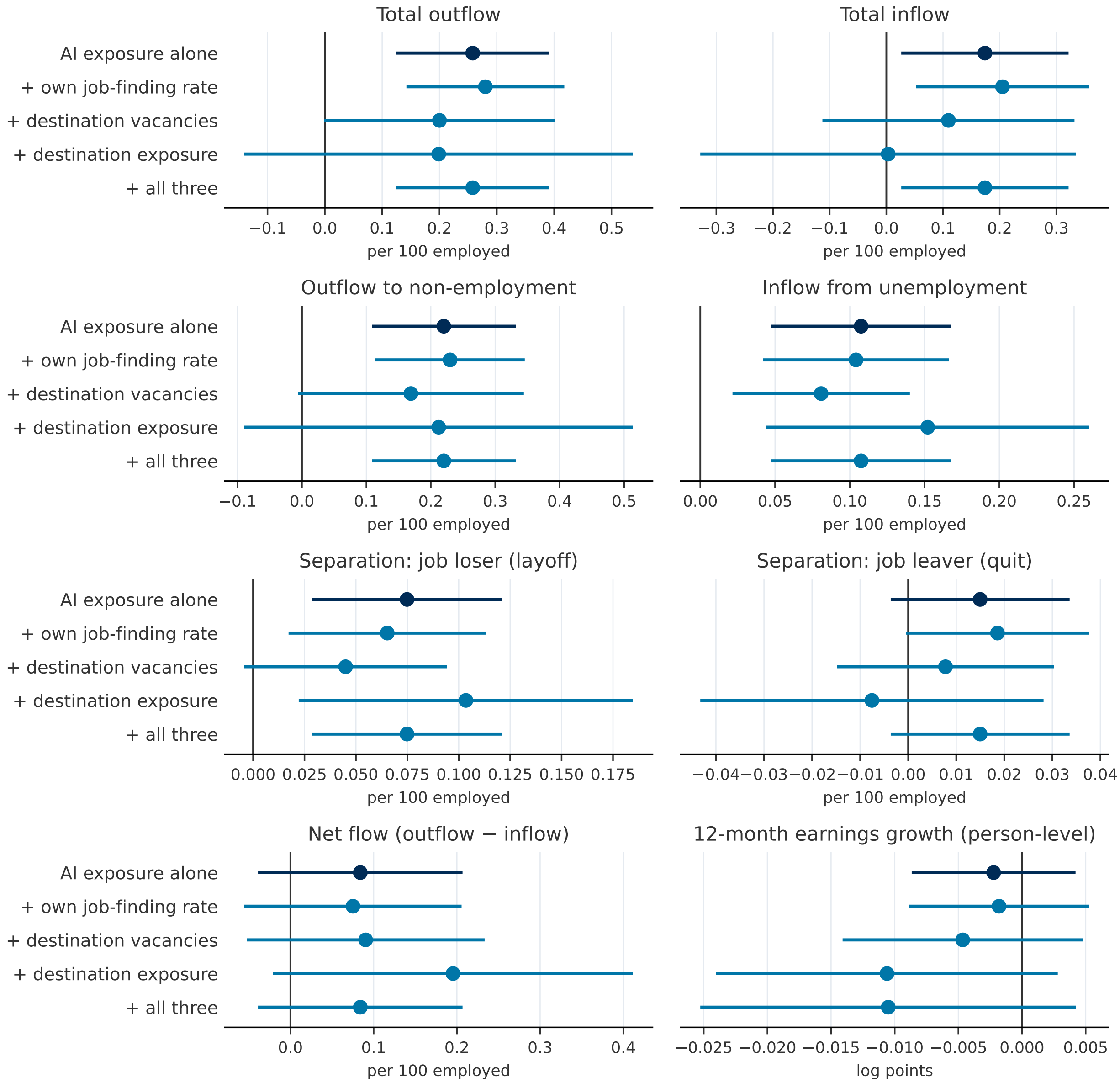
Source: Lightcast and author's calculations.
Notes: Ad-level regressions of log real posted wages on an indicator for mentioning AI-related terms, estimated on a 10 percent random sample of full-time ads that post a wage, 2020Q4–2026Q2. Panel (a) adds fixed effects cumulatively; sample sizes fall across rows as title and employer fixed effects absorb ads whose title or employer appears only once. Panel (b) reports the premium quarter by quarter under the specification with both title and employer fixed effects. Wages are deflated by the CPI-U. Standard errors clustered on employer; shaded range indicates 95 percent confidence intervals.

Figure A6: Posted Wage Event Study by AI Status



Source: Lightcast and author's calculations.
Notes: Figure plots coefficients β_t estimated using Equation 1 separately for ads that mention AI-related terms and ads that do not. Shaded bands are 95 percent confidence intervals from standard errors clustered on occupation.

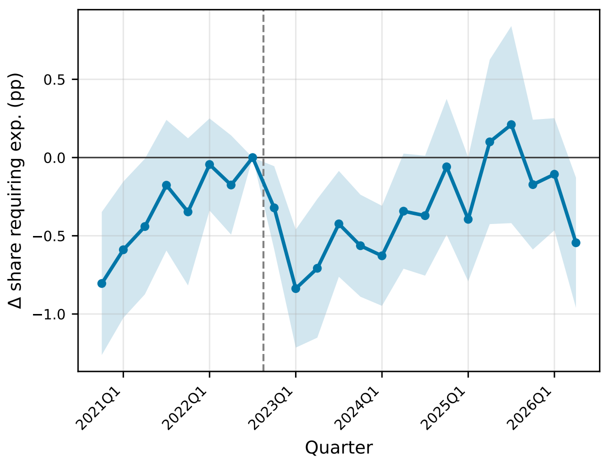
Figure A7: Sensitivity to Inclusion of Measures of Workers' Outside Options



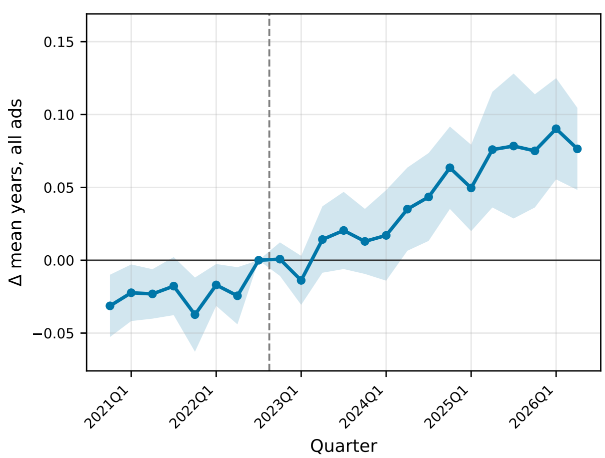
Source: Current Population Survey and author's calculations.
Notes: Each panel reports the coefficient on AI exposure interacted with the period after ChatGPT's release (2022Q4–2026Q2), measured relative to 2020Q4–2022Q3, with 95 percent confidence intervals. The top row repeats the baseline estimate, and the rows below add measures of workers' outside options, one at a time and then jointly. Occupations' own job-finding rates are rates of moving from unemployment to employment. Following Borusyak et al. (2023), destination measures average a characteristic of other occupations, weighted by occupational mobility observed in the CPS before ChatGPT's release. All are measured in the pre-ChatGPT period and enter interacted with a post-ChatGPT indicator. All panels except 12-month earnings growth are estimated on an occupation-quarter panel; earnings growth estimates are based on longitudinally linked individual-level data. All specifications include occupation and quarter fixed effects and controls for age group, sex, race and ethnicity, and education. Standard errors are clustered on occupation.

