Stanford Digital Economy Lab

Research note #1

AI Economic Indicators: June 2026 Update

Stanford Digital Economy Lab

1. Executive Summary

Artificial intelligence is advancing faster than our ability to understand its economic consequences, and the pace of change could accelerate as adoption spreads across sectors and new capabilities emerge. The new *AI Economic Indicators* project from the Stanford Digital Economy Lab addresses this challenge. In this first release, we introduce three related efforts to track the economic impact of AI.

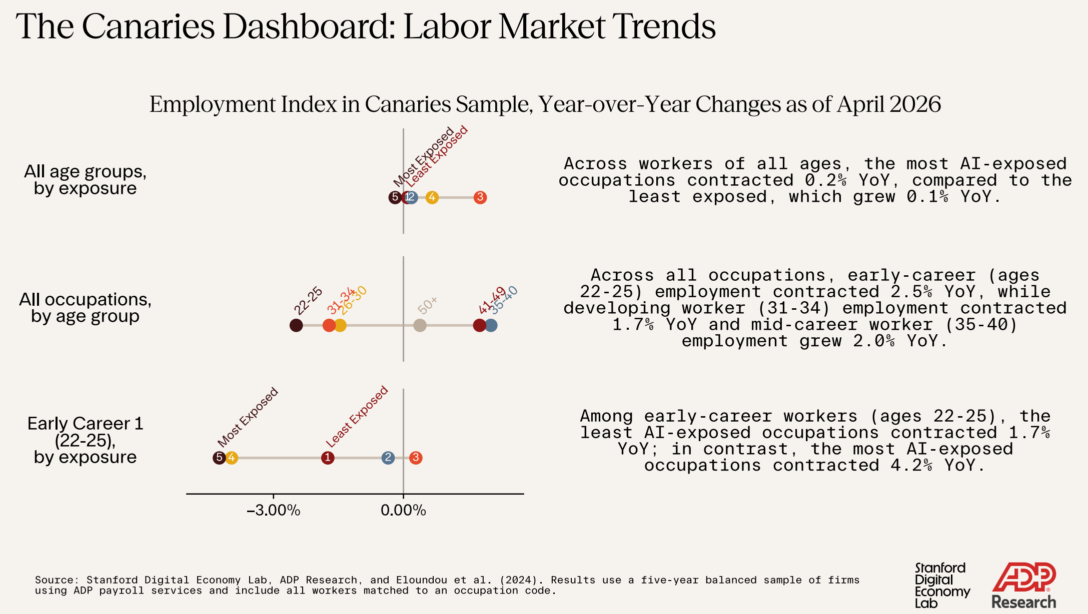


Figure 1: The Canaries Dashboard summarizes employment trends by employee age and occupational AI exposure.

The Canaries Dashboard, launched in partnership with ADP Research, tracks employment trends across workers of all ages and AI exposure levels in a sample of firms using ADP payroll services.

We summarize recent results from the Canaries Dashboard in Figure 1, which reports year-over-year changes in our employment index. The Canaries Dashboard section features results from our entire five-year sample period. We find the following:

- In aggregate, differences in employment trends between AI-exposed and less-exposed occupations since the introduction of ChatGPT are modest.
- However, employment trends for early-career workers (ages 22-25) are noticeably correlated with AI exposure: the least AI-exposed occupations diverge from the

most exposed. Early-career workers comprise 7.4% of employment in our sample, as of November 2022.
- When we consider the pattern of AI usage at the occupation level, we find that automation-related usage is correlated with employment trends, while augmentation-related usage is not. Accordingly, AI's labor market impact could depend on the nature of how AI is used.

