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The Early Impacts of AI on Employment among Recent College Graduates

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Abstract

The impact of AI on the employment prospects of recent college graduates is hotly debated with no consensus on the magnitude of impacts nor even the timing of those potential impacts. Using CPS microdata, we provide the first estimates of the effects of AI on the unemployment of recent college graduates in June, July and August 2026. We provide evidence suggesting that unemployment rates are especially high for summer months and that 2026 might be the first year of widespread enough AI use in the workplace to detect impacts of AI on recent college graduates, the group argued to be most vulnerable to AI replacement. Taking an agnostic approach to defining treatment timing, we find that unemployment rates did not spike in summer 2026 relative to summer months in previous years and did not rise in a significant way relative to older college graduates or young workers without a college degree. We also provide the first analysis of an expanded definition of unemployment that includes those who report “wanting a job” which adds nearly two percentage points to the unemployment rate of recent college graduates but we find no evidence of a statistically significant increase in summer 2026 even after adding these “sidelined unemployed.” We estimate difference-in-differences and event-study interaction models using both older college graduates and young non-college graduates as comparison groups and do not find evidence of an increase in relative unemployment rates. Finally, we estimate models in which we interact 2026 unemployment with AI exposure and remote work availability by occupation and find some evidence of a positive relationship with remote work availability.

JEL classification

J21, J24, J63, J64

Keywords

AI, technological change, unemployment, job loss, college graduates

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1. Introduction

Concerns over the impacts of generative artificial intelligence (AI) on employment opportunities for recent college graduates planning to enter the labor market are widespread. In recent months, sharply different stances have emerged on whether these effects are already appearing. Larry Fink, CEO of BlackRock, said he was "worried that when this year's college graduates enter the workforce, we could see the highest unemployment rate among them in years—even without a recession" (Fore, 2026). Bill Gates wrote on the risks of AI that he was "especially worried about young people, who will enter a workforce with fewer entry-level openings" (Gates, 2026). In contrast, venture capitalist Marc Andreessen argued that AI has been a convenient scapegoat for downsizing, as "AI literally until December [2025] was not actually good enough to do any of the jobs that [firms] are actually cutting" (Angelo, 2026). In a similar spirit, Jensen Huang, CEO of NVIDIA, put it bluntly: "People talk about AI reducing jobs -- complete nonsense," arguing that AI expands rather than contracts demand for labor (Kinghorn, 2026).[1] These contrasting views raise a central question: as AI becomes more capable and widely used by firms, does it reduce or improve access to employment for workers at the very beginning of their careers?

Recent research points in both directions. Automating entry-level tasks may reduce demand for junior workers and reduce opportunities to build up experience, while it could also boost productivity and reduce the expertise required for entering an occupation. The emerging empirical literature has not resolved this ambiguity. Some studies observe sizeable declines in employment, hiring for young workers and unemployment claims in AI-exposed occupations (Brynjolfsson, Chandar and Chen, 2026; Tucker, 2026; Westby, Modestino and Cheng, 2026; Hyman et al., 2026), while others find limited effects, or highlight other explanations for declines in early-career outcomes (Liu and Webber, 2026; Hartley et al., 2026; Emanuel et al., 2026; Frank et al., 2026). One explanation for these mixed findings is that the available evidence thus far has been from a nascent phase of AI diffusion. Thus, whether these developments have translated into greater difficulty entering the labor force among recent college graduates remains an important empirical question.

[1] This disagreement extends to the leaders of the frontier laboratories themselves with Dario Amodei of Anthropic warning in 2025 that AI could eliminate half of entry-level white-collar jobs (Morris, 2025), while Sam Altman of OpenAI has said he expected more displacement by now than has occurred (Schneid, 2026).

The aim of this paper is to provide the first estimates of the potential effects of AI on the unemployment of recent college graduates through summer 2026. Using timely Current Population Survey (CPS) microdata, we examine whether AI impacted unemployment rates among recent college graduates, individuals ages 22-25 whose highest completed degree is a Bachelor's degree and who are no longer enrolled in school, through August 2026. June, July and August are important because these three months capture graduating college students struggling to enter the job market. We show that these three months have the highest unemployment rates for young college graduates in previous years, rates that are nearly two percentage points higher than the rest of the year. This pronounced seasonal increase means that it is crucial to compare against previous summers, and summer 2026 might be the first time in which AI impacts on recent college graduates are sizeable enough to detect. We also use the CPS to examine whether unemployment increased from trend in previous years for college graduates in 2026 and whether it increased faster for this group relative to both older college graduates and young non-college graduates. Given the lack of consensus on when AI use first became widespread and the massive economic disruption caused by COVID, we take an agnostic approach by comparing 2026 to the previous four years. We show below that the choice of the base year is difficult especially because of the pandemic's disruption to labor markets.

Our focus on recent college graduates in summer 2026 reflects both the vulnerability of new entrants and the timing of workplace use. College graduates typically enter the labor force as junior professional workers such as research analysts, programmers and administrative assistants, and generally perform relatively standardized tasks. Firms may respond to changes in technology by reducing hiring before laying off existing workers (Davis, Faberman, and Haltiwanger 2006). Such responses could therefore disproportionately affect workers searching for their first post-college job, even without widespread displacement of existing workers. Because new college graduates typically enter the labor market in a narrow summer window, we expect 2026 to be the first graduating cohort to enter after this shift.

A central contribution of our approach is that we look beyond official unemployment to also include college graduates outside the labor force who report wanting a job, but who are not actively searching. The official unemployment measure generally requires individuals without work to have actively searched in the previous four weeks. Graduates who want to be employed but do not satisfy these criteria are therefore excluded from being counted in the official unemployment rate. Looking only at official unemployment therefore can miss part of the college graduates who are transitioning out of college, in the process of moving, or for other factors have yet to commence active job search. We therefore create an expanded measure that includes these individuals to capture the unmet desire for employment beyond active job search, which we term “sidelined unemployment,” to more fully capture unemployment within recent college graduates. This measure provides a more complete picture of early-career labor market outcomes than standard unemployment alone.

We find that the unemployment rate in summer 2026 follows similar seasonal patterns, rising in June and then starting to trend downwards in July and August. We provide a descriptive analysis of the most recent patterns in unemployment among recent college graduates rather than make strong claims over causation in terms of the effects of AI on unemployment. Under both the official and the expanded measure including “sidelined unemployment,” the estimates for summer 2026 are small and not statistically different from the preceding year average or 2022. This is consistent with no substantial departure from prior summer trends. Comparisons with other groups less likely to be impacted by AI reinforce this finding, as once the seasonal increase in recent college graduates’ unemployment is taken into account, there is no significant difference compared to older college graduates or young individuals without a college degree. There is no evidence of any significant, widespread displacement or reduction in hiring of recent college graduates in absolute or relative levels.

We also examine whether these patterns vary in occupations based on AI exposure or ability for remote work. Point estimates on interactions with both theoretical and observed occupational AI-exposure measures are positive but not statistically significant. The associations between 2026 unemployment and teleworkability reveal a positive and marginally significant relationship. We interpret this as the evidence not yet identifying an employment effect of AI that can be clearly separated from other changes affecting recent college graduates. Taken together, the results provide a timely assessment of early-career labor market conditions without establishing that AI caused the observed changes. They also demonstrate why evaluating access to employment, particularly for recent college graduates, requires factoring in seasonal variations and looking beyond both existing payroll jobs and officially measured unemployment.

2. Background: AI and Labor Market Entry

AI, Training and Early-Career Labor Demand

The implications of AI for recent college graduates seeking to enter the labor force extend beyond whether AI can replace existing entry-level tasks. In fact, entry-level tasks can be seen as more than just producing output, as they also support skill acquisition through learning-by-doing, supervision and general interaction with more experienced colleagues. Automating these entry-level tasks might therefore reduce the immediate value of junior workers' output while changing firms' incentives to hire and train junior workers. Recent research emphasizes how these changes disrupt apprenticeship arrangements and the organic progression from entry-level to experienced work (Garicano and Rayo, 2025; Afrouzi et al., 2026; Catalini et al., 2026; Asriyan et al., 2026). Under this lens, the consequences of automation include not only fewer entry-level positions to begin with but also reduced advancement opportunities in experience-intensive careers.

Whether AI raises or lowers barriers specifically for junior workers depends on which tasks are automated and how the remaining tasks are reorganized (Autor and Thompson, 2025; Gans, 2026; Agrawal, McHale and Oettl, 2026). AI may augment workers and be particularly beneficial to new entrants, as it can simplify difficult tasks, create new tasks, accelerate skill acquisition and provide access to advanced problem-solving capabilities. This may potentially expand the range of work that junior, less-experienced workers can complete (Ide and Talamàs, 2025; Acemoglu et al., 2026; Althoff and Reichardt, 2026). Thus, technical progress can either increase or reduce the advantage of experience.

These mechanisms highlight why it is important to look beyond just job loss alone to understand early effects. Automation could lead firms to hire fewer workers, leaving existing employees unaffected. Conversely, if AI can augment employees and boost productivity, firms may be able to expand their business without needing to change their employment patterns. For recent graduates, especially, the relevant outcome is not only whether those that are employed end up losing jobs but also whether individuals seeking to begin their careers are able to find entry-level jobs to join the labor force.

Firm Adoption and Timing

The availability of chat-based LLMs is not necessarily the point at which AI began to materially affect labor demand. Although ChatGPT was launched in November 2022, firms' employment decisions may respond only after experimentation with how the technology is used and the integration of AI into workflows as its capabilities improve.[2]

Appendix B assembles several indicators of changes to AI use in late 2025 and 2026. In recent months, spending has risen across consumer[3] and business users, while business spending per employee has accelerated both at the median and among the most intensive users. In the Ramp panel, median monthly AI spending per employee more than doubled between December 2025 and July 2026.[4] Enterprise usage activity likewise shows rapid growth, with ChatGPT Enterprise output tokens increasing sevenfold between June 2025 and March 2026, including more intensive use by existing customers (Chatterji et al., 2026). Spending and usage measure different aspects of adoption, but taken together, both point towards a marked deepening in engagement with AI relative to the periods of its initial availability.

Nationally representative firm data also capture an uptick in intensity of AI usage. In the AI supplement to the Census Bureau's Business Trends and Outlook Survey, fielded from November 2025 through February 2026, the share of firms replacing a large number of employee tasks with AI was nearly three times its level in the previous supplement fielded in early 2024, even though the share of firms replacing any employee tasks at all did not rise.[5] Usage data from a frontier AI laboratory suggest why these effects might not have appeared sooner. As of March 2026, computer and mathematical occupations were assessed as 94 percent theoretically feasible for AI but only 33 percent were actually covered in observed usage (Massenkoff and McCrory, 2026). The gap between what AI can do and what it is actually used to do remains large, so we

[2] Measured AI capability has been improving rapidly between 2022 and 2026. For instance, frontier models gained ~30 points on Humanity's Last Exam in a year (Sajadieh et al. 2026), and METR's 50%-success software task horizon rose from minutes (mid-2024) to an estimated ≥16 hours by March 2026, exceeding what its task suite can reliably measure (METR 2026).

[3] On the consumer side, ConsumerEdge data on credit card spending points to an observable increase in purchases on Anthropic and OpenAI starting late 2025 into 2026.

[4] By July 2026, metered usage through application programming interfaces, which captures AI embedded in production workflows rather than individual subscriptions, accounted for more than half of all business AI spending. Data are pulled from the Ramp AI Index, https://ramp.com/data/ai-index. The panel comprises roughly 70,000 firms using a single corporate card platform and is skewed toward venture-backed firms so it should not be interpreted as representative of all U.S. firms.

