ECONPOL
Policy Report

11 | 26
61
Volume 10

AI and the Labor Market: Productivity Driver or Job Killer?

Oliver Falck, Clemens Fuest, and Yuchen Guo

CES ifo

ECONPOL

EconPol Europe is CESifo's economic policy platform. With key support from the ifo Institute, it seeks to leverage CESifo's globe-spanning network of more than 2,000 high-ranked economists – 17 of whom have won the Nobel Prize – and ifo's decades-deep research expertise to provide well-founded advice to European policymakers and to facilitate informed decisions. Drawing on the wide range of specializations of its members, EconPol's mission is to contribute to the crafting of evidence-based, effective economic policy in the face of the rapidly evolving challenges faced by the European economies and their global partners.

EconPol Policy Report
ISSN 2566-9028 (online)

Publisher and distributor: CESifo GmbH
Poschingerstr. 5, 81679 Munich, Germany
Telephone +49 89 9224-0, Email office@cesifo.de
EconPol Europe: www.econpol.eu

Editor: Andrea Balestracci

Editorial Board: Clemens Fuest, Oliver Falck, Lisandra Flach, Sarah Necker, Karen Pittel, Niklas Potrafke, Panu Poutvaara, Andreas Peichl, Helmut Rainer, Marcel Thum, and Ludger Woessmann

Reproduction permitted only if source is stated and copy is sent to EconPol.

AI and the Labor Market: Productivity Driver or Job Killer?

Oliver Falck
Clemens Fuest
Yuchen Guo*

While estimates of AI's long-run productivity gains diverge widely, early signs of its labor market impacts can already be observed. Using administrative data for Germany and the EU Labour Force Survey, we track employment by occupational AI exposure since the arrival of generative AI in late 2022. We find no widespread job losses in exposed occupations. Their employment has held up or grown, continuing a divergence from less exposed occupations that predates the introduction of generative AI. Young workers are the exception, however. In Germany, employment of workers aged 20 to 24 has fallen relative to older workers, especially in highly exposed occupations. Across the EU-27, we find first indications of fewer early-career hires in occupations where AI can automate tasks. These patterns are emerging but match recent evidence for the United States. They provide an early indicator that is available before productivity gains appear in national accounts, and suggest that monitoring of AI's labor market effects should put particular emphasis on labor market entry.

* Oliver Falck (falck@ifo.de), Clemens Fuest (fuest@ifo.de): ifo Institute, CESifo & LMU Munich; Yuchen Guo (guo@ifo.de): ifo Institute.

Executive Summary

This report examines how employment in Germany and the EU has evolved since late 2022, comparing more and less exposed occupations as well as younger and older workers.

The following findings emerge:

1. **Productivity gains**. Depending on the assumptions, estimates of AI's productivity gains vary widely, from 0.07 to 1.24 percentage points of additional growth in total factor productivity (TFP) per year.
2. **AI-exposed jobs**. In Germany, employment in the occupations most exposed to AI has grown by 1.8 percent since the third quarter of 2022 (the last quarter before the introduction of ChatGPT), while employment in the least exposed occupations has fallen by 6.4 percent.
3. **Employment of younger workers**. In Germany, the more exposed an occupation is to AI, the weaker the employment growth of young workers relative to older workers.
4. **Entry-level positions**. Across the EU-27, there is suggestive evidence that firms are hiring fewer early-career workers in occupations where AI can automate tasks.

So far, AI's effects on jobs are concentrated among young workers in exposed occupations. AI tends to augment professional work, while it automates tasks in clerical support and IT occupations.

Will AI Boost Productivity?

Artificial intelligence is advancing at startling speed. Much of what it can do today, from handling customer calls without a human on the line to drafting sophisticated prose, writing working code and even helping to prove long-standing mathematical conjectures, sounded like science fiction only a few years ago. And it is spreading fast: generative AI has been adopted more quickly than the personal computer or the internet (Bick, Blandin and Deming 2026).

Yet estimates of what it will add to productivity diverge widely. Acemoglu (2024) puts the gain in total factor productivity (TFP), the part of growth not explained by more capital or labor, at about 0.7 percent over ten years, or less than 0.1 percentage points a year. Aghion and Bunel (2024), using a task-based approach with more generous assumptions, arrive at up to 1.24 percentage points of additional TFP growth per year, almost twenty times as much.