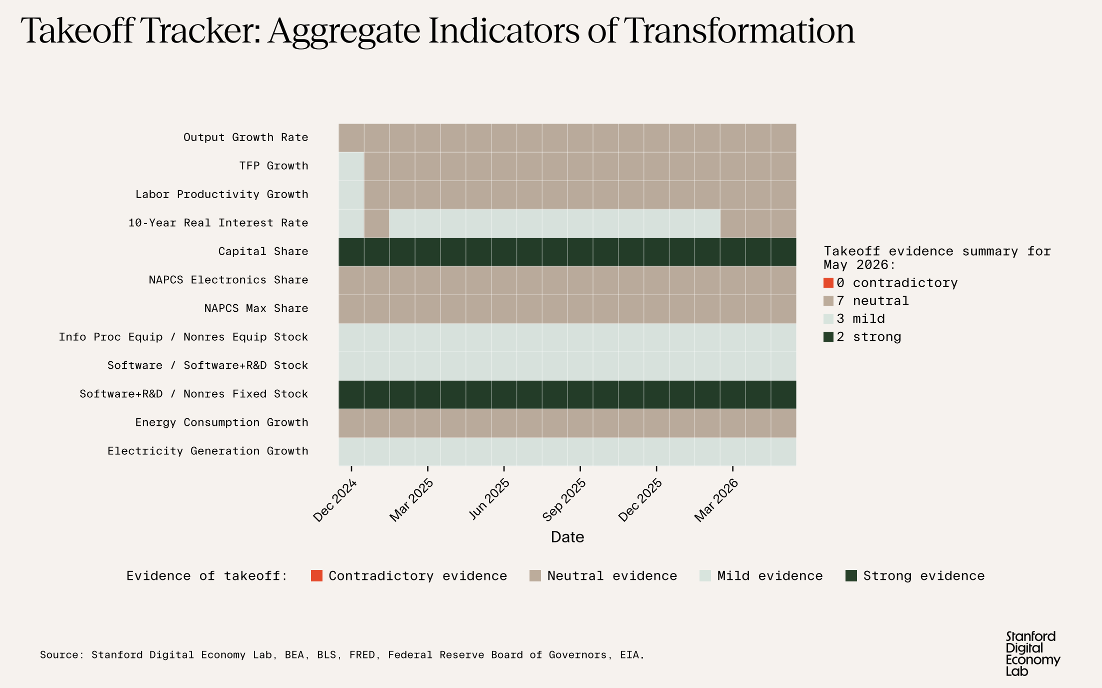
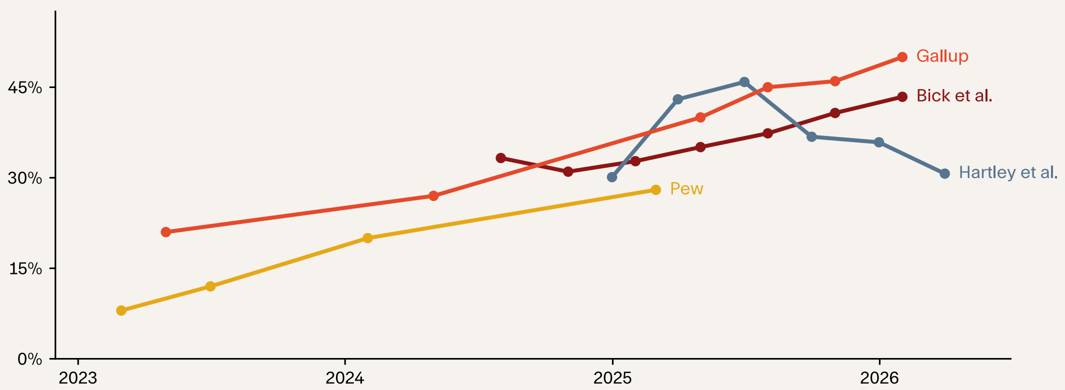


Figure 2: The Takeoff Tracker summarizes the strength of evidence across indicators of AI takeoff.

Takeoff Tracker contains a series of aggregate indicators of 'takeoff' from AI and assesses the extent to which these indicators show evidence of takeoff.

We summarize the key results from the Takeoff Tracker in Figure 2, tracking 12 indicators. As of May 2026, seven series show no evidence of takeoff, while three show mild evidence of takeoff and two show strong evidence of takeoff. Taken as a whole, we do not see decisive evidence of takeoff in these indicators.

Adoption Monitor: Individual and Firm Adoption of AI



Source: Bick, Blandin, and Deming (2026; BBD); Hartley et al. (2026; HJMM); Pew Research Center; Gallup. Note: Pew results are limited to ChatGPT, whereas other sources cover general use of generative AI tools.

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Figure 3: Individual self-reported adoption of AI for work and personal use cases has generally trended upwards, but some recent work on adoption in the workplace shows a reversal in this trend

The *Adoption Monitor* collects survey results on individual and firm adoption of AI. Individual self-reported adoption of AI for work and personal use cases has generally trended upwards, but some recent work on adoption in the workplace shows a reversal in this trend. On the firm side, adoption is widespread and led by U.S. firms. Across all applications excluding text generation using LLMs, firms expect to increase adoption in the next three years. Robotics and autonomous vehicles see relatively large gaps between current and expected adoption.

Letter from Our Director

We are flying blind into one of the most consequential periods in world history. We cannot afford to rely on anecdotes or lagging indicators of AI's effects. We need timely, trusted evidence to understand where AI is creating value, and where it is disrupting work.

The Stanford Digital Economy Lab's goal is to become the most reliable, timely source for understanding AI's economic impact. By combining high-frequency data, rigorous research, and clear visualizations, we will help policymakers, businesses, workers, and researchers respond intelligently.

The purpose of the AI Economic Indicators is simple: to make AI's economic effects broadly visible. We are building measurement infrastructure to track how AI is changing work, productivity, skills, and value creation—so society can shape this transformation, not merely react to it.