[5] Bonney et al. (2026), documenting the Business Trends and Outlook Survey AI supplement fielded November 17, 2025 through February 8, 2026 with more than 117,000 respondents. Among firms substituting AI for employee tasks, the share replacing a large number of tasks rose from 2.5 to 7.0 percent relative to the supplement fielded in early 2024.

posit that it is the closing of that gap rather than the arrival of new capabilities that is the relevant recent change. These indicators do not identify a single treatment date, but together, they motivate examining labor market outcomes, particularly outcomes for new labor market entrants, after a period of significantly more intensive AI use in 2026. Taken together, the adoption evidence makes 2026 particularly informative to examine.

Existing Empirical Evidence

Previous studies examine several margins through which AI could impact employment. Payroll records provide detailed information on filled jobs and their distribution across workers, firms, and occupations. Brynjolfsson, Chandar, and Chen (2026), for example, use ADP records to examine changes in young workers' employment across occupations with different AI exposure. Other studies focus on hiring, entry-level software work, firms' job postings, or unemployment insurance claims (Tucker, 2026; Westby, Modestino, and Cheng, 2026; Liu and Webber, 2026; Hyman et al., 2026).

Each of these approaches captures a different part of the labor market. Payroll records can capture employment changes at firms utilizing specific payroll software, job postings measure advertised labor demand rather than realized hiring, while unemployment insurance claims apply to workers with qualifying prior employment histories. For recent college graduates, however, these data may be limited in their ability to assess new labor market entry.

A separate challenge is cleanly identifying the mechanism. Frank et al. (2026) emphasize deterioration in AI-exposed jobs that predates the launch of ChatGPT, while Emanuel, Harrington, and Pallais (2026) examine how remote work can weaken the informal training and mentoring available to junior workers. These explanations are relevant because occupations exposed to AI may also be those in which remote work is feasible. An association between occupational AI exposure and early-career outcomes could therefore reflect more than one change within firms.

Our analysis complements this emerging literature by leveraging individual-level data from the CPS which covers the population regardless of employment status, making it possible to observe the extensive margins of labor force entry and exit as well as nonparticipation. For recent college graduates specifically, this allows us to observe those who have not found work, those who have stopped searching, as well as those working across different sectors and employment arrangements, giving us a fuller picture of young college graduates' labor market prospects.

3. Data and Definitions

The CPS is the only nationally representative dataset that provides: (i) a measure of unemployment, a measure of not being in the labor force but nevertheless wanting a job, and other underlying variables to create underemployment or mismatch, (ii) information on both age and highest education level achieved of individuals, (iii) occupations, and (iv) college enrollment. Using microdata from the basic monthly files of the Current Population Surveys (CPS), we measure unemployment, wanting a job, underemployment, mismatch and college enrollment at the individual level. These surveys, conducted monthly by the U.S. Bureau of the Census and the U.S. Bureau of Labor Statistics, are representative of the entire U.S. population and contain observations for more than 130,000 people. The CPS is usually released within a month of when the data are collected.

The CPS has been conducted monthly since 1940 and is the underlying source of official government statistics on employment and unemployment. Data are collected by personal interviews. The CPS is the only source of monthly estimates of employment, unemployment, hours worked, college enrollment, and occupations. Although the main purpose of the CPS is to collect information on the employment situation, a secondary purpose is to collect information on the demographics of the population including age.

To estimate unemployment among recent college graduates in the CPS data, we identify all individuals ages 22 to 25 who are not currently enrolled in school and report being unemployed or employed in the survey month (based on the school enrollment question and monthly labor force recode). We expand on the traditional unemployment definition by including those individuals who are not actively looking for a job but report "want a job." We also expand on the unemployment definition by including those individuals who are underemployed by working less than 10 hours a week and those individuals with mismatched occupation based on employment in occupations that do not require formal education. The CPS captures the current work activity of the individual including recent graduates who have a job but have not started yet. These individuals are thus not defined as currently unemployed, unless they actively searched in the previous four weeks.

We define recent college graduates as individuals ages 22-25 who report having a Bachelor's degree (e.g., BA, BS, or AB) as their highest level of school completed or degree received.[6] To isolate the effects on college graduates, we do not include individuals reporting having a Master's, professional school, or doctorate degree. As noted above, we do not include individuals who are currently enrolled in school, which rules out someone having a Bachelor's degree and who is currently working on an advanced degree. We are interested in recent college graduates because changes in labor demand may first appear through reductions in hiring. Firms can reduce employment by hiring fewer workers and relying on attrition, allowing them to adjust without laying off existing employees (Davis, Faberman, and Haltiwanger 2006). Recent college graduates may be especially vulnerable to these adjustments because they are seeking to establish employment relationships and have less work experience than older workers. They also have had less time to acquire skills through work that may complement new technologies.

In addition to providing information on unemployment, college enrollment, and work activity, the CPS data include information on detailed demographic information including age, gender and race, and geographic information on region of the country and central city/suburb/rural location. The data also include information on occupations. The CPS microdata have been used extensively in previous studies of unemployment especially to examine how different groups experienced previous labor market disruptions (see, for example, Hoynes, Miller and Schaller (2012) for the Great Recession, and Couch, Fairlie and Xu (2020) for the COVID recession).

Survey Timing and College Graduation

The CPS survey reference period is generally the calendar week that contains the 12th day of the month. For June 2026, the reference week was Sunday, June 7 through Saturday, June 13, 2026. For July, the week was Sunday, July 12 through Saturday, July 18, and for August the week was Sunday, August 9 through Saturday, August 15. The last day of final examinations for semester-based colleges is typically in mid-May, and the last day of final examinations for quarter-based colleges is typically mid-June. For example, finals ended on Friday, May 15, 2026

[6] We follow Brynjolfsson, Chandar, and Chen (2026) in defining young workers as individuals aged 22–25, capturing recent college graduates who are entering or just entered the labor market and might be the most exposed to AI skill replacement.

at UC Berkeley (semester system) and on June 12, 2026 at UCLA (quarter system). Given that college graduation started before this reference week, the June 2026 release might be the first CPS survey covering non-negligible early-stage impacts of AI on the employment outcomes of recent college graduates.

Appendix Figure A.1 displays unemployment rates by month for the period from 2012 to 2019 and 2022 to 2025. The years 2020 and 2021 are excluded because of the economic disruption caused by COVID and resulting high unemployment rates during these years. Unemployment rates and other economic outcomes returned to pre-pandemic levels near the beginning of 2022 (Fairlie 2026). The unemployment rate among young college graduates follows a clear seasonal pattern: the rate is low from January to May, then increases sharply over the summer (June to August), and then starts to decrease again in the fall. Given these patterns we separate winter, summer, and fall in the analysis defined as January to May, June to August, and September to December, respectively. The summer months are especially important as unemployment rates are nearly 2 percentage points higher than the base average of 5 percent for other months.

Unemployment Measures including "Sidelined" Definition

The CPS microdata provide information on basic measures of work, unemployment, school enrollment and labor force attachment. Among individuals ages 22-25 who have a Bachelor's degree as their highest level of school completed or degree received, 22.5 percent are currently enrolled in school. This group is removed from the analysis sample of young, recent college graduates. Among the non-enrolled, 7.1 percent of individuals report not being in the labor force (NILF), which are also removed from the main sample. Among our sample of young, recent college graduates in the labor force, 5.7 percent are unemployed during the period from 2022 to 2026.[7]

The official CPS unemployment definition is based on actively looking for work in the survey reference period. To be classified as unemployed, a person: (i) does not have a job, (ii)

[7] Using information on the reason for unemployment we find that less than 17 percent of unemployed recent college graduates lost jobs because of layoffs or other involuntary job loss. The predominant reason for unemployment among this group is not finding a job.

has actively looked for work in the previous four weeks, and (iii) is currently available for work.[8] One exception to meeting these criteria is that workers who expect to be recalled from temporary layoff are considered unemployed.

If a person is not currently employed and does not fit this definition of unemployment then they are classified as not in the labor force (NILF). Among the NILF group, some individuals report that they did not actively search for a job in the last four weeks but report currently "want a job."[9] These individuals might be very interested in working but do not meet the specific criteria that the BLS uses to define unemployment especially around actively looking for work. For example, simply reading job postings, attending a job training program, or taking a break after graduation with no job lined up does not meet the criteria. Among all young college graduates, 1.9 percent report NILF and "want a job." Adding this group to the unemployed results in an expanded measure of unemployment of 7.6 percent. This group of expanded unemployed, which we term "sidelined unemployment," might be important to add when examining the labor market outcomes of college-educated individuals ages 22-25 who are not enrolled in school. This sidelined group does not typically fall into the most common forms of NILF such as retirement or taking time off for family reasons and are thus very likely to be interested in working if a job was available.

We also create a measure of "underemployment" defined as adding individuals who are currently employed but work less than 10 hours in the survey week. Adding this group to the unemployed results in an "underemployed" rate of 6.8 percent. Finally, we create a measure of job or occupation mismatch to capture recent college graduates who are employed in occupations that require no formal education. We continue to exclude, as for all unemployment measures, individuals who are currently enrolled in school to rule out employment in part-time jobs while in college. To create the job mismatch variable we use information on the typical education needed for entry into an occupation from the BLS data on education and training assignments by occupation.[10] We define recent college graduates employed in occupations that are classified as

[8] Actively looking for work may consist of any of the following activities: 1) contacting an employer directly or having a job interview, contacting a public or private employment agency, contacting friends or relatives, or contacting a school or university employment center, 2) submitting resumes or filling out applications, 3) placing or answering job advertisements, 4) checking union or professional registers, or 5) some other means of active job search (BLS 2026).

[9] The question asks the person: "Do you currently want a job, either full or part time?"

[10] See Table 5.4 Education and training assignments by detailed occupation, https://www.bls.gov/emp/tables/education-and-training-by-occupation.htm

having “No formal educational credential” as job mismatches. Adding this group to the original unemployment definition results in an unemployed plus job mismatch rate of 14.8 percent.[11]

AI Exposure

We use measures of AI exposure and remote work percentage to interact with our time period measures for recent college graduates. We link the reported occupation of each individual to the AI exposure and remote work percentage for each occupation. Some recent college graduates who are unemployed do not have reported occupations because of their limited experience in the labor market. These observations are lost from the sample (15.5 percent for unemployment and 35.8 percent for the expanded sidelined unemployment measure).

To narrow in on whether any observed patterns are driven by AI-affected occupations, we examine both theoretical and observed occupational exposure to AI. For theoretical exposure, we use the measure developed by Eloundou et al. (2024) which categorizes O*NET tasks using a combination of ChatGPT-4 and human labeling. We focus on the GPT-4 LLM-coded one which is the author-preferred measure. For observed exposure, we use the Anthropic Economic Index by Massenkoff et al. (2026), whose measure relies on actual Claude usage patterns to derive occupational exposure. Because both classification approaches use SOC 2018 occupation codes, we map the classifications using the Census CPS-SOC bridge.

Remote Work Exposure

Recent work has suggested an alternative possibility for reduced junior level positions (Emanuel, Harrington and Pallais, 2026). Studying an earlier period, they estimate that the growth of remote work impedes the informal training and mentoring that junior workers require, which makes firms more reluctant to hire inexperienced workers. We treat this as an alternative mechanism to compare against AI exposure, using the teleworkable classification of Dingel and Neiman (2020), which scores occupations on whether their tasks can plausibly be performed from home. We construct an occupation-level teleworkable measure.[12] Among recent college

[11] The most common occupations are: retail salespersons; waiters and waitresses; cashiers; fast food and counter workers; laborers and freight, stock and material movers, hand; and stockers and order fillers.