Figure A8: AI Exposure and Experience Requirements

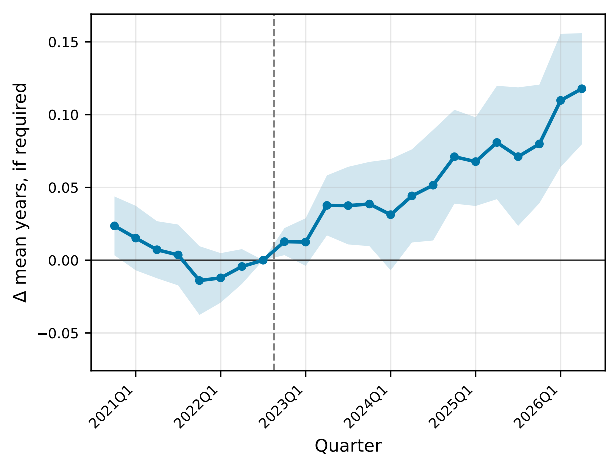
(a) Share of ads requiring experience



(b) Mean years required, all ads



(c) Mean years required, ads requiring any



Source: Lightcast and author's calculations.
Notes: Plotted points are coefficients β_t estimated using Equation 1 with 95 percent confidence intervals, 2022Q3 omitted and exposure measured as the first principal component of the exposure measures based on large language models, in standard deviations. Panel (a) is the share of an occupation's ads stating a minimum experience requirement above zero, in percentage points; panel (b) the mean minimum required across all ads, with an ad with no stated requirement counting as zero years; and panel (c) the same mean among only the ads that state one. Sample includes only ads for full-time jobs. All regressions include occupation and quarter fixed effects and weight occupations by their average quarterly ad count before ChatGPT's release. Standard errors are clustered on occupation.

Table A1: Decomposition of 2024 AI-Mentions Spike

	All AI mentions	"Artificial intelligence" only
Share of ads, base window	1.97%	0.30%
Share of ads, spike window	4.68%	2.50%
Change	**+2.71pp**	**+2.20pp**
Within employer	+2.41pp (+89%)	+2.09pp (+95%)
Between employers	+0.23pp (+8%)	+0.04pp (+2%)
Entry	+0.11pp (+4%)	+0.07pp (+3%)
Exit	−0.04pp (−2%)	≈0

Source: Lightcast and author's calculations.
Notes: The table decomposes the change in the share of ads for full-time jobs mentioning AI between 2023Q4–2024Q2 and the spike quarters 2024Q3–2024Q4. The first column counts any AI reference, including generic "AI" language; the second counts only ads whose sole AI term is the phrase "artificial intelligence." The within-employer term holds each employer's share of ads fixed and lets its own mention rate change; the between-employer term holds mention rates fixed and lets the distribution of ads across employers change; entry and exit cover employers posting in only one of the two windows. Each term is evaluated at the average of the two windows' weights, so the four sum to the total change exactly. Percentages in parentheses are shares of the total change.

Table A2: Correlations between AI Exposure and Outside Options

	(1)	(2)	(3)	(4)
(1) AI exposure (PC1)				
(2) Destination exposure	0.85			
(3) Destination vacancies	0.65	0.78		
(4) Destination earnings	0.57	0.67	0.77	
(5) Own job-finding rate	−0.29	−0.20	−0.28	−0.23

Source: Current Population Survey, Lightcast, and author's calculations.
Notes: AI exposure is the first principal component of the exposure measures based on large language models. Destination measures average a characteristic of other occupations, weighted by occupational mobility observed in the CPS before ChatGPT's release; the job-finding rate is the occupation's own rate of moving from unemployment to employment. All are measured before ChatGPT's release.

Table A3: Employment Flows by Worker Age

	Early career (1)	Older (2)	Difference (3)
A. Outflows, all channels (per 100 employed)			
Total outflow	0.338**	0.173***	0.165
	(0.132)	(0.056)	(0.134)
to another occupation (job-to-job)	0.105*	-0.012	0.117**
	(0.055)	(0.026)	(0.059)
to non-employment	0.234**	0.185***	0.048
	(0.107)	(0.050)	(0.112)
to unemployment	0.095**	0.090***	0.005
	(0.043)	(0.027)	(0.049)
job loser (layoff)	0.101***	0.072***	0.030
	(0.037)	(0.026)	(0.041)
job leaver (quit)	0.008	0.015	-0.007
	(0.018)	(0.009)	(0.020)
out of the labor force	0.138	0.093**	0.045
	(0.093)	(0.043)	(0.100)
B. Inflows, all channels (per 100 employed)			
Total inflow	0.043	0.177***	-0.134
	(0.140)	(0.068)	(0.142)
from another occupation (job-to-job)	0.085	-0.009	0.093
	(0.075)	(0.028)	(0.075)
from non-employment	-0.042	0.186***	-0.228*
	(0.107)	(0.062)	(0.119)
from unemployment	0.061	0.118***	-0.057
	(0.048)	(0.042)	(0.066)
from non-participation	-0.103	0.068*	-0.171
	(0.096)	(0.038)	(0.108)
C. Net and gross turnover (per 100 employed)			
Net flow (outflow − inflow)	0.295**	-0.004	0.299**
	(0.133)	(0.070)	(0.150)
through non-employment only	0.275***	-0.001	0.276**
	(0.104)	(0.064)	(0.129)
Gross turnover (outflow + inflow)	0.381	0.351***	0.030
	(0.238)	(0.103)	(0.231)
through non-employment only	0.192	0.372***	-0.180
	(0.188)	(0.092)	(0.191)
D. Hiring volume			
Log hires from non-employment	-0.133**	-0.057	-0.076
	(0.062)	(0.060)	(0.082)
E. Realized earnings (log points)			
12-month wage growth	-0.016***	0.004	-0.020***
	(0.006)	(0.004)	(0.007)
Weekly earnings, level	-0.003	-0.009***	0.006
	(0.004)	(0.003)	(0.005)
continuously employed	-0.005	-0.009***	0.005
	(0.004)	(0.003)	(0.004)
new hires	0.003	0.007	-0.004
	(0.011)	(0.015)	(0.020)
job-to-job hires	-0.008	0.003	-0.011
	(0.017)	(0.012)	(0.021)

Source: Current Population Survey and author's calculations.
Notes: Early career workers are those under 35. Estimates are produced using a specification analogous to that described in footnote 11, but with cells for the two age groups stacked and fixed effects fully interacted with age.

Appendix B Text Analysis

This section describes the methodology used in the text analysis presented in Figure B3. My approach produces three measures aimed at capturing differences between AI ads and non-AI ads, excluding direct mentions of AI, in terms of simple text (excess cosine dissimilarity), the ability of the text to predict AI status, and the work activities they reflect.

Appendix B.1 Tagging AI-related Terms in Job Ads

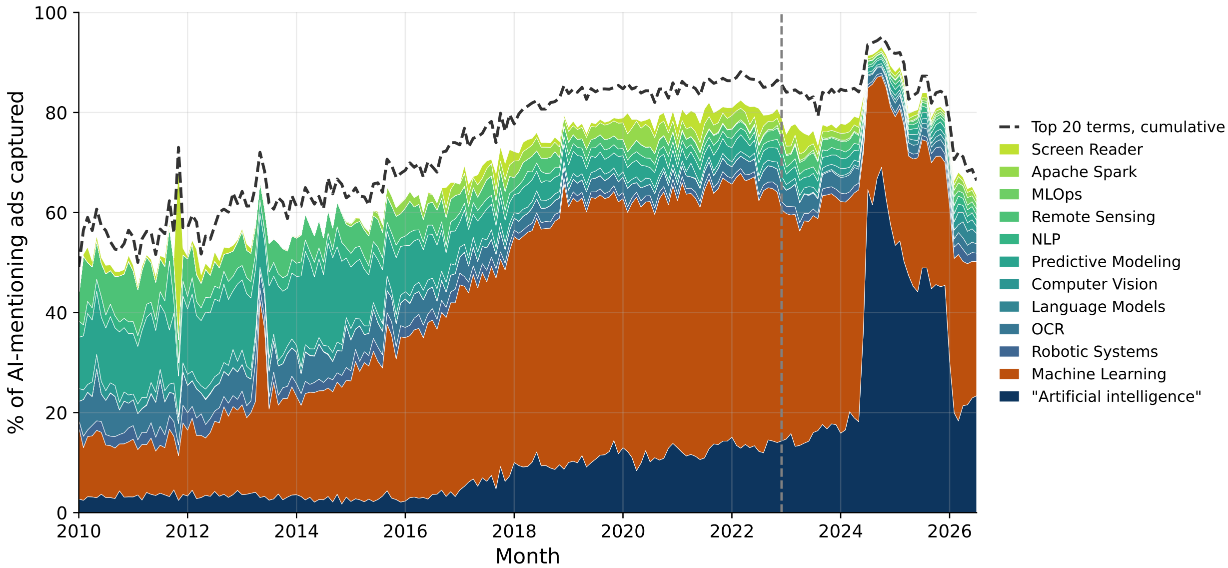
I search the text of job ads obtained from Lightcast for mentions of terms related to AI. The core of this search is based on a set of 350 AI-related skills, provided by Lightcast. For terms that are often used interchangeably with a well-known initialism (e.g., NLP, OCR, etc.), I also search for the initialism.