Erik Brynjolfsson, Director of Stanford DEL

2. The Canaries Dashboard

Based on a collaboration between the Stanford Digital Economy Lab and ADP Research, the Canaries Dashboard provides a monthly update on the changing labor market conditions across both AI exposure and worker age. The Canaries Dashboard extends the work of Brynjolfsson, Chandar, and Chen (2025).

The ongoing debate on AI's labor market effects

Brynjolfsson, Chandar, and Chen (2025) identify an emergent decrease in employment in exposed occupations among early-career workers in the U.S. following the introduction of ChatGPT. Less-exposed occupations and older workers show no such disruption, leading to small aggregate changes in employment. These patterns remain when controlling for changes in interest rates and remote work, as well as when excluding the technology industry. Further, they have intensified in the nine months since the paper was first released.

Hosseini Maasoum and Lichtinger (2026) similarly find that junior employment declines sharply in firms that adopt AI relative to non-adopters, while senior employment trends remain largely unchanged. This decline is concentrated in occupations most exposed to generative AI, and within occupations, generative AI-exposed tasks are increasingly removed from junior job postings.

Humlum and Vestergaard (2025) replicate these age-based employment patterns in Denmark, but they find that firm-level changes are unrelated to whether or not a firm encourages AI adoption. Lambert and Schindler (2026) find declines in the junior hiring share in AI-exposed jobs, but these patterns can be explained by exposure to remote work.

The Budget Lab at Yale (2026) finds little relationship between exposure to AI and changes in aggregate employment, using the monthly Current Population Survey (CPS) to study the U.S. labor market. A follow-up study accounts for underlying differences between exposed and non-exposed occupations, similarly finding no evidence of a relationship between exposure to AI and changes in aggregate employment (Gimbel, Kendall, and Nunn 2026). Eckhardt and Goldschlag (2025) likewise find no aggregate labor market impacts from AI.

Johnston and Makridis (2026) use U.S. data through 2024 and find that exposure to AI is associated with sector-level *increases* in employment. In contrast, Tucker (2026) finds decreases in early-career hiring within exposed industry-state cells immediately following the introduction of ChatGPT. However, after adjustment, some of these trends may predate the introduction of ChatGPT.

The labor market impacts of AI remain a subject of active debate. The Canaries Dashboard is designed to provide ongoing data on changes in the labor market to help clarify the discussion.

2.1. Methodology and Data

The Canaries Dashboard uses data from ADP, a global leader in HR and payroll solutions that provides payroll services for one in six workers in the United States. We largely follow the methodology of Brynjolfsson, Chandar, and Chen (2025) to construct the Canaries Dashboard from ADP payroll data.

We group occupations by the AI exposure scores of Eloundou et al. (2024), and then track employment trends within each group. We also group workers by age.

ADP provides low-latency data on employment trends for a large sample of firms with a high degree of occupational granularity. We track employment for more than 730 occupations.[1] Accordingly, our analysis is a complement to the other studies cited above.

We use a five-year balanced sample of firms from ADP payroll data, removing firms that enter or exit the sample during the period. This restriction limits the extent to which our analysis reflects reallocation of employment between firms, entry and exit of firms, and firms that change their payroll provider. Additionally, we limit our sample to workers who have been assigned an occupation code in ADP payroll data.

Our analysis focuses on the evolution of employment for this fixed sample. The Canaries sample does not represent the entire U.S. labor market. Further, due to our selection criteria, the sample does not represent the universe of employers using ADP payroll services, unlike the more comprehensive payroll data that underlie the National Employment Report (ADP Research 2026). Rather, the Canaries sample is intended to capture potential early signals for broader employment and wage trends.

ADP monthly payroll data include information on more than 26 million workers, but the distribution of firms using ADP services does not exactly match the distribution of those across the broader U.S. economy as defined by the Quarterly Census of Employment and Wages (QCEW). The QCEW is based on tax data and provides a quarterly snapshot of almost all U.S. employment. Further detail on differences in firm composition can be found in Brynjolfsson and Richardson (2025).

Description of the Canaries Sample

Our balanced sample of firms using ADP payroll services, spanning the five years ending in April 2026, consists of **25,000 firms**.

In November 2022, these firms employed **4.6 million workers** successfully matched to an occupation code.

Additionally, this sample contains over **730 unique occupations**. Drawing on Eloundou et al. (2024), we rank each of these occupations by AI exposure. In November 2022, the least exposed quintile accounts for 6.4% of employment in our sample, while the most exposed quintile accounts for 38.3%. The middle three quintiles constitute 13.7%, 13.9%, and 27.7%, respectively.