[12] Dingel and Neiman classify occupations using O*NET task and work-context descriptors. Their measure is built on 2010 O*NET-SOC codes, which we bridge to 2018 Census occupation categories using the Census occupation code crosswalk. We assign a teleworkable value to a Census category only when every one of its 2010 predecessor codes is representatively covered, meaning covered by its O*NET .00 profile or by a complete breakout of that

graduates, 45 percent are in occupations with a teleworkable value of 1, and 34 percent are in occupations with a teleworkable value of 0.[13]

We find that these two sets of measures are overlapping but not identical, which is intuitive as AI-exposed work and work that can be done from home are largely the same type of cognitively intensive, desk-based work. In our sample, the correlation between observed AI exposure and the teleworkable measure is 0.58, and the theoretical AI exposure and teleworkable measure is 0.66.

4. Estimation

To test whether AI had disproportionate impacts on college graduates, we estimate regressions in which unemployment is the dependent variable and control for prior trends in unemployment. The inclusion of a control for prior trends in unemployment might be important in identifying potential disruptions created by AI. We start by using winter and summer 2026 as the AI event but then move to a more flexible specification that explores the possibility of earlier effects. The base equation is:

$$(4.1) \quad Y_{it} = \alpha + \delta_{26}^{S} Sum26_t + \delta_{26}^{W} Win26_t + \gamma^{S} Sum_t + \gamma^{W} Win_t + \beta' X_{it} + \lambda_t + \varepsilon_{it}$$

where Y_{it} is monthly unemployment for individual *i* in month *t*, $Sum26_t$ is a dummy variable for June, July and August 2026, $Win26_t$ is a dummy variable for January-May 2026, Win_t is a dummy variable for January to May for all years, Sum_t is a dummy variable for June to August for all years, X_{it} includes individual and geographical characteristics, λ_t is a linear time trend, and ε_{it} is the error term. The parameter of primary interest is δ_{26}^{S}, which captures the estimate of the effects of AI on unemployment by comparing June, July and August, 2026 to June, July and

profile. Under this rule, 87.4 percent of employment in our 2022-2026 sample is fully covered, 10.5 percent is partially covered, and 2.1 percent is uncovered.

[13] Because Dingel and Neiman (2020) classifies occupations at the O*NET level, which is more detailed than the Census occupation categories reported in the CPS, the measure is not binary once mapped to CPS occupations. Among the 525 Census occupation categories observed in our data, 132 (25 percent) have a value of 1, 280 (53 percent) have a value of 0, 62 (12 percent) take a fractional value because the Census occupation category combines O*NET occupations with different classifications, and 51 (10 percent) cannot be assigned a value because they are not assigned in Dingel and Neiman (2020). For example, software developers, accountants, and financial managers are assigned to a value of 1 for the teleworkable/remote measure. In contrast, registered nurses, social workers, and pharmacists are assigned a value of 0. Credit counselors and loan officers, for example, are assigned 0.5 because credit counselors can work from home whereas loan officers cannot.

August averaged over the previous 4-year period. Any potential AI effects in winter 2026 relative to the winter 2022-25 average can be detected by δ_{26}^{W}. For this base specification, we are implicitly assuming that there were either no or only small AI effects prior to 2026, however, we are not making strong claims about treatment timing which is consistent with the lack of consensus over when AI use was widespread and findings of impacts in other studies (as noted above).

The analysis period covers January 2022 to August 2026. January 2022 is a useful starting point because 2022 has been described as a turning point in the pandemic and its labor market effects (Fairlie 2026). By the beginning of 2022, the national unemployment rate returned to pre-pandemic levels. The regressions control for individual characteristics (age, gender, race), and geographic characteristics (region of the country and central city/suburb/rural location). The main specification includes a linear time trend to capture longer-term pre-trends in unemployment. All specifications are estimated with OLS using CPS sample weights.

To expand on this specification, we explore potential earlier AI effects by including a full set of year dummies instead of a linear time trend. This “event-study” style regression is specified as follows:

$$(4.2)\quad Y_{it} = \alpha + \sum_{j=23}^{26} \delta_j^S\, Sum(j)_t + \sum_{j=23}^{26} \delta_j^W\, Win(j)_t + \sum_{j=23}^{25} \delta_j^F\, Fall(j)_t + \gamma^S\, Sum_t + \gamma^W Win_t + \beta' X_{it} + \varepsilon_{it}$$

where the reference year is j=0 (year=2022), and $Sum(j)_t$, $Win(j)_t$ and $Fall(j)_t$ are dummy variables each year’s June-August, January-May and September-December period, respectively. This event-study approach estimates unemployment in all season-years using 2022 as the base year. We choose 2022 here as the base year to minimize effects from AI because ChatGPT was not released until the end of 2022. For example, δ_{25}^{S} captures unemployment in summer 2025 relative to summer 2022. For the event-study regression we are implicitly assuming that 2022 is the only non-affected, pre-ChatGPT reference year and that earlier years were affected by COVID. The approach has the disadvantage that it only uses information from 2022 to characterize the non-AI labor market, and 2022 is a full four years before 2026.

Comparison to Older, More-Experienced College Educated Workers

To test whether AI had disproportionate impacts on unemployment for recent college graduates relative to similarly-educated workers who have more experience, we estimate additional regressions that include interactions between the two groups and winter and summer 2026 dummy variables. We also control for the prior trend in overall unemployment and the trend in the young-older gap in unemployment which might be important for identifying the effects of AI. The maintained assumption in this case would be that AI did not affect unemployment among older college educated workers with more experience (ages 30-49) but that other factors such as macroeconomic conditions affected both young and older college graduates similarly in 2026. To start, we estimate the following base equation:

$$(4.3) \quad Y_{it} = \alpha + \delta^C YC_i + \gamma_{26}^S Sum26_t + \gamma_{26}^W Win26_t + \delta_{26}^{SYC} Sum26_t * YC_i + \delta_{26}^{WYC} Win26_t * YC_i + \gamma^S Sum_t + \gamma^W Win_t + \delta^{SYC} Sum_t * YC_i + \delta^{WYC} Win_t * YC_i + \beta' X_{it} + \lambda_t + \lambda_t * YC_i + \varepsilon_{it}$$

where YC_i is a dummy variable for young recent college graduates (ages 22-25) for individual *i*. The parameter of interest is δ_{26}^{SYC}, which captures the effects of AI on unemployment for young college graduates relative to older college graduates in the key summer 2026 time period (relative to the summer average over 2022-25). The specification includes interactions between the young college graduate indicator and the winter and summer indicators, as well as a linear time trend and a linear time trend interacted with the young college graduate group (λ_t and $\lambda_t * YC_i$).

Equation (4.3) is in the nature of a "difference-in-differences" estimator of the impact of AI on unemployment among recent college graduates. But dissimilar to most difference-in-differences applications, the control group (in this case older, more experienced college educated workers) might have also been affected by AI. For example, in this application there is no cleanly defined control group in which a policy was designed to not have an effect through ineligibility.

Another approach is to include a full set of season-by-year dummies and their interactions with the young college graduate dummy instead of including only differential pre-trends. This "event-study" style regression allows the young college graduate interaction to differ in each year potentially capturing earlier impacts. The event-study regression estimates young-older disparities in each year prior to 2026.

Comparison to Young Non-College Graduates

We also estimate (4.3) using young non-college graduates as the comparison group instead of middle-age college graduates. Although young individuals who did not graduate from college might also be affected by changes in AI use in the workplace they are likely to be less affected than recent college graduates given that AI likely replaces standardized technical tasks more so than consumer-facing or physical work.

(4.4) $$Y_{it} = \alpha + \delta^{C} CG_i + \gamma_{26}^{S} Sum26_t + \gamma_{26}^{W} Win26_t + \delta_{26}^{SCG} Sum26_t * CG_i + \delta_{26}^{WCG} Win26_t * CG_i + \gamma^{S} Sum_t + \gamma^{W} Win_t + \delta^{SCG} Sum_t * CG_i + \delta^{WCG} Win_t * CG_i + \beta' X_{it} + \lambda_t + \lambda_t * CG_i + \varepsilon_{it}$$

where CG_i is a dummy variable for college graduate for individual *i*, the parameter of interest is the δ_{26}^{SCG}, which captures the effects of AI on unemployment for young college graduates relative to young non-college graduates in the key summer 2026 time period (and relative to the summer average over 2022-25, i.e. difference-in-differences). The specification again includes the group-by-season interactions, a linear time trend and a linear time trend interacted with the college graduate group.

5. Results

Unemployment Rate Trends

Figure 1 displays unemployment rates by month for recent college graduates (ages 22-25) from January 2022 to August 2026.[14] In addition to the standard unemployment rate, the figure reports the expanded measure that includes individuals who are not in the labor force but report wanting a job, the "sidelined unemployed." Both measures show substantial variation over each year, with unemployment following a clear seasonal pattern across all years, in which unemployment among recent college graduates rises sharply during the summer months and then

[14] Due to the federal government shutdown in fall 2025, the CPS data are missing the October 2025 data collection. As noted by the BLS, "CPS data were not collected for October 2025 due to the lapse in appropriations and were not collected retroactively. All CPS operations were suspended during the federal government shutdown, which began before and continued beyond the scheduled collection period for October data." See https://www.bls.gov/cps/methods/2025-federal-government-shutdown-impact-cps.htm#1.

declines during the fall. The seasonal pattern is similar to the pattern in earlier years as shown in Appendix Figure A.1. The expanded measure follows many of the same movements as the standard measure of unemployment, although the difference between the two rates also varies over time. The increase in summer 2026 is evident under both definitions, making comparisons with the same months in previous years especially important.

Figure 2a displays the standard unemployment rate by calendar month for each year stacked over each other, allowing us to examine these seasonal patterns more directly. Unemployment among recent college graduates averaged 5.3 percent in winter 2026, compared with 5.7 percent in winter 2025. The rate increased from 5.4 percent in May 2026 to 7.8 percent in June, before declining slightly to 7.4 percent in July and 6.8 percent in August. Averaging over June, July and August, unemployment was 7.3 percent in 2026, compared with 7.1 percent in 2022, 6.3 percent in 2023, 7.8 percent in 2024 and 7.2 percent in 2025. The unemployment rate in summer 2026 is therefore higher than in 2022, 2023 and 2025, but below 2024. Examining these levels, unemployment in summer 2026 remains within the range observed since 2022, and the summer increase follows a pattern that is also evident in earlier years.

Figure 2b displays the corresponding seasonal comparison for the expanded unemployment measure. As noted above, this measure includes young college graduates who are "sidelined," those not officially defined as being in the labor force but nonetheless report "wanting a job." The expanded unemployment rate increased from 7.9 percent in May 2026 to 11.1 percent in June and then declined slightly to 10.7 percent in July and 9.4 percent in August. Averaging over June, July and August, the expanded measure was 10.4 percent in 2026, compared with 9.4 percent in 2022, 9.3 percent in 2023, 10.1 percent in 2024 and 9.4 percent in 2025. Summer 2026 is the highest of the five summers under this definition, although it exceeds the previous high by only 0.3 percentage points. Including individuals who want a job raises the summer 2026 rate by 3.1 percentage points relative to standard unemployment, compared with 2.2 percentage points in summer 2025. The expanded measure thus indicates a larger increase relative to 2025, while also showing that high rates in the summer are not unique to 2026.[15]

[15] We also examined an underemployment measure that adds graduates working fewer than ten hours per week to the unemployed and an occupational mismatch measure that adds graduates employed in occupations requiring no formal educational credential (Appendix Figure A.2). Averaging over June, July and August, the underemployment proxy measure was 9.1 percent in 2026 compared with 8.2 percent in 2022, and the occupational mismatch proxy measure was 17.1 percent compared with 15.6 percent in 2022.