The most commonly used terms capture a large majority of the ads that mention any AI-related terms. In 2026Q2, the top two terms, machine learning and artificial intelligence, capture more than 40 percent of ads that mention any AI-related terms, as shown in Figure B1. The top 20 terms capture nearly 70 percent of ads in that quarter and over 90 percent of ads at their peak.

Not every mention of an AI-related term provides information about the content of the job, and simply counting mentions of these terms can be misleading. In particular, I attempt to correct for three issues: terms that have pre-existing meanings that are unrelated to AI, terms used in employer branding or other contexts that do not pertain to the content of the job being advertised, and terms used in the context of disclosing AI use in hiring processes.

To address potential ambiguity around terms that have both AI-related and non-AI meanings (e.g., “transformer” could also refer to an electrical transformer, “torch” could also refer to the welding tool, etc.), I do not count as mentioning AI any ad that mentions only an ambiguous term, unless the ambiguous term is mentioned in the same sentence as at least one term related to machine learning (e.g., language model, deep learning, data science,

Figure B1: Marginal Share of AI-mentioning Job Ads Captured by Top Terms



Source: Lightcast and author's calculations.
Notes: Each band is the share of AI-mentioning full-time ads that a term captures on the margin, beyond all higher-ranked terms, so the bands do not double count. Terms are ranked by their share over the full period. The top 12 terms are presented individually, and the dashed line shows the combined share captured by the top 20 terms. The dashed vertical line represents the release of ChatGPT.

various Python package names, etc.).

To identify mentions of AI that are part of employer branding or otherwise used in ways that are unlikely to reflect the content of the job being advertised, I search for "AI" used in combination with various fairly generic words (e.g., AI-powered, advanced AI, predictive AI, AI company, AI products, leverage AI, etc.).

To identify mentions of AI-related terms that occur in the context of disclosing AI use in hiring processes, I look within the sentence containing each mention of an AI-related term (up to 250 characters before and after the mention) for terms related to hiring processes: hiring, recruit, applicant, candidate, interview, talent acquisition, employment decision, selection process, job application, fair chance, background check, lie detector, polygraph, e-verify. Ads that mention one or more AI-related terms but only within sentences that also include hiring-process terms are classified as making disclosure-only mentions of AI; these are shaded in purple in Figure 1a.

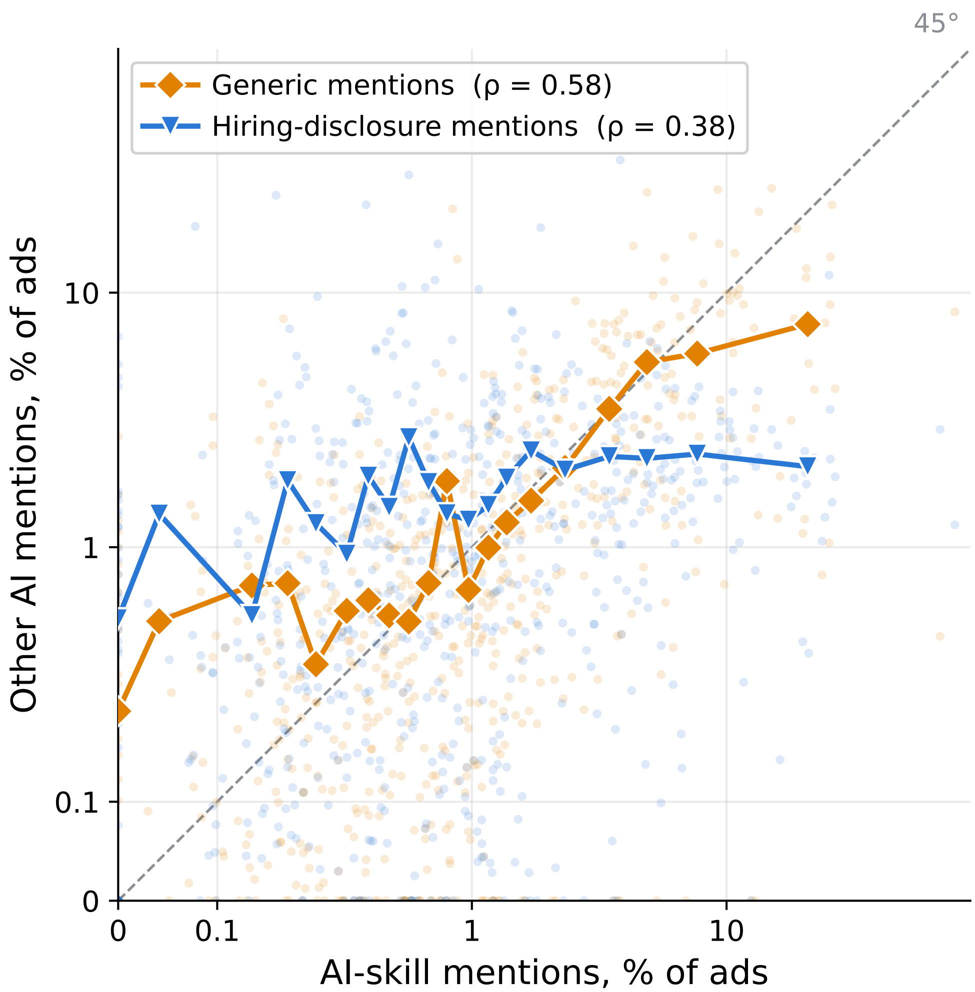
At the end of the period considered, both hiring process disclosure mentions of AI and more generic/branding-related mentions are positively correlated with mentions of AI skills at the occupation level (see Figure B2). This suggests that naive measurement could overstate the degree to which employers are mentioning AI skills in job ads.

After tagging ads' AI-mention status, I save a version of the text of each AI-mentioning ad that has had AI-related terms stripped from it. This version is used in subsequent comparisons across types of ads, in order to focus on differences in text across groups beyond that generated by defining the groups based on differences in text (i.e., mentions of AI-related terms).

Appendix B.2 Cosine Similarity Analysis

To compare AI and non-AI ads using cosine similarity, I convert the AI-masked text of ads into vectors of terms, with each term consisting of one or two words. I exclude terms that appear exactly once across ads and those that appear in more than 90 percent of ads. I

Figure B2: Occupational AI Mention Rates by Type of Mention, 2026Q2



Source: Lightcast and author's calculations.
Notes: Each faint point is a five-digit occupation in 2026Q2 with at least 125 full-time ads. The horizontal axis is the share of the occupation's ads mentioning "artificial intelligence" or a specific AI-related skill; the vertical axis is the share mentioning only generic "AI" language or hiring-disclosure language. Heavy markers are means within twenty equal-count bins of the horizontal axis, which the two series share. Axes are on a symmetric log scale, and the diagonal is the 45-degree line.

apply term frequency-inverse document frequency (TF-IDF) weights to the remaining terms such that for term t:

$$\begin{aligned}\text{Weighted Frequency} = \; & \text{Term Frequency Weight} \times \text{Inverse Document Frequency Weight} \\ = \; & (1 + \ln(n)) \times \left(ln \left(\frac{1+N}{1+df(t)} \right) + 1 \right)\end{aligned} \tag{B1}$$

where n is the unweighted number of times term t appears in an ad, $df(t)$ is the number of times term t appears across all ads in the comparison set (in this case, an occupation-quarter cell), and N is the number of ads. The weighted vector is then normalized to have length $=$ 1.