2.2. Results

In contrast to Figure 1, which reports year-over-year changes, this section reports annual growth rates since the introduction of ChatGPT in November 2022. In aggregate, differences in employment trends between AI-exposed and less-exposed occupations are modest. Across workers of all ages, the most AI-exposed

[1] We aggregate some six-digit SOC codes to allow for mapping between various exposure datasets and the ADP data.

occupations are growing at 1.1% per year, compared to the least exposed, which are growing at 2.0% per year.

We next consider the interaction of age and exposure, summarized in Figure 4. Among early-career workers (22-25 years old), however, noticeable differences emerge: employment in AI-exposed occupations is contracting at 3.8% per year, compared to the least exposed, which are growing at 2.0% per year.

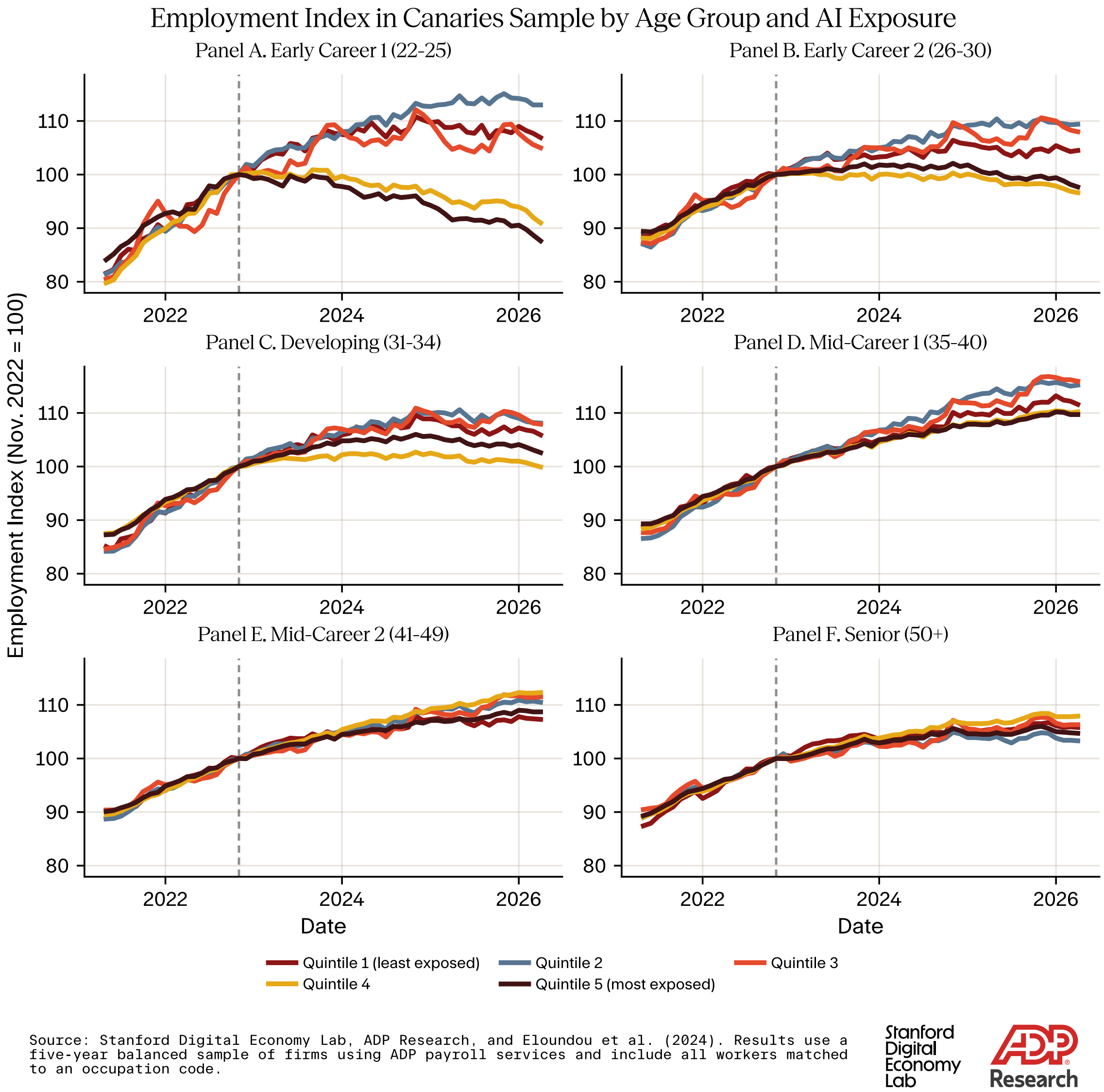

Figure 4: We group employees by their age and AI exposure scores, comparing employment trends across these groups. For early-career workers (22-25), the two most exposed groups of occupations see noticeable declines since the introduction of ChatGPT, while the other three occupation groups see growth. These patterns become less stark, and ultimately disappear, as we consider older workers.