Figures 3a and 3b display unemployment rates for young college graduates (ages 22-25) and older college graduates (ages 30-49). Figure 3a shows that unemployment among older graduates is lower and exhibits less pronounced seasonal variation. Their unemployment rate increased from 2.7 percent in summer 2025 to 2.8 percent in summer 2026, while the rate among young graduates increased from 7.2 to 7.3 percent. The young-older gap therefore was stable at 4.5 percentage points. Figure 3b shows a larger widening when sidelined individuals outside the labor force who want a job are included. Under the expanded definition, the rate among young college graduates increased from 9.4 to 10.4 percent, compared with an increase from 4.1 to 4.2 percent among older college graduates. The expanded gap widened from 5.3 percentage points in summer 2025 to 6.2 percentage points in summer 2026. For this expanded measure there might be a deterioration in the relative position of young graduates compared with 2025.

Figure 4a displays standard unemployment rates for young college graduates and young individuals without a college degree. This comparison shows a more pronounced change in summer 2026. Unemployment among young non-college graduates fell from 7.5 percent in summer 2025 to 6.8 percent in summer 2026, while unemployment among young college graduates increased slightly from 7.2 to 7.3 percent. Young college graduates consequently had an unemployment rate of about 0.5 percentage points higher than young non-college graduates in summer 2026, compared with a rate 0.3 percentage points lower in summer 2025. The standard rate was also slightly higher among young college graduates in summers 2022 and 2024, but the 2026 gap is larger. This comparison is worth examining further because the two groups are in the same age range and face the same broad macroeconomic conditions, although changes in labor demand may affect them differently.

Figure 4b displays the same comparison using the expanded unemployment measure that includes the sidelined unemployed. The rate among young college graduates increased from 9.4 percent in summer 2025 to 10.4 percent in summer 2026, while the rate among young non-college graduates declined from 11.6 to 10.7 percent. The gap favoring college graduates therefore narrowed from 2.2 percentage points to only 0.3 percentage points, the smallest of the five summers. The two groups had nearly equal expanded rates in summer 2026, with the rate among college graduates remaining slightly lower. We next use regressions to examine these comparisons after accounting for differences in individual characteristics, seasonal patterns and prior trends.

Trend, Event-Study and Difference-in-Differences Regressions

Table 1 reports regression estimates from equations (4.1) and (4.2) for recent college graduates. The estimated coefficient on the summer 2026 dummy is -0.008 with a standard error of 0.007 for the standard unemployment measure (Specification 1) and 0.001 with a standard error of 0.009 for the expanded measure that adds those not officially in the labor force but report wanting a job (Specification 3). The estimate controls for a slight positive pre-trend and implicitly compares 2026 to the de-trended average of the previous four years. Neither coefficient estimate is statistically significant. In Specifications 2 and 4, we report the "event-study" like regression estimates. In this specification, we are comparing 2026 seasons to the same seasons in 2022 (e.g. summer 2026 compared to summer 2022). We find a similar result in these specifications, no statistically significant increase in unemployment rates in summer 2026. Taken on its own, this suggests no unusual increase in unemployment in summer 2026 among recent college graduates. We also do not find a statistically significant increase in unemployment rates in winter 2026 in any specification.

Robustness Checks

The pattern of no evidence of an increase in unemployment rates among recent college graduates in 2026 is robust to alternative samples and specifications. First, we estimate the model excluding 2025. If college graduates had an AI effect in 2025 then this could limit our ability to detect a change from the summer 2022-25 average to summer 2026. As noted above, in Specifications 1 and 3 we use 2022-25 as the base period. We continue to find statistically insignificant coefficients on summer 2026 after removing 2025 from the base period. Second, we estimate the base model without including the time trend. These models can sometimes be sensitive to the inclusion of pre-trends because the assumption is that these trends will continue into the treatment period. Similarly, we continue to find no evidence of an increase in unemployment rates in 2026 after removing the time trend. Finally, we increase the age range to ages 22-27. We continue to find statistically insignificant coefficients for summer 2026.

Comparison Group Regressions

Table 2 reports estimates from equation (4.3), which compares recent college graduates with “middle-age” college graduates, ages 30-49. The interaction between the young college graduate indicator and summer 2026 is -0.007 (0.008) in the specification with a linear trend and -0.005 (0.009) in the event-study specification, and 0.002 (0.009) and 0.004 (0.010) respectively for the expanded unemployment measure. None of the coefficient estimates is statistically significant, and the point estimates are small in magnitude. The interactions for summers 2023 to 2025 in the event-study specification are also close to zero, so no summer since 2022 stands out. The interaction between the young graduate indicator and the summer indicator, in contrast, is large and precisely estimated (0.014 to 0.030), confirming that the summer increase in unemployment is much larger for recent college graduates than for older college graduates in general.

Table 3 reports estimates from equation (4.4), which uses young non-college graduates as the comparison group for the difference-in-difference regressions and event-study regression interactions. The interaction between the college graduate indicator and summer 2026 is 0.002 (0.009) in the specification with a linear trend and 0.006 (0.010) in the event-study specification for the standard measure, and 0.013 (0.011) and 0.012 (0.012) for the expanded measure. All four point estimates are positive but none is statistically significant. The point estimates for the expanded measure that includes the sidelined unemployed are the largest relative point estimates we find. One factor driving these relative positive point estimates of note is that there is some evidence that unemployment was lower in summer 2026 for young non-college graduates. In two of the specifications, we find a negative (but only marginally significant at the 0.10 level) coefficient estimate on the main summer 2026 effect which captures the change in unemployment for non-college graduates from the summer 2022-25 average. As in Table 2, the interactions for earlier summers are close to zero, and the summer increase in unemployment is larger for college graduates than for young non-college workers.

For both comparison groups, the estimates are robust to alternative samples and specifications. First, we expand the age range for middle-age college graduates to ages 26 to 55. We find similar coefficient estimates and continue to find no statistically significant relative effect. Second, we restrict the young non-college graduate group to only those with a high school education (which represents most of the non-college total sample). Using this group as the comparison group we find similar relative coefficient estimates and no statistical significance for any coefficient estimate. Finally, we estimate both models without the time trend and its interactions with the comparison group used. We continue to find similar estimates and no evidence of a statistically significant change in summer 2026 for recent college graduates relative to either comparison group.

Taken together, these estimates tell a consistent story in which unemployment among recent college graduates in summer 2026 was not unusually high relative to earlier summers. The change in unemployment to summer 2026 was also not unusually large relative to the change for two very different comparison groups.

AI Exposure and Remote Work

While the aggregate comparisons do not detect an increase in unemployment among recent college graduates in summer 2026, they could mask increases in the occupations most exposed to AI that are offset by decreases elsewhere. We use the occupational exposure measures described in Section 3 to ask whether unemployment rose in the occupations most consistent with an AI explanation. We return to focusing on recent college graduates and the base specification that compares summer 2026 to the de-trended average of summer 2022 to 2025.[16] The event-study specification adds interactions between the AI exposure measure and each season-year indicator, so that 2026 is compared with the same season of 2022.

Tables 4 and 5 report estimates for observed AI exposure from the Anthropic Economic Index measure and the theoretical AI exposure measure of Eloundou et al. (2024), respectively, using the base difference-in-differences and event-study specifications. Across the eight specifications, the point estimates are consistently positive but none are statistically significant. The point estimates are also somewhat sensitive to when we remove time trends or specific reference years. These findings do not provide consistent evidence for the AI-related unemployment story.

Table 6 reports the analogous estimates with the teleworkability measure. We find statistically significant, positive point estimates using both the standard and expanded measure,

[16] As noted above, among recent college graduates, 16 percent of the unemployed and 36 percent of the unemployed plus sidelined unemployed (i.e. “want a job”) groups do not report an occupation. Furthermore, AI-exposure information is not available for all occupation codes in the CPS. The estimates in Tables 4, 5 and 6 therefore focus only on recent college graduates who report a current or previous occupation.

in both the base difference-in-differences and event-study specifications. The summer 2026 coefficient itself, which applies to graduates in occupations that cannot be performed from home, is negative in every column, pointing to the differential capturing not only higher unemployment in teleworkable occupations but also lower unemployment in non-teleworkable occupations. These estimates are at least somewhat consistent with evidence that remote work has weakened labor market entry for junior workers (Emanuel, Harrington and Pallais, 2026). More broadly, because AI-exposed occupations and teleworkable occupations overlap substantially, these estimates illustrate why the AI and remote work explanations are difficult to separate.

6. Conclusion

Concerns that AI will displace jobs, and especially the entry-level jobs held by recent college graduates, are widespread, but there has been little direct evidence on whether these effects have started to appear in the labor market. Summer 2026 provides a useful first test given recent accelerations in firms' AI usage intensity and summer is when the graduating cohort enters the labor market. Using CPS microdata from January 2022 to August 2026, we examine whether unemployment among recent college graduates increased in summer 2026 relative to previous summers and increased relative to two comparison groups of workers who were arguably less likely to have been affected by AI.

We do not observe an unusually large increase in the unemployment rate for recent college graduates in summer 2026. Averaging over June, July and August, the official unemployment rate for college graduates ages 22-25 was 7.3 percent. This rate is higher than in 2022, 2023 and 2025 but lower than the 7.8 percent recorded in 2024, suggesting that it is within the normal range of variation. The regression estimates are consistent with this comparison of raw rates, as the coefficient on summer 2026 is small and not statistically distinguishable from zero in all specifications, and the event-study estimates do not place the largest increases in summer 2026. The estimates therefore do not document a clear break from the range seen in 2022 to 2025.

This finding persists when recent college graduates are compared with other workers. Relative to older college graduates ages 30-49, the summer 2026 estimates are statistically insignificant, and relative to young workers without a college degree estimates are also statistically insignificant. While neither group is a clean control, the fact that recent graduates did not lose significant ground against two very different groups nevertheless reinforces the conclusion from the level estimates.

We also do not find evidence that unemployment among recent college graduates rose in the occupations that AI is most likely to affect. The coefficient estimates of interactions between summer 2026 and both measures of occupational AI exposure are positive, but not statistically significant. The point estimate of the interaction with occupational teleworkability is positive but difficult to separate cleanly from AI exposure. These patterns suggest some caution in interpreting estimates of the effects of AI-exposure and remote work availability. Separating the two explanations is difficult because AI-exposed occupations and occupations that can be performed remotely are correlated. Also, many recent college graduates who are unemployed or out of the labor force but want a job do not report an occupation because of their lack of previous experience in the workforce. Thus, we lose part of the group that we are potentially most concerned about with expanded AI use in the workplace. This limitation is potentially more problematic when using aggregate employment numbers by occupation to study AI impacts instead of using individual-level data such as the CPS microdata. Aggregate numbers of unemployment, employment, job postings and UI claims by occupation might not adequately capture the denominator (i.e. numbers of labor force entrants). More research along these lines with careful consideration of reference time periods, missing occupations for the unemployed, and overlap in effects is clearly needed.