I compare ads with and without mentions of AI-related terms within five-digit SOC occupation-quarter cells. I focus on cells with at least 50 ads of each type. I sample up to 500 AI ads and up to 2000 non-AI ads within each occupation-quarter and take the cosine of the vectors for the ads within each cross-type pair of ads within that sample. For comparison, I also take the cosine between the vectors for all distinct pairs of non-AI ads. I then average these pairwise cosine values within cells to produce average similarity of AI ads to non-AI ads and average similarity of non-AI ads to each other. I difference these to produce a measure of excess dissimilarity within each occupation-quarter cell:

$$\text{Excess Dissimilarity} = \overline{\cos(n, n')} - \overline{\cos(a, n)} \tag{B2}$$

where n and n' represent all pairs of distinct non-AI ads and a and n represent all pairs of AI and non-AI ads. The overall excess dissimilarity measure, which is plotted in Figure B3, is an aggregation of cell-level measures weighted by the number of ads that mention AI-related terms.

Appendix B.3 Classifier Discriminability Analysis

I also produce a measure of how distinctive the non-AI portions of AI-mentioning ads are within their occupations. Operating within occupation-quarter cells that contain at least 25 ads that mention AI-related terms, I train a classifier to predict AI status based on the same AI-masked, TF-IDF weighted text of job ads used in the cosine similarity analysis. Each cell is split into five equal segments, and predictions for each segment are based on training conducted using the other four.

Using each ad's predicted probability of being an AI-mentioning ad, I then compare every possible pair of one AI ad with one non-AI ad within the cell to determine the share for which the classifier estimated a higher probability of being an AI ad for the ad that actually is an AI ad. This share is equivalent to the area under the curve (AUC) for the classifier's receiver operating characteristic (ROC) curve and serves as a measure of the discriminability of AI ads from non-AI ads. As with the cosine similarity analysis above, this measure excludes the influence of actual AI-related terms by construction.

The series plotted in Figure B3 is again an aggregation of cell-level AUC measures. As in the cosine similarity analysis, cells are weighted by the number of AI ads they contain.

Appendix B.4 O*NET Task Content Analysis

Finally, I consider a measure of how the job-related content of AI and non-AI ads aligns with a known set of work activities obtained from O*NET. I use a small sentence-embedding model (all-MiniLM-L6-v2) accessed through Hugging Face to vectorize O*NET work activity statements (for both general and detailed work activities) and each sentence in the text of each job ad. To limit computational requirements, I use a 10 percent sample of job ads and begin the analysis in 2020Q4, two years prior to the introduction of ChatGPT.

Each sentence from each ad is then matched to its closest work activity, based on cosine similarity of their vectors. Job ad sentences that are not sufficiently close to any work activity are skipped. Once activities have been assigned to sentences, I construct a vector giving the distribution of work activities in each ad. This vector has one entry for each work activity (there are 41 general work activities and 2,087 detailed work activities). Each entry in the vector is the number of sentences matched to a work activity divided by the total number of sentences matched to any work activity.

Within occupation-quarter cells with at least 5 AI ads and 5 non-AI ads, I then average the work activity distribution vectors within the sets of AI and non-AI ads. I then calculate the Jensen-Shannon (JS) divergence between these two average vectors:

$$JSD\left(A||N\right) = \frac{1}{2}D\left(A||M\right) + \frac{1}{2}D\left(N||M\right) \tag{B3}$$

where A is the average distribution of work activities in AI ads, N is the average distribution of work activities in non-AI ads, M is the average of A and N, and D is the Kullback-Leibler divergence between each ad type's vector and M. In general, the Kullback-Leibler divergence between two probability distributions P and Q is given by

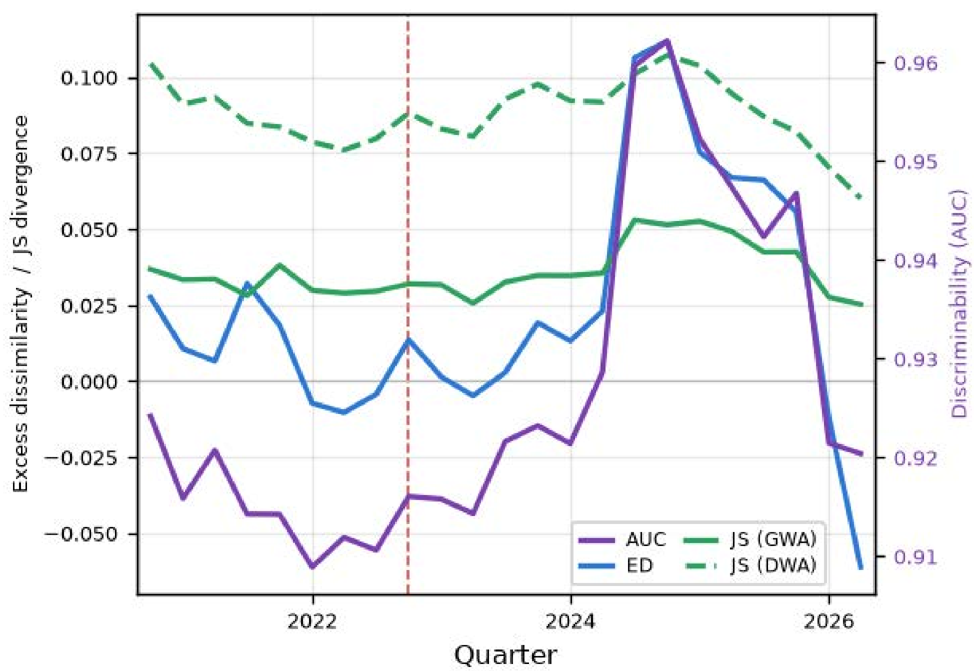
$$D_{KL}(P,Q) = \sum_{x \in X} P(x) \log \frac{P(x)}{Q(x)}. \tag{B4}$$

I also split non-AI ads into two halves at random and calculate the JS divergence between the two halves as a measure of baseline differences between ads in each cell.

As in the prior analyses, the national estimates reported in Figure B3 are aggregations of cell-level measures constructed by averaging across cells with the number of AI ads in each cell as weights. Figure B3 reports excess JS divergence between AI ads and non-AI ads by subtracting the average placebo distance between random sets of non-AI ads from the average distance between AI ads and non-AI ads.

Each of these measures shows the content of AI and non-AI ads diverging temporarily around the spike in AI mentions in job ads that reverts by the end of the period considered.

Figure B3: Measures of Text Similarity between AI and non-AI Job Ads



Source: Lightcast and author's calculations.
Notes: National quarterly aggregates of the three cell-level measures described in this appendix, comparing AI-mentioning ads with other ads in the same five-digit occupation after masking the AI terms themselves. Excess dissimilarity (ED) and the Jensen–Shannon divergences over general (GWA) and detailed (DWA) work activities are read on the left axis, each net of a placebo computed between random halves of the non-AI ads; classifier discriminability (AUC) is read on the right axis. Cells are weighted by their number of AI-mentioning ads. The dashed vertical line marks the release of ChatGPT.