Exposure to AI includes multiple patterns of use, and these types of usage could have different implications for the labor market (Brynjolfsson 2022). We use the Anthropic Economic Index (Massenkoff et al. 2026), which summarizes total usage at the occupation level and further decomposes this usage into automation and augmentation patterns. Under automation, users fully delegate tasks, whereas augmentation usage features collaboration between humans and an AI system.

We report employment trends among early-career workers (22-25 years old) by these usage patterns in Figure 5. We find no clear monotonic relationship between the share of usage classified as augmentation (augmentation ratio) and employment trends. As we move to the automation ratio, we find a noticeable relationship. Occupations with usage skewed towards automation see declines or more muted increases in the employment index. Accordingly, the type of AI usage could influence the labor market effects of AI.

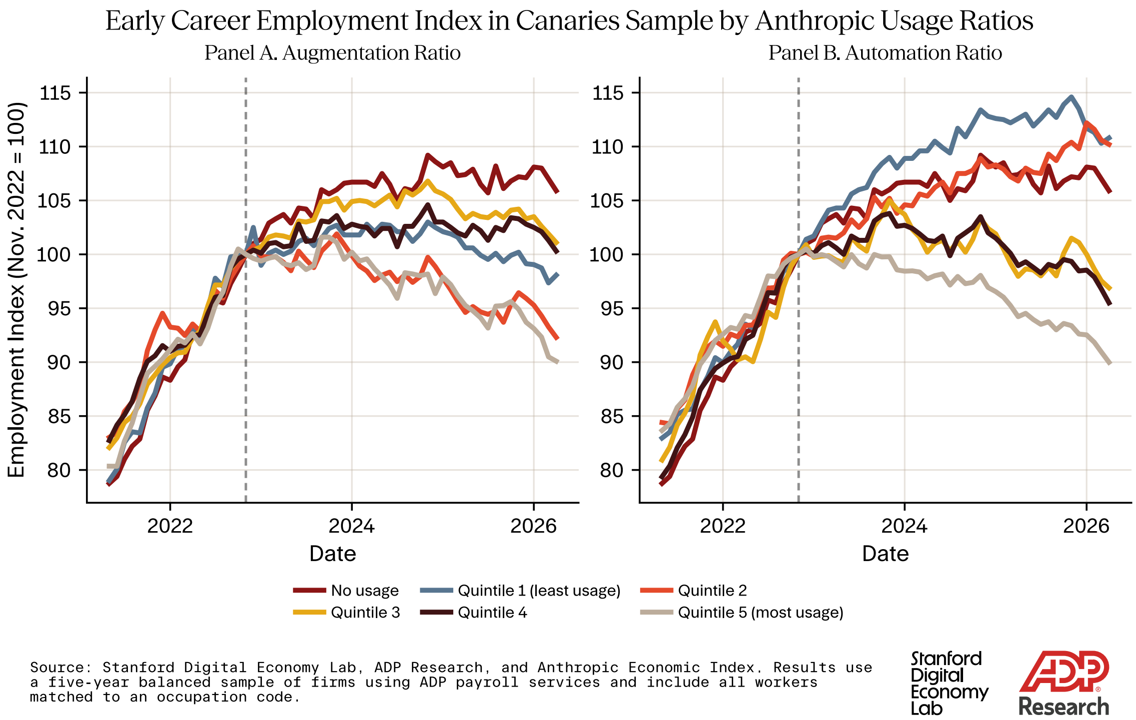

Figure 5: We group early-career workers by their occupations' Anthropic Economic Index augmentation and automation ratios. The automation ratio shows a noticeable relationship with employment trends in our sample: occupations with a higher automation ratio see decreases or smaller increases in the employment index. In contrast, augmentation usage does not appear correlated with employment trends.

In summary, we find:

1. *Across workers of all ages, modest divergence for exposed occupations:* Since the introduction of ChatGPT in November 2022, all exposure groups see employment growth, but the rate of expansion is slowest for the two most-exposed occupation groups. However, these differences remain modest.
2. *Pronounced divergence for early-career workers:* Less-exposed occupations for early-career workers show growth, while the employment declines in exposed occupations not only persist, but deepen. This divergence is still concentrated among early-career workers, but we see muted evidence of similar patterns for workers up to age 34.
3. *Specific occupations illustrate these disparate trends:* For example, early-career software developers and customer service workers show substantial employment declines. On the other hand, home health aides, a less-exposed occupation, show employment increases for the youngest workers. Employment changes continue to be unevenly distributed throughout the labor market.