Previous studies document early labor market shifts associated with AI using payroll records, job postings, and unemployment insurance claims (Brynjolfsson et al., 2026; Tucker, 2026; Liu and Webber, 2026; Hyman et al., 2026). These data sources provide valuable evidence on different aspects of the labor market such as employment at certain firms, advertised labor demand, and job loss among workers with prior employment. Our focus is distinctly on recent college graduates and unpacking whether they are without work and seeking employment, or want a job despite being defined as outside the official labor force. The CPS is uniquely poised to let us examine this question, providing us with individual-level information on current school enrollment, own educational attainment, and detailed labor force status, beyond any particular employer or platform. Importantly, our main analysis includes graduates who have not established an occupational history, even though these individuals cannot always be included in the occupational-exposure analysis. We also extend measurement beyond official unemployment to include those outside the labor force who report wanting a job. This expanded "sidelined unemployment" measure highlights unmet desire for employment that official unemployment does not capture and is at its highest level of the five summers in summer 2026. Neither the official nor the expanded measure, however, exhibits a statistically significant departure from earlier summers.

Taken together, the results provide a descriptive picture of the labor market for recent college graduates in the first summer in which AI use in the workplace was widespread enough to expect observable effects on employment. The findings do not support the conclusion that AI led to a large increase in unemployment among recent college graduates in summer 2026. This null result holds across specifications and comparison groups. Recent increases in the intensity of workplace AI use make this an informative period to examine, but neither the timing of adoption nor the available comparison groups provides a clean basis for causal interpretation. These findings do not rule out larger effects in the future. If the intensity of AI use in the workplace continues to increase, the graduating classes of 2027 and later might be more affected than the class of 2026, and additional years of data will be needed to hone in on whether effects emerge as workplace use of AI deepens. Importantly, evaluating this will require measuring not only the jobs firms add or remove, but also measuring the graduates who have yet to gain a foothold in the labor force in the first place.

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Figures and Tables

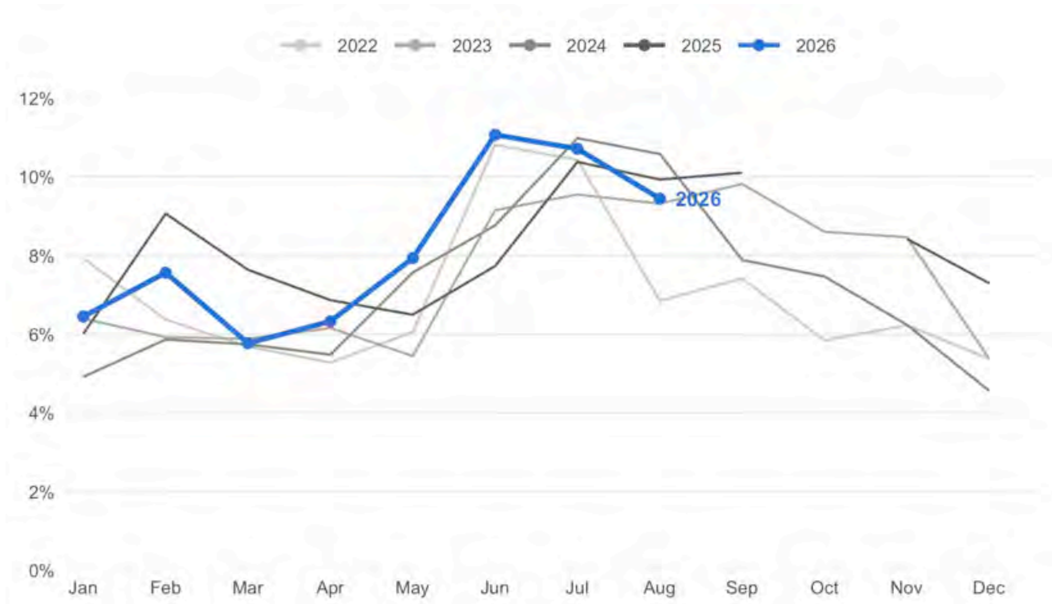
Figure 1. Unemployment among recent college graduates

Notes: Official and expanded measures using Current Population Survey basic monthly files, January 2022 to August 2026. The October 2025 survey was not conducted so the series breaks at that month. Recent college graduates are individuals ages 22 to 25, not enrolled in school, whose highest completed degree is a Bachelor's degree.

Figure 2a. Unemployment rate of recent college graduates, by month of year

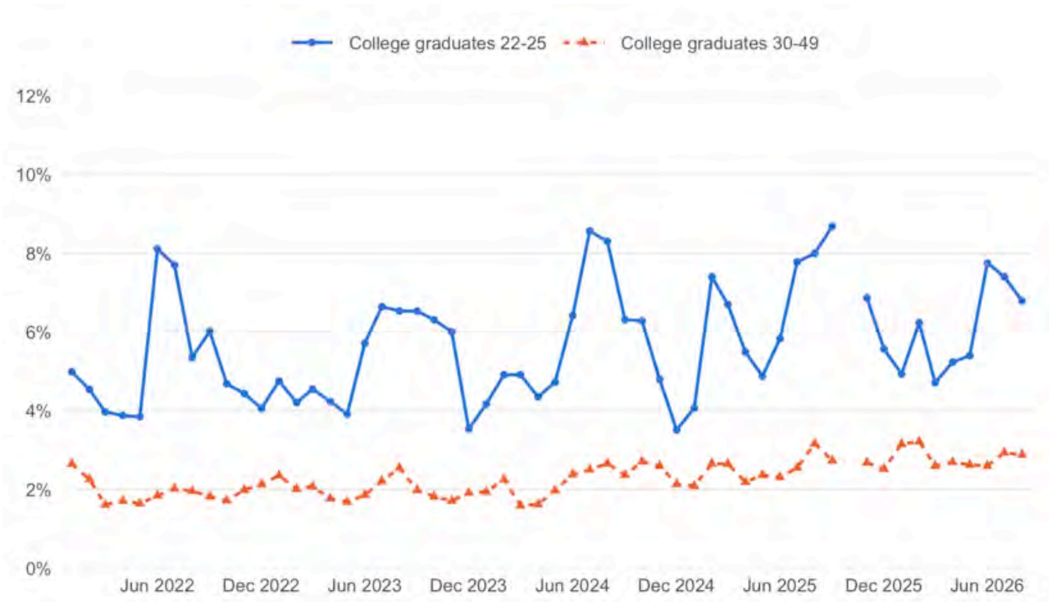
Notes: Official measure using Current Population Survey basic monthly files, January 2022 to August 2026. The October 2025 survey was not conducted so the series breaks at that month. Each line is one calendar year against month of year, earlier years in lighter grey, 2026 in blue and observed through August. Recent college graduates are individuals ages 22 to 25, not enrolled in school, whose highest completed degree is a Bachelor's degree.

Figure 2b. Unemployment or wants a job ("sidelined unemployed"), recent college graduates, by month of year



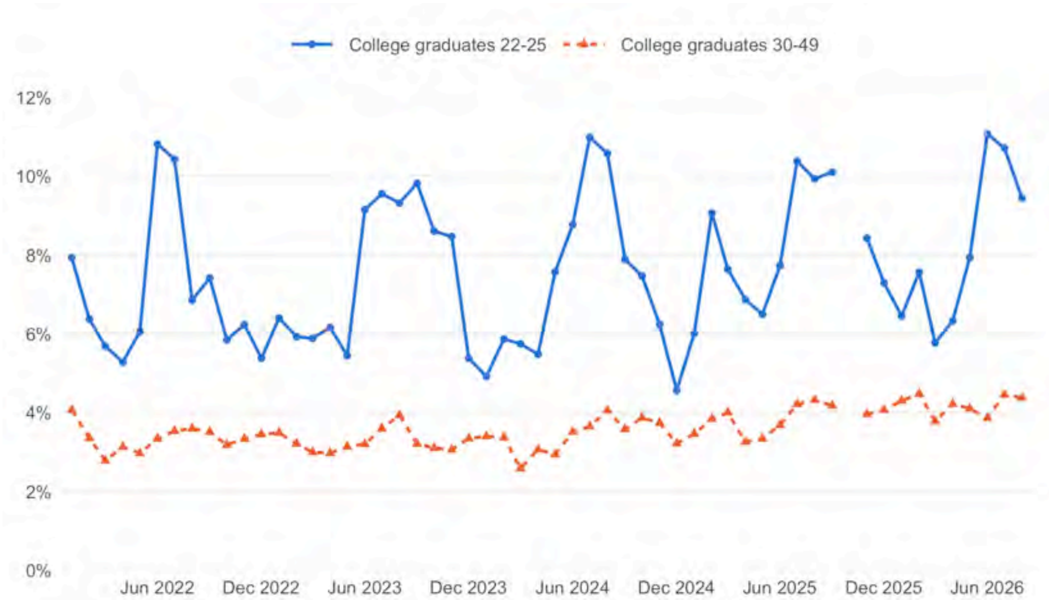
Notes: Expanded unemployment measure calculations using Current Population Survey basic monthly files, January 2022 to August 2026. The October 2025 survey was not conducted so the series breaks at that month. Each line is one calendar year against month of year, earlier years in lighter grey, 2026 in blue and observed through August. Recent college graduates are individuals ages 22 to 25, not enrolled in school, whose highest completed degree is a Bachelor's degree.

Figure 3a. Unemployment rate, young and older college graduates



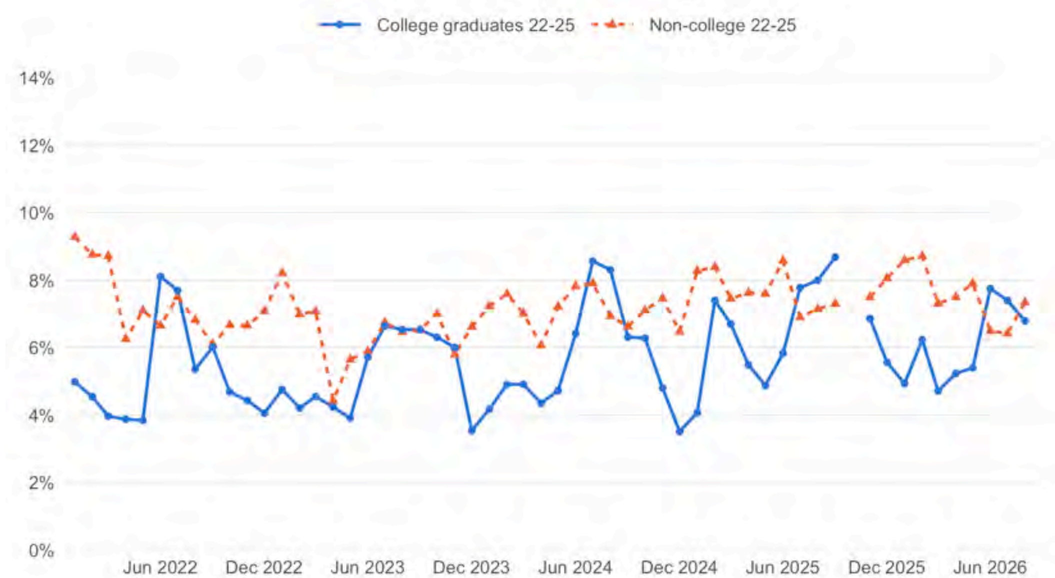
Notes: Official unemployment measure using Current Population Survey basic monthly files, January 2022 to August 2026. The October 2025 survey was not conducted so the series breaks at that month. Recent college graduates are individuals ages 22 to 25, not enrolled in school, whose highest completed degree is a bachelor's. Comparison group is college graduates ages 30 to 49, whose highest completed degree is a Bachelor's degree.