Appendix C AI Exposure Measures

Table C1: Occupation-level AI exposure measures

Source (shorthand)	What it is intended to capture	How it is constructed
Felten et al. (2021) *(AIOE)*	Potential exposure of an occupation to progress in AI broadly, working through the human abilities the occupation requires. A capability-based measure of exposure, agnostic about whether the effect is substituting or complementary.	Ten AI applications (from the Electronic Frontier Foundation's AI Progress Measurement benchmarks) are linked to 52 O*NET abilities via a crowdsourced application–ability relatedness matrix. An ability-level exposure is formed as the (equally weighted) sum of the ten relatedness scores, then aggregated to the occupation by weighting each ability by its O*NET prevalence and importance. Continuous AIOE score by 6-digit SOC (774 occupations).
Felten et al. (2023) *(LM-AIOE)*	The same ability-based exposure concept, but reweighted to capture exposure specifically to *language modeling* (ChatGPT-type generative language AI) rather than to AI in general.	Identical AIOE framework and the same application–ability relatedness matrix, but the application weights are changed from equal (all ten set to 1) to 1 for the single "language modeling" application and 0 for the other nine. The ability-level exposure therefore counts only abilities related to language modeling; occupation aggregation (prevalence- and importance-weighted) is unchanged. 6-digit SOC (774 occupations).
Eloundou et al. (2024) *(Eloundou β)*	The share of an occupation's work tasks for which access to LLMs (and LLM-powered software built on them) could substantially cut the time to complete the task—a task-based measure of generative-AI capability exposure.	Each O*NET task is rated based on the ability of direct LLM access *or* additional LLM-powered software to reduce task time by $\geq$50%. Occupation exposure is the exposed task share. Paper provides ratings done by GPT-4 and by human; focus here on the GPT-4 ratings and the β formulation of the exposed task share, which gives less weight to tasks that require additional LLM-powered software to realize task time gains. 923 O*NET-SOC occupations.

Continued on next page

Table C1, continued

Source (shorthand)	What it is intended to capture	How it is constructed
Frey and Osborne (2017) *(Frey–Osborne)*	The probability that an occupation could be fully automated given foreseeable advances in machine learning and mobile robotics. A pre-LLM automation-susceptibility benchmark.	Seventy occupations are hand-labeled automatable/not by ML experts; nine O*NET variables capturing three "engineering bottlenecks" (perception and manipulation, creative intelligence, social intelligence) are used to predict computerization probabilities for other occupations via a Gaussian-process classifier (702 occupations, 6-digit 2010 SOC).
Handa et al. (2025) *(Anthropic AEI)*	Realized, usage-based exposure: how much AI is actually being used to perform an occupation's work today, rather than how much it could be in principle.	A large sample of real Claude.ai conversations is mapped to the O*NET tasks they correspond to, and then to occupations. Occupation exposure is the share of the occupation's O*NET tasks observed being performed in Claude conversations (756 occupations, current SOC).
Eisfeldt et al. (2025) *(ESTZ GenAI)*	The share of an occupation's tasks that current generative AI can make more productive—a generative-AI capability exposure built independently of Eloundou β.	GPT-4 classifies each of ∼19,000 O*NET tasks (as of March 2023) for whether GPT-4-level tools raise productivity on the task; occupation exposure is the resulting task share. Total exposure decomposes into core + supplemental tasks; here consider *total* and *core* measures (840 occupations, 6-digit 2010 SOC).
Brynjolfsson et al. (2018) *(BMR SML)*	Suitability for machine learning—how amenable an occupation's work is to being performed by supervised ML. A pre-generative-AI task-automation benchmark, distinct from Frey–Osborne's full-job automation probability (it scores activities, not whole jobs).	Crowd raters score each O*NET Detailed Work Activity on a 21-item ML-suitability rubric; the DWA scores are spread to all O*NET tasks and importance-weighted to occupations. Higher = more ML-suitable (771 occupations, 6-digit 2010 SOC, from O*NET release 21.1).

Continued on next page

Table C1, continued

Source (shorthand)	**What it is intended to capture**	**How it is constructed**
Webb (2020) *(Webb AI)*	Exposure to AI as revealed by what AI has actually been invented to do: an occupation is exposed to the extent that the tasks it is made of are the tasks AI patents describe performing.	Verb–object pairs are extracted from the text of AI patents and, separately, from O*NET task descriptions. An occupation's score is the extent to which the verb–object pairs in its tasks appear among those in AI patents, aggregated across the occupation's tasks and expressed as a percentile across occupations. Webb constructs parallel scores for software and industrial robots; the focus here is on the AI series (`pct_ai`). Published on `occ1990dd` codes, here mapped to 2018 SOC (768 scored occupations).

Table C2: Comparing AI Exposure Measures

(a) Cross-occupation correlations among exposure measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) AIOE	1							
(2) LM-AIOE	0.98	1						
(3) Eloundou β	0.86	0.84	1					
(4) ESTZ GenAI	0.80	0.79	0.89	1				
(5) Anthropic AEI	0.57	0.58	0.65	0.68	1			
(6) BMR SML	0.30	0.28	0.33	0.30	0.26	1		
(7) Frey–Osborne	−0.44	−0.46	−0.28	−0.20	−0.15	0.08	1	
(8) Webb AI	0.07	0.03	0.08	0.08	0.02	0.02	−0.13	1

(b) Cross-occupation rank correlations among exposure measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) AIOE	1							
(2) LM-AIOE	0.97	1						
(3) Eloundou β	0.87	0.86	1					
(4) ESTZ GenAI	0.84	0.83	0.91	1				
(5) Anthropic AEI	0.70	0.71	0.74	0.73	1			
(6) BMR SML	0.29	0.29	0.34	0.32	0.32	1		
(7) Frey–Osborne	−0.37	−0.39	−0.23	−0.22	−0.23	0.09	1	
(8) Webb AI	−0.01	−0.06	0.02	0.01	0.02	−0.04	−0.10	1

(c) Ten highest-exposure occupations under a generative-AI measure, Frey–Osborne, BMR, and Webb

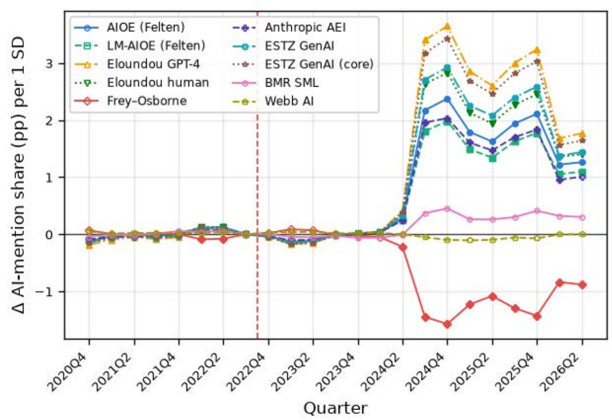
	LM-AIOE (generative AI)	**Frey–Osborne p(automation)**	**BMR SML (ML suitability)**	**Webb AI (patent text)**
1	Telemarketers	Telemarketers	Mechanical Drafters	Buyers and Purchasing Agents, Farm Products
2	English Language and Literature Teachers, Postsecondary	Mathematical Technicians	Concierges	Chemical Engineers
3	Foreign Language and Literature Teachers, Postsecondary	Title Examiners, Abstractors, and Searchers	Morticians, Undertakers, and Funeral Directors	Materials Engineers
4	History Teachers, Postsecondary	Cargo and Freight Agents	Brokerage Clerks	Atmospheric and Space Scientists
5	Law Teachers, Postsecondary	Insurance Underwriters	Psychologists, All Other	Optometrists
6	Philosophy and Religion Teachers, Postsecondary	Watch Repairers	Gaming Cage Workers	Pest Control Workers
7	Sociology Teachers, Postsecondary	Library Technicians	Multi-Media Artists and Animators	Construction and Building Inspectors
8	Political Science Teachers, Postsecondary	New Accounts Clerks	Ushers, Lobby Attendants, and Ticket Takers	Elevator and Escalator Installers and Repairers
9	Criminal Justice and Law Enforcement Teachers, Postsecondary	Photographic Process Workers and Processing Machine Operators	Office Machine Operators, Except Computer	Water and Wastewater Treatment Plant and System Operators
10	Sociologists	Tax Preparers	File Clerks	Inspectors, Testers, Sorters, Samplers, and Weighers

Source: Frey and Osborne (2017); Brynjolfsson et al. (2018); Webb (2020); Felten et al. (2021, 2023); Eloundou et al. (2024); Handa et al. (2025); Eisfeldt et al. (2025); and author's calculations.