4. *The type of AI usage relates to the labor market effects of AI:* There is no clear monotonic relationship between the share of usage classified as augmentation and employment trends. However, the automation ratio shows a clear correlation with employment trends: occupations with a higher share of automation in total usage see declines or more muted increases in the employment index. Accordingly, the character of AI usage could shape the labor market effects of AI.

The Canaries Dashboard features more results and will be updated on a monthly basis. The website features additional, updated results from Brynjolfsson, Chandar, and Chen (2025), including occupation-level employment trends for software developers, customer service representatives, and home health aides.

2.3. Future Work

Future work will explore alternative measures of "exposure" to AI, including data from the AI Jobs Transition Framework (Richmond 2026). Importantly, our current measures of exposure do not account for how demand responds to price changes induced by AI-driven productivity gains.

3. Takeoff Tracker

We track 12 aggregate U.S. indicators of 'takeoff'—explosive economic growth driven by AI. Under this scenario, capital substitutes well enough for labor that capital accumulation can drive growth on its own. We summarize the evidence for each indicator in Figure 2, and we provide three example indicators below. We describe the rules we use to classify the strength of evidence for each indicator on the Takeoff Tracker page.

Figure 6 plots the capital share. Under a move to explosive economic growth, the shift away from human labor to capital in production will drive capital's share of factor income toward 100%. We see continued increases in the capital share, and this persistent growth places the indicator in the strong evidence category.

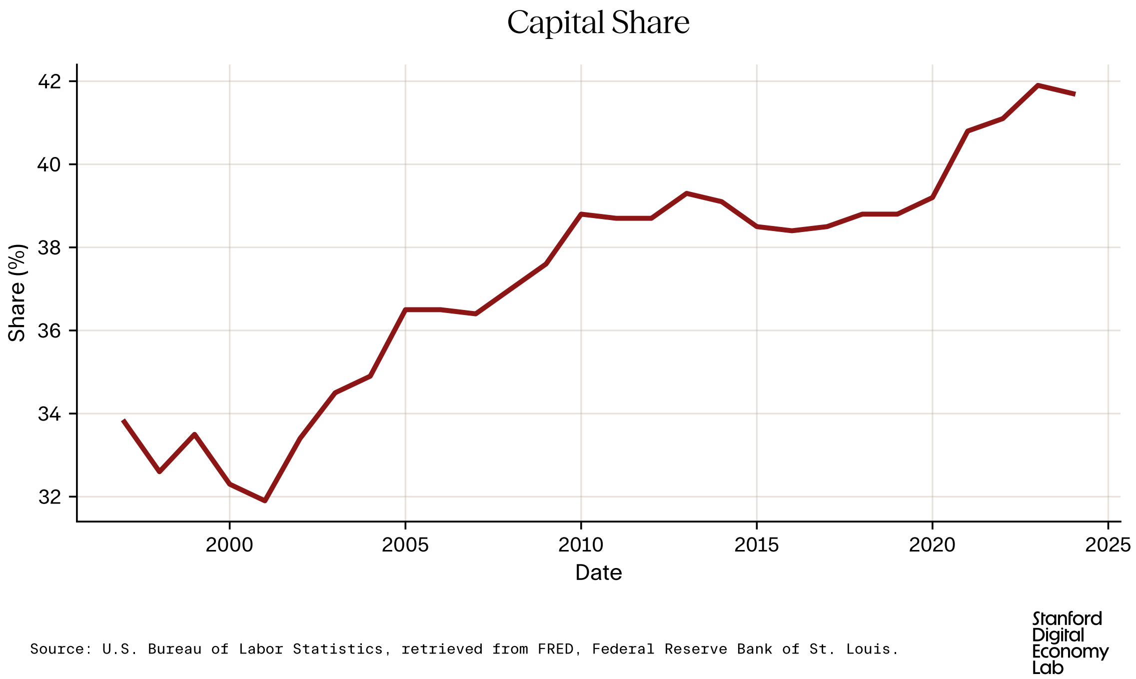

Figure 6: The capital share continues its long-running upward trend.

Figure 7 reports total factor productivity (TFP) growth. TFP captures change in output not directly attributable to changes in labor or capital input. TFP is commonly used as a proxy for economy-wide efficiency. Accordingly, increases in TFP growth underlie a takeoff scenario. We see no evidence of a break from recent levels in TFP growth, so the indicator is classified as neutral.