Figure 3b. Unemployment or wants a job ("sidelined unemployed"), young and older college graduates



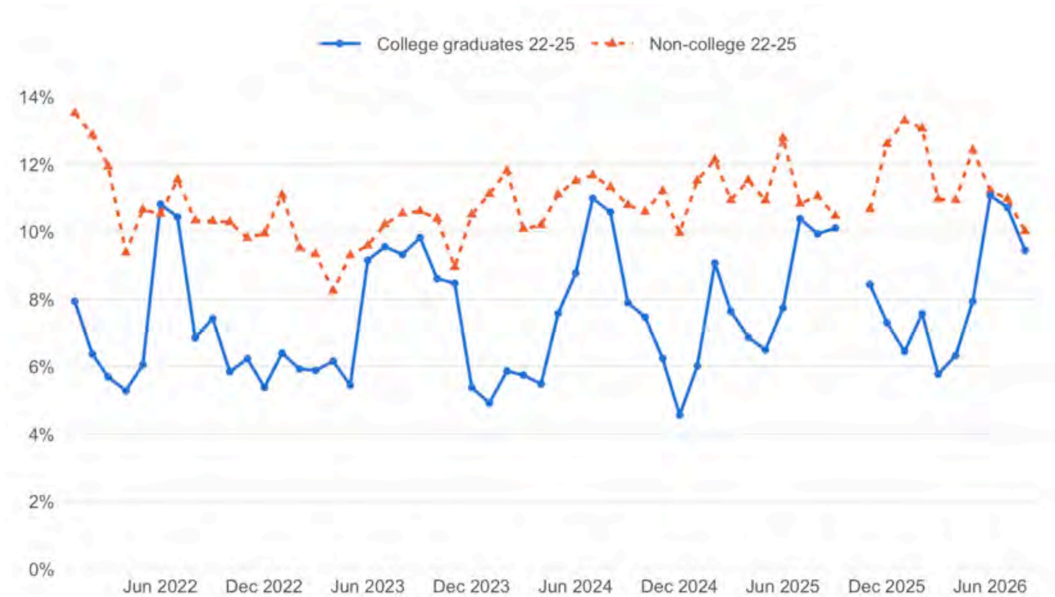
Notes: Expanded measure using Current Population Survey basic monthly files, January 2022 to August 2026. The October 2025 survey was not conducted so the series breaks at that month. Recent college graduates are individuals ages 22 to 25, not enrolled in school, whose highest completed degree is a bachelor's. Comparison group is college graduates ages 30 to 49, whose highest completed degree is a Bachelor's degree.

Figure 4a. Unemployment rate, college and non-college ages 22 to 25



Notes: Official measure using Current Population Survey basic monthly files, January 2022 to August 2026. The October 2025 survey was not conducted so the series breaks at that month. Recent college graduates are individuals ages 22 to 25, not enrolled in school, whose highest completed degree is a bachelor's. Comparison group is non-college which are individuals ages 22 to 25 without a Bachelor's degree.

Figure 4b. Unemployment or wants a job ("sidelined unemployed"), college and non-college ages 22 to 25



Notes: Expanded measure using Current Population Survey basic monthly files, January 2022 to August 2026. The October 2025 survey was not conducted so the series breaks at that month. Recent college graduates are individuals ages 22 to 25, not enrolled in school, whose highest completed degree is a bachelor's. Comparison group is non-college which are individuals ages 22 to 25 without a Bachelor's degree.

Table 1. Unemployment among college graduates ages 22–25

Specification	Standard (1) Linear trend	Standard (2) Event study	Expanded (3) Linear trend	Expanded (4) Event study
Summer 2026	-0.008 (0.007)	0.001 (0.008)	0.001 (0.009)	0.008 (0.010)
Winter 2026	-0.005 (0.006)	0.007 (0.006)	-0.003 (0.006)	0.001 (0.007)
Summer 2023		-0.007 (0.008)		-0.000 (0.009)
Summer 2024		0.006 (0.008)		0.007 (0.009)
Summer 2025		0.002 (0.008)		-0.000 (0.009)
Winter 2023		-0.002 (0.005)		-0.007 (0.006)
Winter 2024		0.002 (0.005)		-0.006 (0.006)
Winter 2025		0.012** (0.006)		0.006 (0.006)
Fall 2023		0.007 (0.006)		0.017** (0.007)
Fall 2024		0.005 (0.006)		0.004 (0.007)
Fall 2025		0.023*** (0.007)		0.024*** (0.008)
Observations	45,816	45,816	46,734	46,734

Notes: 1) Estimates are from 2022-26 CPS Microdata. 2) The sample includes college graduates ages 22-25 who are not enrolled in school. 3) The standard unemployment definition is used in Columns 1 and 2, and the expanded definition, unemployment plus NILF wants a job ("sidelined unemployed"), is used in Columns 3 and 4. 4) Heteroscedasticity-consistent standard errors are reported in parentheses below linear probability model coefficient estimates. 5) Statistical significance levels are denoted with: *p<0.1; **p<0.05; ***p<0.01. 6) Winter denotes January–May, summer June–August, and fall September–December. 7) All specifications include age, gender, race and ethnicity, region, and metropolitan-area controls, as well as seasonal indicators.

Table 2. Unemployment among young relative to older college graduates

Specification	Standard (1) Linear trend	Standard (2) Event study	Expanded (3) Linear trend	Expanded (4) Event study
Young × Summer 2026	-0.007 (0.008)	-0.005 (0.009)	0.002 (0.009)	0.004 (0.010)
Young × Winter 2026	-0.007 (0.006)	0.001 (0.006)	-0.007 (0.007)	-0.004 (0.007)
Summer 2026	-0.000 (0.002)	0.008*** (0.002)	0.001 (0.002)	0.006** (0.003)
Winter 2026	0.003** (0.002)	0.008*** (0.002)	0.005*** (0.002)	0.008*** (0.002)
Young × Summer	0.014*** (0.004)	0.022*** (0.007)	0.021*** (0.004)	0.030*** (0.008)
Young × Winter	-0.006* (0.003)	-0.006 (0.006)	-0.006* (0.004)	0.002 (0.007)
Young × Summer 2023		-0.009 (0.008)		-0.000 (0.009)
Young × Summer 2024		0.002 (0.008)		0.005 (0.009)
Young × Summer 2025		-0.006 (0.008)		-0.006 (0.009)
Observations	350,187	350,187	355,101	355,101

Notes: 1) Estimates are from 2022-26 CPS Microdata. 2) The sample includes college graduates ages 22-25 and ages 30-49 who are not enrolled in school. 3) The standard unemployment definition is used in Columns 1 and 2, and the expanded definition, unemployment plus NILF wants a job (“sidelined unemployed”), is used in Columns 3 and 4. 4) Heteroscedasticity-consistent standard errors are reported in parentheses below linear probability model coefficient estimates. 5) Statistical significance levels are denoted with: *p<0.1; **p<0.05; ***p<0.01. 6) Winter denotes January–May, summer June–August, and fall September–December. 7) All specifications include age, gender, race and ethnicity, region, metropolitan-area, time controls, group and seasonal indicators, and interactions between the group indicator and the seasonal indicators. The event-study specifications also include season-by-year indicators for 2023 to 2025 and their interactions with the group indicator; only the summer interactions are reported.

Table 3. Unemployment among college relative to non-college graduates

Specification	Standard (1) Linear trend	Standard (2) Event study	Expanded (3) Linear trend	Expanded (4) Event study
College × Summer 2026	0.002 (0.009)	0.006 (0.010)	0.013 (0.011)	0.012 (0.012)
College × Winter 2026	-0.007 (0.007)	0.008 (0.007)	-0.009 (0.008)	-0.002 (0.009)
Summer 2026	-0.010* (0.005)	-0.004 (0.006)	-0.011* (0.006)	-0.003 (0.007)
Winter 2026	0.002 (0.005)	0.000 (0.005)	0.006 (0.005)	0.005 (0.006)
College × Summer	0.012*** (0.005)	0.018** (0.009)	0.017*** (0.005)	0.023** (0.010)
College × Winter	-0.011*** (0.004)	-0.018** (0.007)	-0.012*** (0.004)	-0.013 (0.008)
College × Summer 2023		-0.002 (0.009)		0.006 (0.011)
College × Summer 2024		-0.000 (0.010)		-0.002 (0.011)
College × Summer 2025		-0.004 (0.010)		-0.008 (0.011)
Observations	150,488	150,488	155,408	155,408

Notes: 1) Estimates are from 2022-26 CPS Microdata. 2) The sample includes college and non-college graduates ages 22-25 who are not enrolled in school. 3) The standard unemployment definition is used in Columns 1 and 2, and the expanded definition, unemployment plus NILF wants a job ("sidelined unemployed"), is used in Columns 3 and 4. 4) Heteroscedasticity-consistent standard errors are reported in parentheses below linear probability model coefficient estimates. 5) Statistical significance levels are denoted with: *p<0.1; **p<0.05; ***p<0.01. 6) Winter denotes January–May, summer June–August, and fall September–December. 7) All specifications include age, gender, race and ethnicity, region, metropolitan-area, time controls, group and seasonal indicators, and interactions between the group indicator and the seasonal indicators. The event-study specifications also include season-by-year indicators for 2023 to 2025 and their interactions with the group indicator; only the summer interactions are reported.

Table 4. Unemployment and observed AI exposure (Anthropic) among college graduates ages 22–25

Specification	Standard (1) Linear trend	Standard (2) Event study	Expanded (3) Linear trend	Expanded (4) Event study
Summer 2026 × AI exposure	0.006 (0.007)	0.008 (0.008)	0.006 (0.007)	0.009 (0.008)
Winter 2026 × AI exposure	-0.003 (0.006)	0.002 (0.006)	-0.004 (0.006)	0.002 (0.006)
Summer 2026	-0.011 (0.007)	-0.003 (0.008)	-0.009 (0.007)	-0.000 (0.008)
Winter 2026	-0.008 (0.006)	0.006 (0.005)	-0.007 (0.006)	0.007 (0.006)
AI exposure	-0.008* (0.005)	-0.007 (0.004)	-0.010** (0.005)	-0.009** (0.005)
Summer × AI exposure	-0.005 (0.004)	-0.004 (0.007)	-0.005 (0.004)	-0.002 (0.007)
Winter × AI exposure	0.007** (0.003)	0.005 (0.006)	0.008** (0.003)	0.007 (0.006)
Summer 2023 × AI exposure		-0.002 (0.008)		-0.003 (0.008)
Summer 2024 × AI exposure		0.007 (0.008)		0.006 (0.008)
Summer 2025 × AI exposure		-0.003 (0.007)		-0.004 (0.007)
Observations	42,648	42,648	42,718	42,718

Notes: 1) Estimates are from 2022-26 CPS Microdata. 2) The sample includes college graduates ages 22-25 who are not enrolled in school. 3) The standard unemployment definition is used in Columns 1 and 2, and the expanded definition, unemployment plus NILF wants a job ("sidelined unemployed"), is used in Columns 3 and 4. 4) AI exposure is defined using the standardized AI-exposure measure from Massenkoff et al. (2026) which is the Anthropic Economic Index based on Claude usage patterns. 5) Heteroscedasticity-consistent standard errors are reported in parentheses below linear probability model coefficient estimates. 6) Statistical significance levels are denoted with: *p<0.1; **p<0.05; ***p<0.01. 7) All specifications include age, gender, race and ethnicity, region, and metropolitan-area controls; as well as seasonal indicators. The linear-trend specifications include a linear time trend and its interaction with the exposure measure. The event-study specifications include season-by-year indicators for 2023 to 2025 and their interactions with the exposure measure; only the summer interactions are reported.