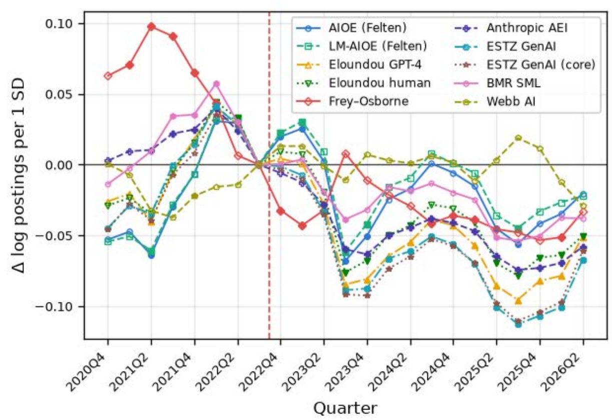
Notes: Panel (a) reports Pearson correlations and panel (b) reports rank correlations between the listed exposure measures, computed pairwise (each cell uses the occupations the two measures share). Panel (c) lists the ten occupations that select measures score highest using the source authors' occupation titles.

Figure C1: Lightcast Event Study Estimates, All Exposure Measures

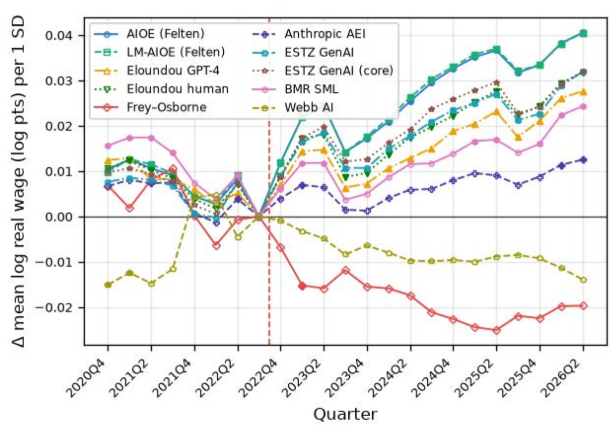
(a) Percent mentioning AI-related terms



(b) log(job ads)



(c) log(real posted wage)



Source: Lightcast and author's calculations.
Notes: Plotted points are coefficients β_t estimated using the specification described in Equation 1, estimated separately for each exposure measure, with 2022Q3 omitted and exposure measured in standard deviations. Confidence intervals are omitted for legibility; markers are filled where the estimate differs from zero at the 5 percent level. Standard errors clustered on occupation.

Appendix D Selection into Wage Posting

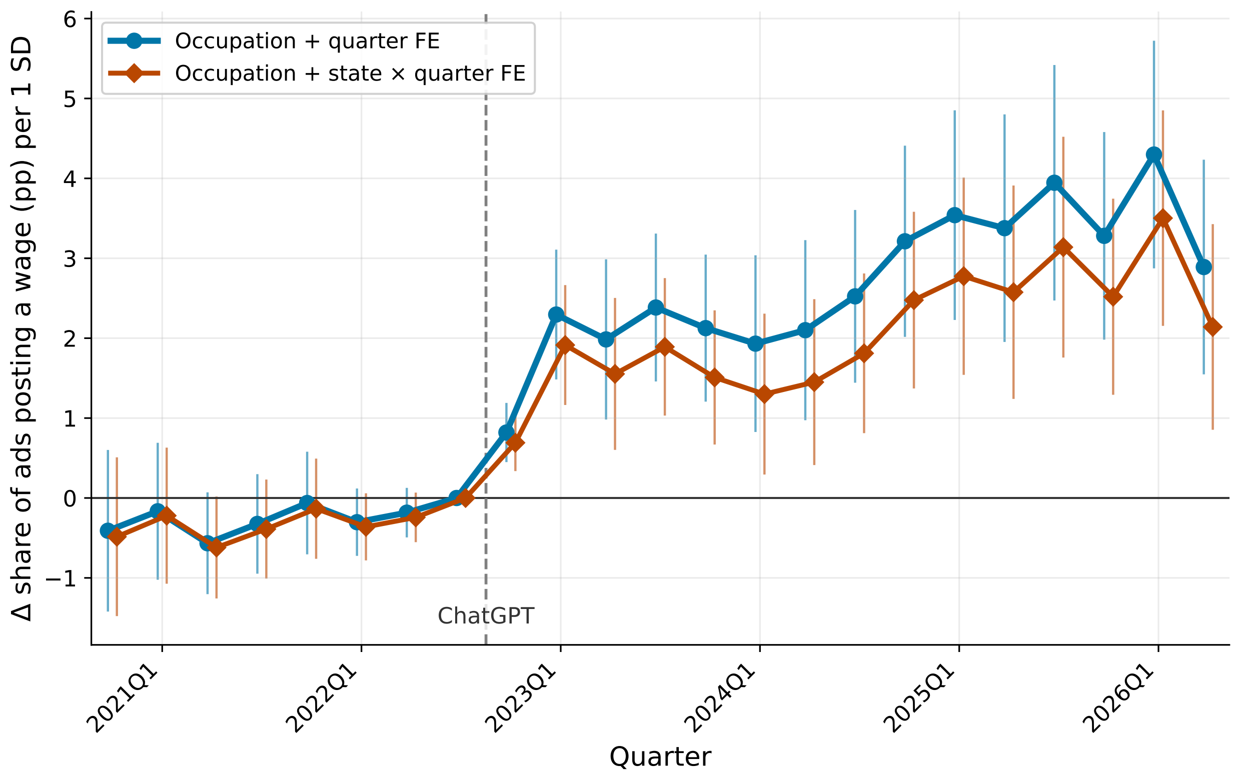
It has become much more common for job ads to include wage information, especially over the last five years or so, regardless of whether ads mention AI-related terms. Shifts of this magnitude raise questions about the composition of firms that post wages and the comparability of posted wage measures over time, given potential changes in composition.

Compositional concerns are heightened by the fact that wage posting has become more common particularly in more AI-exposed occupations since the release of ChatGPT. Figure D1 shows systematically higher wage posting rates in occupations with higher levels of LLM/GenAI-related exposure, beginning at the end of 2022. Increases in wage posting over the period of interest are not only substantial, but also clearly correlated with exposure to AI. This could make comparisons of aggregate wage information over time deceiving if, for example, firms or jobs that unobservably make more productive use of AI and pay higher wages are also more likely to include wage information in job ads now than they used to.

Unrelated changes in policy requiring wage information to be included in job ads in some places and for some types of firms further complicate the analysis of posted wages. Table D1 describes state-level laws passed recently that require firms to post wage information in job ads, while Table D2 describes other laws related to pay transparency that either were passed by substate jurisdictions or require wage information to be provided in some way other than in job ads.

An event-study analysis of the state-level policies listed in Table D1 that were in effect during the period considered shows that the rate at which employers include wage information in job ads increases substantially when they are required to do so. Figure D2 shows that, following a modest trend up in wage posting ahead of these laws taking effect (which could reflect anticipatory compliance following enactment), wage posting rates jump more than 10 percentage points in the quarter in which the law takes effect. Wage posting rates continue to rise in subsequent quarters, reaching roughly 20 percentage points above the reference period and about 25 percentage points above the trend that prevailed a year before

Figure D1: Relationship between AI Exposure and Wage Posting, by Exposure Measure



Source: Lightcast and author's calculations.
Notes: Lightcast online job ads for full-time positions, 2020Q4–2026Q2. Plotted points are coefficients β_t estimated based on the specification described in Equation 1 (circles) and the same specification with state-quarter fixed effects (diamonds), with the share of an occupation's ads that post a wage as the outcome, in percentage points, estimated using the first principal component of the LLM-based exposure measures. 2022Q3 is omitted and exposure is measured in standard deviations. Standard errors are clustered on occupation, and lines extending from plotted points represent 95 percent confidence intervals.