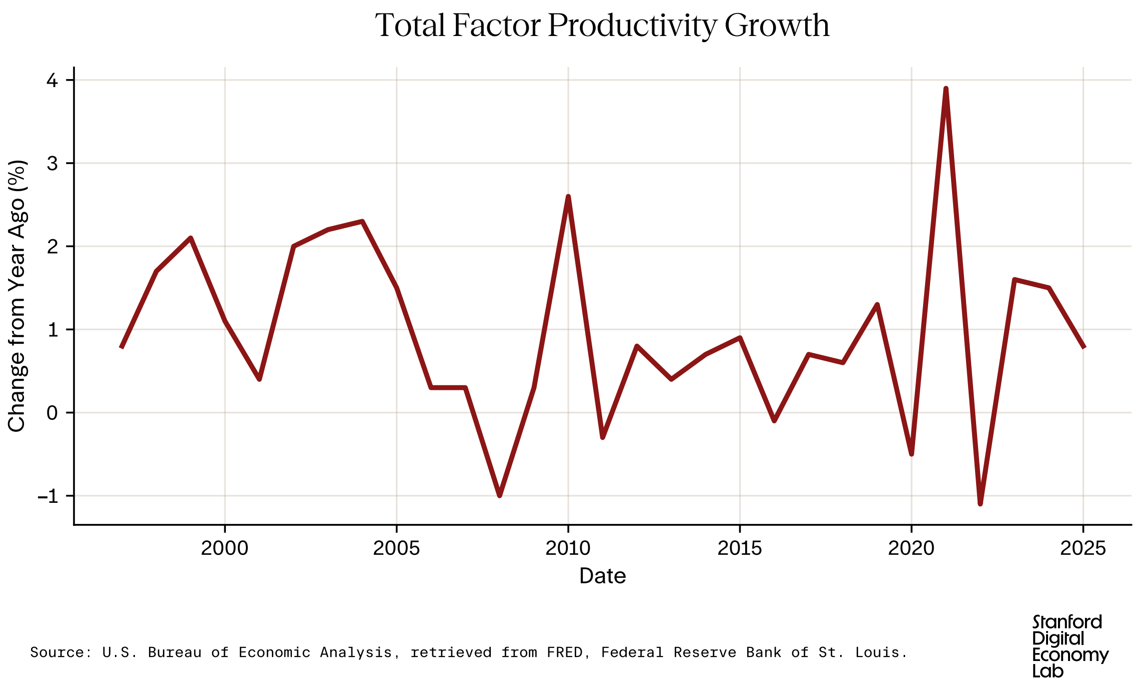

Figure 7: TFP growth shows no break from recent levels.

Figure 8 plots information processing (IP) equipment as a share of private nonresidential equipment. Explosive economic growth driven by AI will necessitate a shift toward IP equipment, i.e., semiconductors and other computing equipment. IP equipment's share in the private nonresidential equipment stock fell from 2000 until 2015, but it has since recovered to levels last achieved in the early 2000s. This increasing concentration of IP equipment in the stock of capital equipment lands the indicator in the mild evidence category.

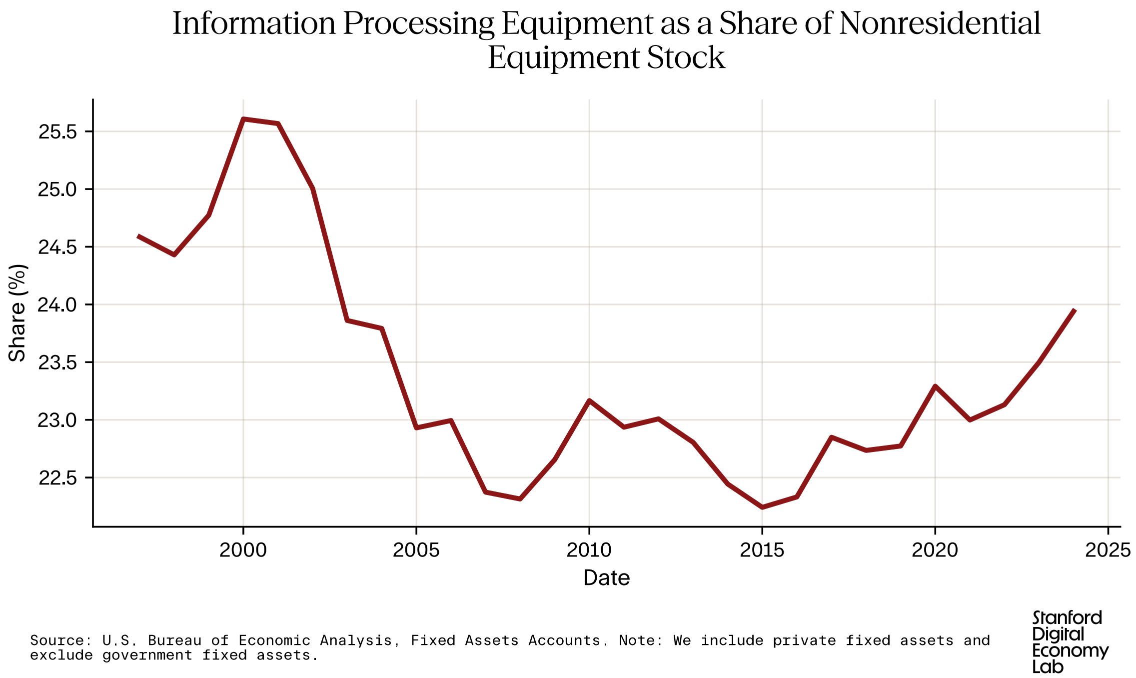

Figure 8: Information processing (IP) equipment's share in the private nonresidential equipment stock continues its recovery.