Table 5. Unemployment and theoretical AI exposure (Eloundou et al., 2024) among college graduates ages 22–25

Specification	Standard (1) Linear trend	Standard (2) Event study	Expanded (3) Linear trend	Expanded (4) Event study
Summer 2026 × AI exposure	0.009 (0.008)	0.012 (0.009)	0.008 (0.008)	0.012 (0.009)
Winter 2026 × AI exposure	-0.003 (0.006)	0.001 (0.006)	-0.004 (0.006)	-0.000 (0.006)
Summer 2026	-0.009 (0.007)	-0.003 (0.008)	-0.006 (0.007)	0.000 (0.008)
Winter 2026	-0.006 (0.005)	0.007 (0.005)	-0.005 (0.006)	0.008 (0.005)
AI exposure	-0.015*** (0.005)	-0.012*** (0.005)	-0.017*** (0.005)	-0.014*** (0.005)
Summer × AI exposure	-0.011*** (0.004)	-0.014* (0.008)	-0.011*** (0.004)	-0.012 (0.008)
Winter × AI exposure	0.005 (0.003)	0.002 (0.006)	0.006* (0.003)	0.004 (0.006)
Summer 2023 × AI exposure		-0.006 (0.008)		-0.007 (0.008)
Summer 2024 × AI exposure		0.005 (0.009)		0.006 (0.009)
Summer 2025 × AI exposure		0.005 (0.008)		0.004 (0.008)
Observations	44,093	44,093	44,166	44,166

Notes: 1) Estimates are from 2022-26 CPS Microdata. 2) The sample includes college graduates ages 22-25 who are not enrolled in school. 3) The standard unemployment definition is used in Columns 1 and 2, and the expanded definition, unemployment plus NILF wants a job (“sidelined unemployed”), is used in Columns 3 and 4. 4) AI exposure is defined using the measure from Eloundou et al. (2024) which is GPT-4 LLM-coded. 5) Heteroscedasticity-consistent standard errors are reported in parentheses below linear probability model coefficient estimates. 6) Statistical significance levels are denoted with: *p<0.1; **p<0.05; ***p<0.01. 7) All specifications include age, gender, race and ethnicity, region, and metropolitan-area controls; as well as seasonal indicators. The linear-trend specifications include a linear time trend and its interaction with the exposure measure. The event-study specifications include season-by-year indicators for 2023 to 2025 and their interactions with the exposure measure; only the summer interactions are reported.

Table 6. Unemployment and teleworkability among college graduates ages 22–25

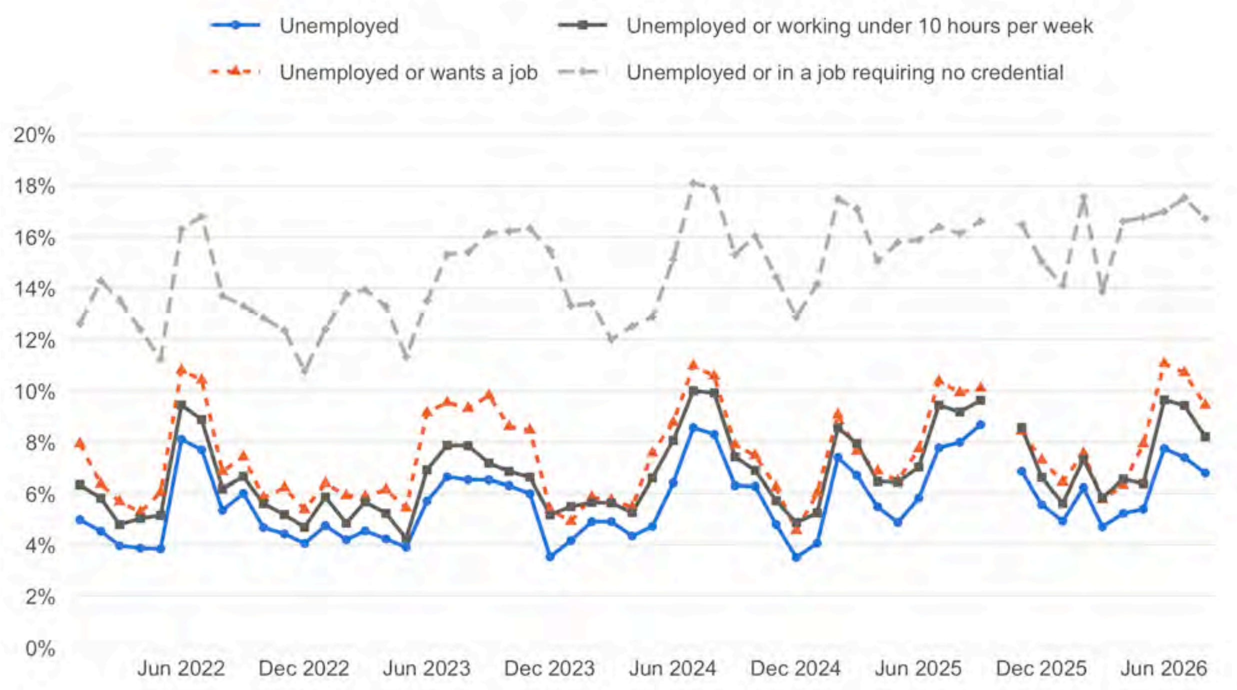
Specification	Standard (1) Linear trend	Standard (2) Event study	Expanded (3) Linear trend	Expanded (4) Event study
Summer 2026 × Teleworkable	0.028* (0.015)	0.040** (0.017)	0.028* (0.016)	0.039** (0.018)
Winter 2026 × Teleworkable	-0.007 (0.012)	0.003 (0.012)	-0.008 (0.012)	0.004 (0.012)
Summer 2026	-0.024** (0.012)	-0.021 (0.013)	-0.022* (0.012)	-0.017 (0.014)
Winter 2026	-0.003 (0.010)	0.006 (0.009)	-0.002 (0.010)	0.006 (0.010)
Teleworkable	-0.025*** (0.010)	-0.036*** (0.009)	-0.028*** (0.010)	-0.041*** (0.010)
Summer × Teleworkable	-0.007 (0.008)	-0.001 (0.015)	-0.007 (0.008)	0.005 (0.015)
Winter × Teleworkable	0.007 (0.007)	0.015 (0.012)	0.009 (0.007)	0.018 (0.012)
Summer 2023 × Teleworkable		0.007 (0.016)		0.004 (0.017)
Summer 2024 × Teleworkable		0.024 (0.017)		0.020 (0.018)
Summer 2025 × Teleworkable		0.002 (0.017)		-0.001 (0.017)
Observations	44,357	44,357	44,431	44,431

Notes: 1) Estimates are from 2022-26 CPS Microdata. 2) The sample includes college graduates ages 22-25 who are not enrolled in school. 3) The standard unemployment definition is used in Columns 1 and 2, and the expanded definition, unemployment plus NILF wants a job ("sidelined unemployed"), is used in Columns 3 and 4. 4) Teleworkable is the measure developed in Dingel and Neiman (2020). 5) Heteroscedasticity-consistent standard errors are reported in parentheses below linear probability model coefficient estimates. 6) Statistical significance levels are denoted with: *p<0.1; **p<0.05; ***p<0.01. 7) All specifications include age, gender, race and ethnicity, region, and metropolitan-area controls; as well as seasonal indicators. The linear-trend specifications include a linear time trend and its interaction with the exposure measure. The event-study specifications include season-by-year indicators for 2023 to 2025 and their interactions with the exposure measure; only the summer interactions are reported.

Appendix Figure A.1. Unemployment rate by month of the year, recent college graduates

Notes: Official measure using Current Population Survey basic monthly files, 2012 to 2025. Each point is that calendar month pooled across 2012 to 2025, excluding 2020 and 2021, so the figure shows the average seasonal profile rather than a time series.

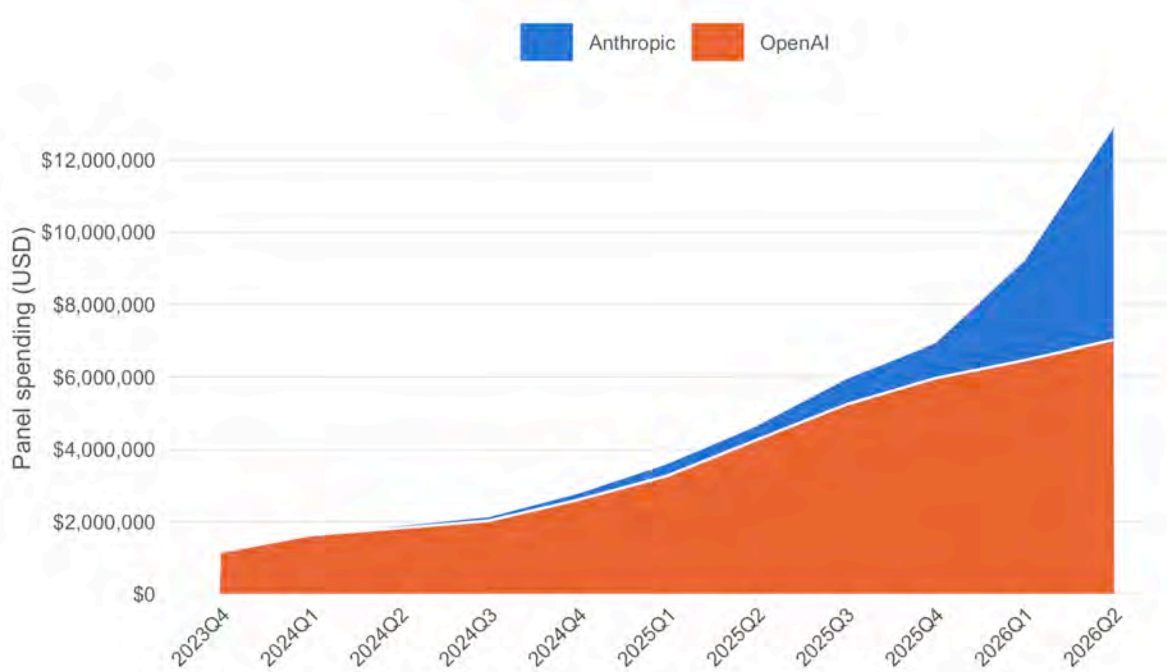
Appendix Figure A.2 Alternative measures of unemployment of recent college graduates



Notes: Official unemployment and all three expanded measures (including “sidelined unemployed,” “underemployment” defined as adding individuals who are currently employed but work less than 10 hours in the survey week, and a measure of job or occupation mismatch to capture recent college graduates who are employed in occupations that require no formal education). We use Current Population Survey basic monthly files, January 2022 to August 2026. The October 2025 survey was not conducted so the series breaks at that month. Recent college graduates are individuals ages 22 to 25, not enrolled in school, whose highest completed degree is a bachelor's.