Table D1: Pay-transparency posting requirements

State	Effective	Quarter	Coverage
Panel (a): In force within the estimation window			
Colorado	Jan. 1, 2021	2021Q1	All employers
California	Jan. 1, 2023	2023Q1	15+ employees
Washington	Jan. 1, 2023	2023Q1	15+ employees‡
New York	Sep. 17, 2023	2023Q3	4+ employees‡
Hawaii	Jan. 1, 2024	2024Q1	50+ employees‡
District of Columbia	Jun. 30, 2024	2024Q2	All employers
Maryland	Oct. 1, 2024	2024Q4	All employers
Illinois	Jan. 1, 2025	2025Q1	15+ employees
Minnesota	Jan. 1, 2025	2025Q1	30+ employees†
New Jersey	Jun. 1, 2025	2025Q2	10+ employees
Vermont	Jul. 1, 2025	2025Q3	5+ employees
Massachusetts	Oct. 29, 2025	2025Q4	25+ employees†
Panel (b): Effective after the estimation window			
Virginia	Jul. 1, 2026	2026Q3	All employers
Maine	Jul. 29, 2026	2026Q3	10+ employees‡
Connecticut	Oct. 1, 2026	2026Q4	All employers
Delaware	Sep. 26, 2027	2027Q3	More than 25 employees‡

Source: Effective dates are from industry pay-transparency law trackers and coverage from the statute or the enforcing state agency, accessed July and August 2026.

Notes: Table reports state laws requiring employers to include pay information in the job posting itself. An ad is treated as covered from the quarter containing the effective date onward, keyed on the state in which the job is posted. Panel (a) lists the eleven states plus the District of Columbia with laws in force within the estimation window (through 2026Q2) and used in the analysis; panel (b) lists requirements taking effect after the estimation window. Coverage is the employer-size threshold at which the requirement binds, where "all employers" means any employer with at least one employee. Thresholds marked † count in-state employees only and those marked ‡ are left unspecified by the statute; the analysis of these laws conducted here applies no size screen. Substate ordinances, and laws requiring disclosure only on request, are listed in Table D2.

Table D2: Pay-transparency laws excluded from the mandate indicator

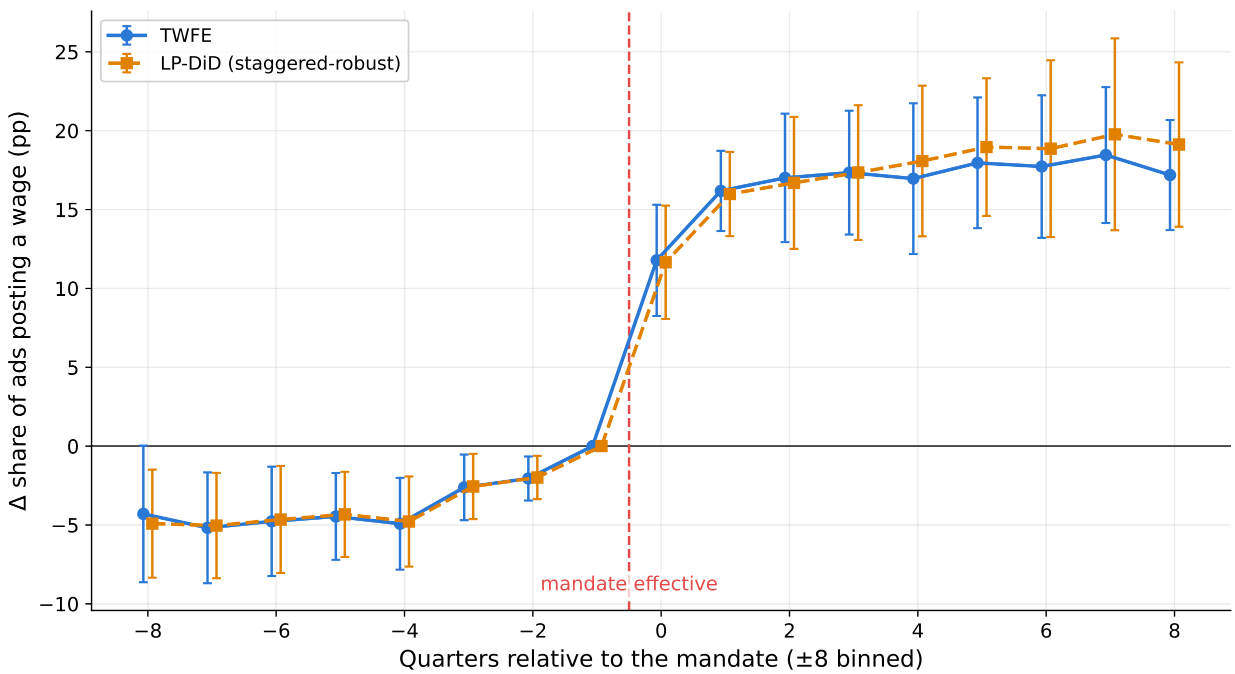
Jurisdiction	Effective	Detail
Panel (a): State laws requiring disclosure outside the advertisement		
Maryland	2020	On applicant request. Superseded by Maryland's Oct. 1, 2024 posting requirement, which is used
Connecticut	2021	On applicant request. Superseded by Connecticut's Oct. 1, 2026 posting requirement, which falls after the window
Nevada	Oct. 2021	Provided automatically after an interview
Rhode Island	Jan. 2023	On applicant request
Panel (b): Substate ordinances requiring disclosure outside the advertisement		
Cincinnati, OH	Mar. 13, 2020	Pay scale on request, after a conditional offer
Toledo, OH	Jun. 25, 2020	Pay scale on request, after a conditional offer
Panel (c): Substate ordinances requiring disclosure in the advertisement		
Jersey City, NJ	Apr. 2022	Precedes New Jersey's Jun. 1, 2025 law
Ithaca, NY	Sep. 1, 2022	Precedes New York's Sep. 17, 2023 law
New York City, NY	Nov. 1, 2022	Precedes New York's Sep. 17, 2023 law
Westchester County, NY	Nov. 6, 2022	Precedes New York's Sep. 17, 2023 law
Albany County, NY	Feb. 12, 2023	Precedes New York's Sep. 17, 2023 law
Cleveland, OH	Oct. 2025	Ohio has no state posting law

Source: As in Table D1.

Notes: Table reports pay-transparency laws in force during the estimation window that either do not require pay disclosure in job ads or are enforced by jurisdictions below the state level. The laws in panels (a) and (b) require an employer to supply a pay range on request, at interview, or after a conditional offer, but not to publish one in the advertisement, so they do not mechanically raise the share of ads that disclose a wage. The ordinances in panels (b) and (c) are enforced by substate jurisdictions.

the laws took effect. Effects are similar whether estimated using a traditional two-way fixed effects approach or the Dube et al. (2025) local projections approach.

Figure D2: Wage Posting Rates Around the Introduction of State-level Pay-transparency Laws



Source: Lightcast and author's calculations.
Notes: Figure presents event-study estimates of the effect of state wage posting mandates on the share of ads that post a wage, estimated on a state-quarter panel with state and quarter fixed effects and event time measured from the quarter in which a mandate takes effect. Estimates are shown based on a two-way fixed effects specification and using the local projections estimator of Dube et al. (2025), which is robust to mandates taking effect in different quarters across states. Treated states are listed in Table D1. Standard errors clustered on state; 95 percent confidence intervals.