The remaining indicators are available on the Takeoff Tracker page.

4. Adoption Monitor

We report results from a collection of surveys on individual and firm adoption of AI: Bick, Blandin, and Deming (2026), Gallup (2026), Sidoti and McClain (2025), Hartley et al. (2026), and Yotzov et al. (2026). We summarize self-reported adoption of AI for work in Figure 3. Individual self-reported adoption of AI for work and personal use cases has generally trended upwards, but some recent work on adoption in the workplace shows a reversal in this trend. We report further results on individual adoption, including frequency of use, on the Adoption Monitor page.

We additionally report results from a survey of firms in the U.S., the UK, Germany, and Australia from Yotzov et al. (2026) in Figure 9. Adoption is widespread and led by U.S. firms. Across all applications excluding text generation using LLMs, firms expect to increase adoption in the next three years. Robotics and autonomous vehicles see relatively large gaps between current and expected adoption. We disaggregate the results by country on the Adoption Monitor page.

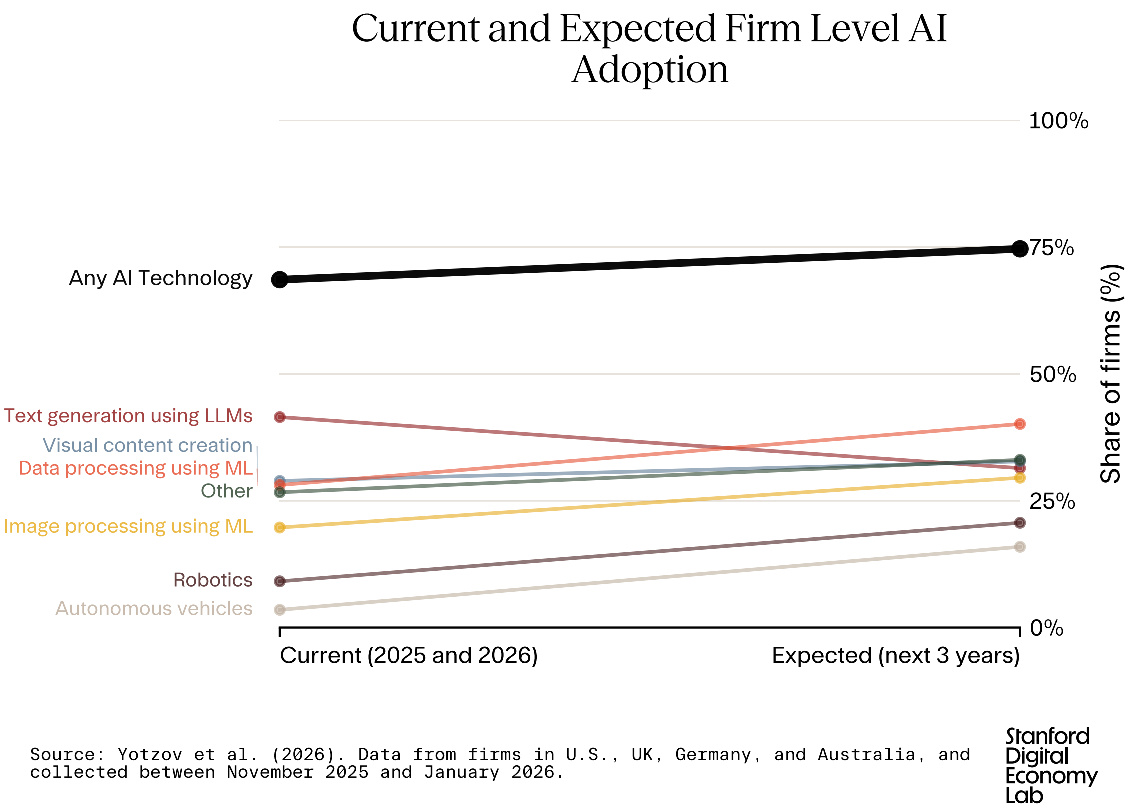

Figure 9: Across all applications excluding text generation using LLMs, firms expect to increase adoption in the next three years. Robotics and autonomous vehicles see relatively large gaps between current and expected adoption.

Cite this work

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