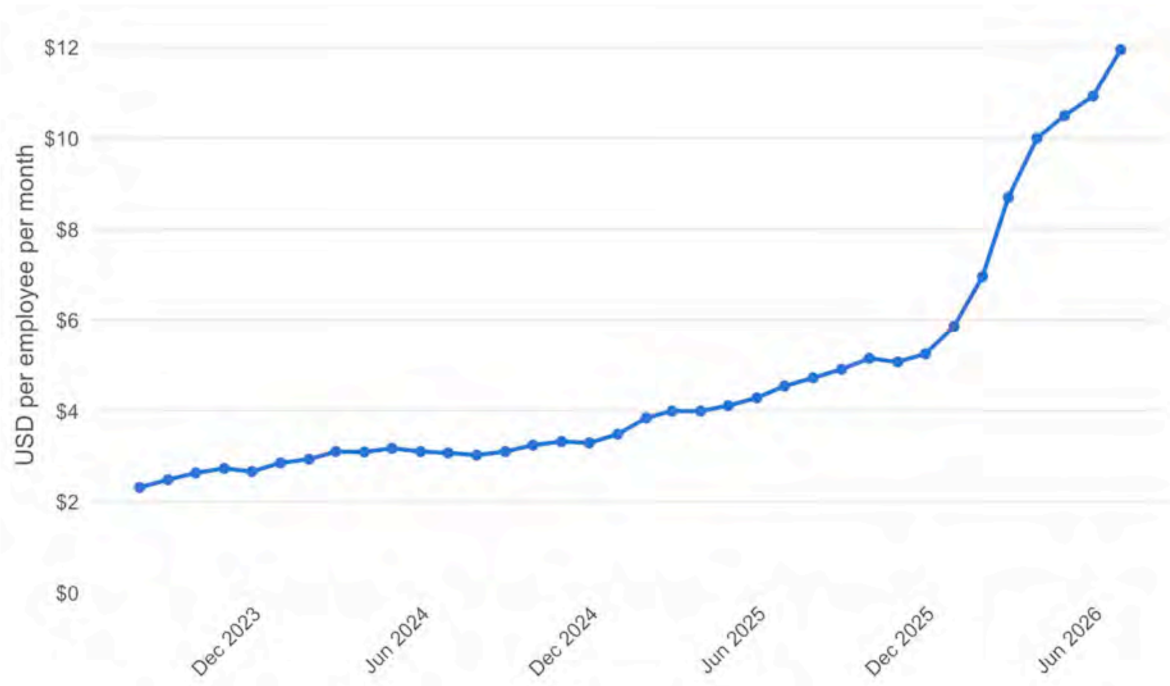
Appendix B - Evidence on AI Usage Timing

Appendix Figure B1. Combined consumer spending on AI assistants, quarterly



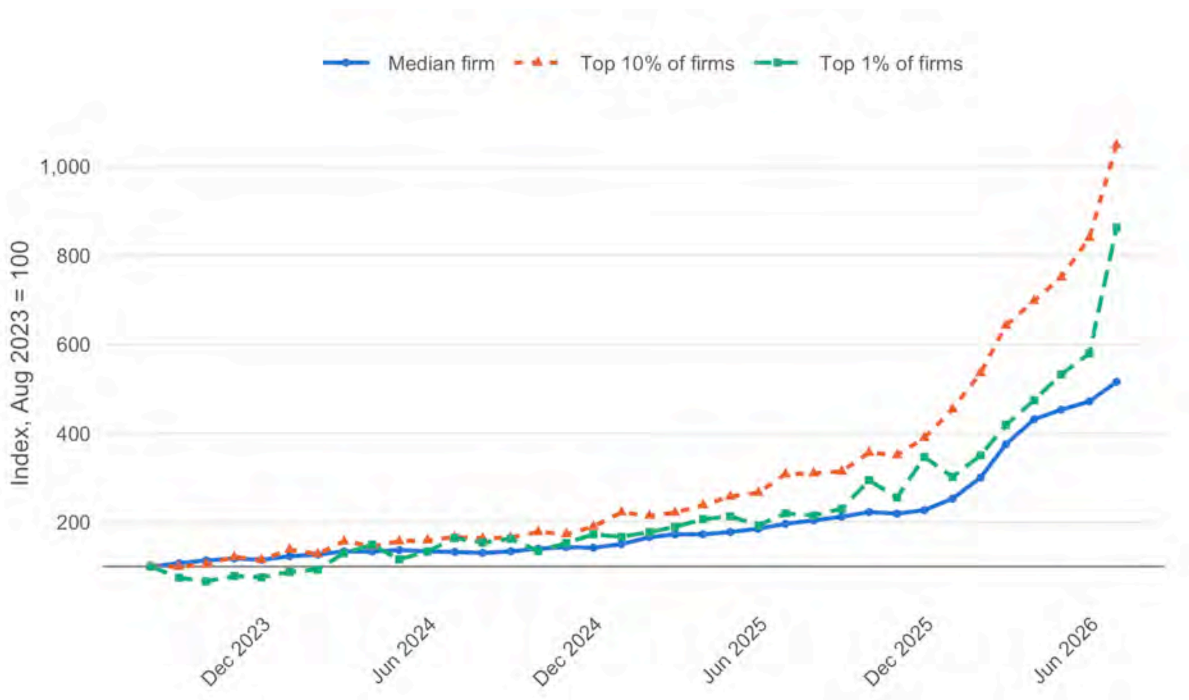
Note: ConsumerEdge card-panel spending on Anthropic and OpenAI, aggregated to complete calendar quarters. These are panel totals rather than projections to the U.S. population. Spending is added across brands.

Appendix Figure B2. Median business AI spending per employee, monthly



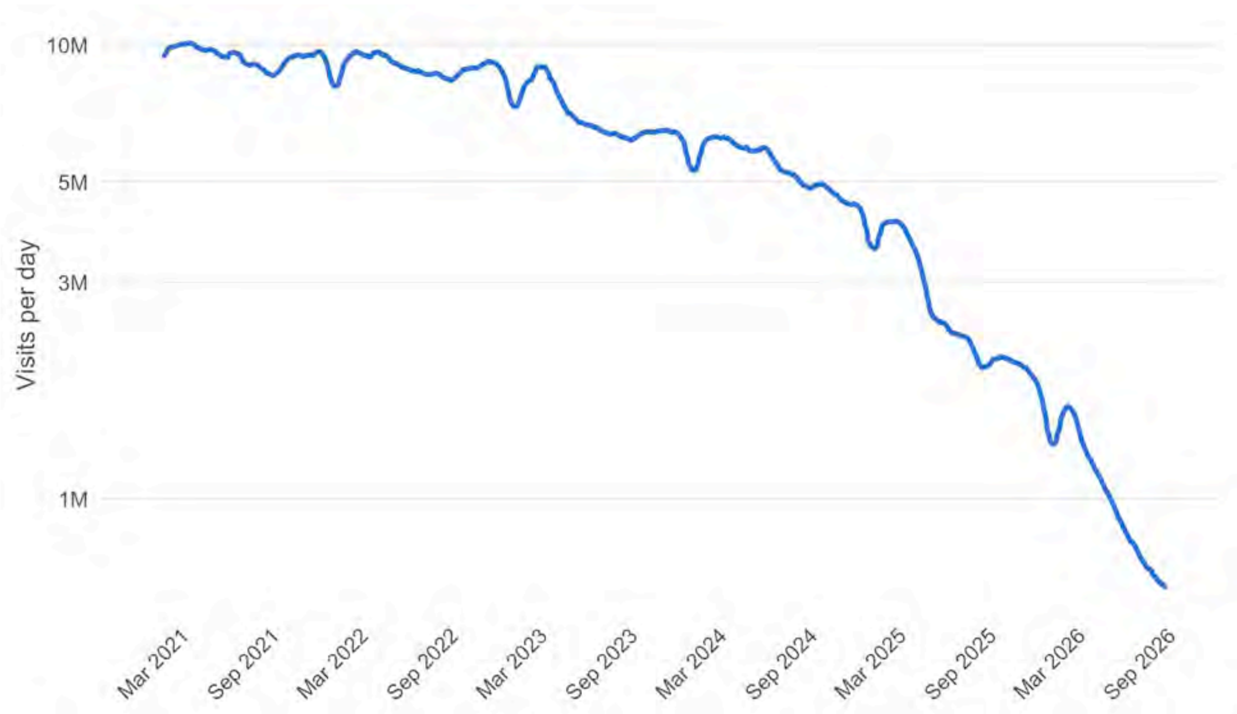
Note: Ramp AI Index data obtained in August 2026 for firms on the Ramp corporate-card platform. The sample is skewed toward venture-backed firms and is therefore not nationally representative. Further details are available here: https://ramp.com/data/ai-index#spend-per-employee#overall.

Appendix Figure B3. Business AI spending per employee, indexed to August 2023



Note: Ramp AI Index data obtained in August 2026 for firms on the Ramp corporate-card platform. The sample is skewed toward venture-backed firms and is not nationally representative. The median of the top 1 percent, top 10 percent, and full sample of firms in terms of AI spend per employee are plotted separately on one axis. A steeper line indicates faster growth, not a higher spending level. Further details are available here: https://ramp.com/data/ai-index#spend-per-employee#overall.

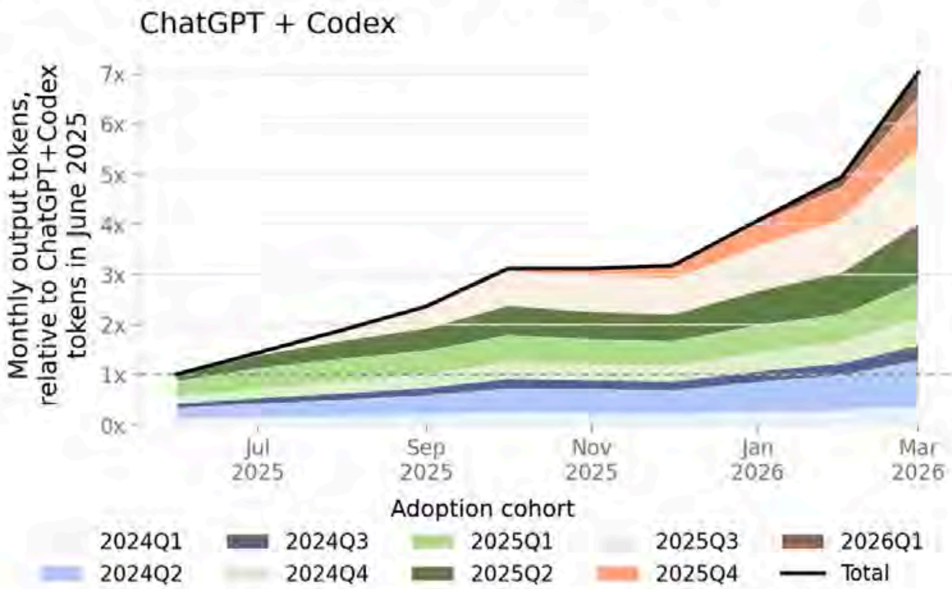
Appendix Figure B4. Stack Overflow daily visits



Note: Worldwide visits to stackoverflow.com. The blue line shows a 28-day trailing mean. The vertical axis is logarithmic, so a constant slope represents a constant growth rate.

Appendix Figure B5. Enterprise output token growth

Fig. 3: ENTERPRISE OUTPUT TOKEN GROWTH



Note: This figure plots monthly ChatGPT and Codex output tokens for firms in the ChatGPT Enterprise analysis sample, stacked by the quarter in which each firm first adopted ChatGPT Enterprise. Tokens are counted only after each firm's ChatGPT Enterprise adoption date. Values are indexed to total combined ChatGPT and Codex output tokens in June 2025, with the dashed horizontal line marking 1.0 and the black line showing the aggregate total across cohorts.

Note: Monthly ChatGPT and Codex output tokens for firms in the ChatGPT Enterprise analysis sample, stacked by adoption cohort and indexed to total output tokens in June 2025. Source: Chatterji et al. (2026), Figure 3.