To address potential concerns about how changing selection into wage posting could affect wage estimates, Figure D3 presents estimates from alternative specifications intended to limit the influence of selection in various ways:

- Incumbent pairs: produce posted wage estimates using a sample that includes only employer-occupation pairs that are observed with posted wages both before and after the introduction of ChatGPT, reducing the scope for selection into wage posting on the extensive margin to affect estimates

- Employer-occupation fixed effects: do not restrict the sample, but include employer-occupation fixed effects in the estimation, so that extensive margin selection into wage posting does not contribute to identification of the relationship between AI exposure and posted wages

- DiNardo et al. (1996) reweighting: reweight ads within occupation-quarter cells to match the pre-ChatGPT period's joint distribution of state and education requirements among ads that posted wages, countering the influence of any selection into wage posting on these observable dimensions

- Hainmueller (2012) entropy balancing: reweight occupation-quarter cells to match the pre-ChatGPT means of education and experience requirement and wage posting law measures among ads that posted wages, keeping weights as close to uniform as possible, another approach to countering the influence of selection on observables

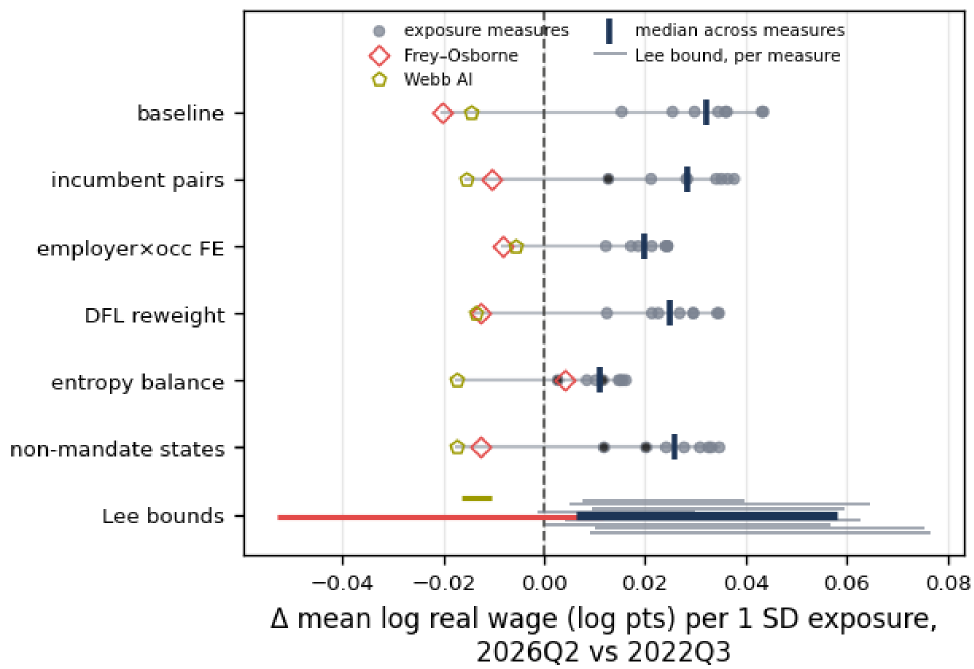
- Non-mandate states: produce posted wage estimates using only states that did not have a wage posting law in effect during the period considered, sidestepping the large increase in wage posting associated with such laws

- Lee (2009) bounds: trim each occupation-quarter cell's "excess" wage posting from the top/bottom of the distribution to match trend growth in wage posting for the median occupation, then re-estimate effects on posted wages.

Figure D3 summarizes how these approaches alter the wage estimate for 2026Q2. In all cases, more LLM-exposed occupations see higher real posted wages in that quarter. In most cases, the Lee bounds lie entirely above zero.

While a Heckman (1979) correction may seem like a natural option for addressing selection in this context, especially since pay disclosure laws shift rates of wage posting, it seems less suitable upon closer examination. Wage posting laws seem unlikely to satisfy the exclusion restriction. Figure D4 shows the estimated effects of the introduction of state-level wage posting laws on posted wages, estimated using a stacked difference-in-differences approach

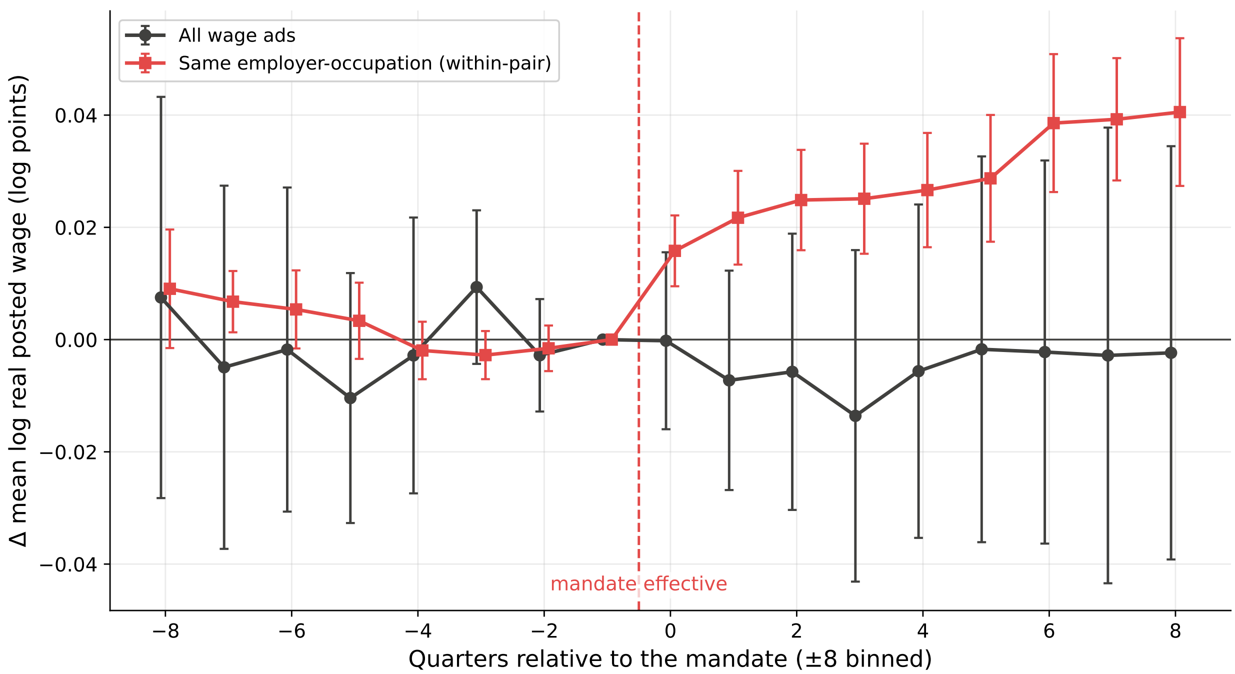
Figure D3: Wage Selection Adjustments



Source: Lightcast and author's calculations.
Notes: Estimates give the change in the occupation-level mean of log real posted wages between 2022Q3 and 2026Q2 per standard deviation of AI exposure, re-estimated under each correction for selection into wage posting described above. Each gray point is one LLM-based exposure measure and the vertical bar is the median across measures; the pre-LLM full job automation measure (Frey–Osborne) and the patent-based measure (Webb) are marked separately. The bottom row reports Lee (2009) bounds: thin lines are the bounded interval for each measure and the thick bar spans the median lower and upper bounds.

with clean controls analogous to the approach taken in Cengiz et al. (2019). The figure shows effects estimated using all ads, which appear to be flat, though somewhat imprecise, and effects estimated using only employer-occupation pairs that were posting wages before the wage posting laws took effect, which shows a clear, immediate increase in posted wages after these laws take effect. The magnitude increases to about 4 percent by two years later. Together, these estimates highlight the importance of the selection concerns and illustrate that wage posting laws affect the wage level directly and therefore do not satisfy the exclusion restriction required in a Heckman-style analysis.

Figure D4: Posted Wages around the Introduction of State-level Wage Posting Laws



Source: Lightcast and author's calculations.
Notes: Plotted points are event-study coefficients estimated via a stacked difference-in-differences approach (Cengiz et al., 2019) with the log of posted wages as the outcome. Estimates are produced separately using 1) all job ads with wage information and 2) ads in employer-occupation cells that had ads with wage information prior to the adoption of wage posting requirements. Standard errors are clustered on state, and the lines extending from plotted points represent 95 percent confidence intervals.