This spread reflects the assumptions behind the estimates. Task-based estimates (e.g., Acemoglu 2024; Aghion and Bunel 2024; Filippucci, Gal and Schief 2024; Misch, Park, Pizzinelli and Sher 2025) multiply three factors: the share of tasks exposed to AI, the share of these tasks in which AI is profitably adopted, and the cost savings from AI found in micro studies. Because these factors are multiplied, small differences in assumptions compound quickly.

While the long-run productivity gains remain uncertain, AI's early effects on the labor market can already be measured. Which occupations are exposed to current AI, and how has their employment evolved since generative AI became widely available in late 2022?

Whether exposure results in fewer or more jobs depends on whether AI substitutes for the tasks performed in an occupation or complements them (Acemoglu and Autor 2011; Autor and Thompson 2025). Moreover, the impact need not be the same for all workers within the same occupation. AI may substitute most readily for codified, textbook-type knowledge, which is typically acquired in formal education and which entrants bring to their first jobs. By contrast, AI may complement the tacit knowledge that more experienced workers have built up on the job (Autor and Thompson 2025; Brynjolfsson, Chandar and Chen 2026). If so, labor market effects should show up first among job entrants. Consistent with this, Brynjolfsson, Chandar and Chen (2026) find no evidence of widespread job losses in the United States, but declining employment among young workers in AI-exposed occupations.

Whether the same pattern holds in Europe is an open question. Facius and Iacono (2026) study the labor market impact of AI in Norway and conclude: "Overall, we observe no significant deterioration of the Norwegian labor market in response to GenAI, neither for early-career workers nor for incumbents" (ibid., p.24).[1] Early evidence for France, in contrast, suggests that young people are indeed hired less in firms stating in surveys that they use AI (Palladino, Bergeaud, Bertheau, Bunel and Degos 2026).

This report examines how employment in Germany and the EU has evolved since late 2022, comparing more and less exposed occupations as well as younger and older workers.

To this end, we draw on two data sources: administrative records covering all employees subject to social security contributions in Germany, and the EU Labour Force Survey (EU-LFS) for all 27 EU member states. Following Brynjolfsson, Chandar and Chen (2026) and the recent literature on generative AI and labor markets (e.g., Bick, Blandin and Deming 2026; Humlum and Vestergaard 2025), we measure AI exposure

[1] Their data runs until March 2025. As a note of caution they point out that "accelerating event-study coefficients towards the end of our sample suggest that it may simply be too early to detect any robust effects.", ibid, p.24.

using the β ratings of Eloundou, Manning, Mishkin and Rock (2024). These capture the share of an occupation's tasks that a worker with access to a large language model (LLM) such as ChatGPT could complete in half the time or less without any loss in quality.[2] At the top of the exposure ranking are keyboard operators, software developers, numerical clerks, administrative secretaries, and authors and journalists; at the bottom are food preparation assistants, building cleaners, welders and building finishers.

Two findings emerge. First, there is no sign of widespread job losses in exposed occupations, either in Germany or in the EU-27. However, young workers are the exception. In the most exposed occupations, their employment in Germany and their hiring in the EU-27 have declined relative to older workers since 2022. These patterns are descriptive and cannot rule out other forces acting on young workers' employment, such as demographic change or educational choices after the COVID-19 pandemic. Still, they offer an early indication of how European labor markets are adjusting to generative AI, similar to evidence for the United States (Brynjolfsson, Chandar and Chen 2026).

[2] We map the Eloundou et al. (2024) ratings defined for US occupations (O*NET-SOC) to three-digit occupations in the EU-LFS (ISCO-08) and in the German administrative records (KldB 2010) using official crosswalks and divide the 118 ISCO occupations into quintiles of equal size by exposure. SOC is mapped to ISCO-08 with the crosswalk of Hardy, Keister and Lewandowski (2018). Mean exposure in the top ISCO-08 quintile (0.63) is more than six times that in the bottom quintile (0.10).

Germany: Exposed Occupations Grow, Young Workers Fall Behind

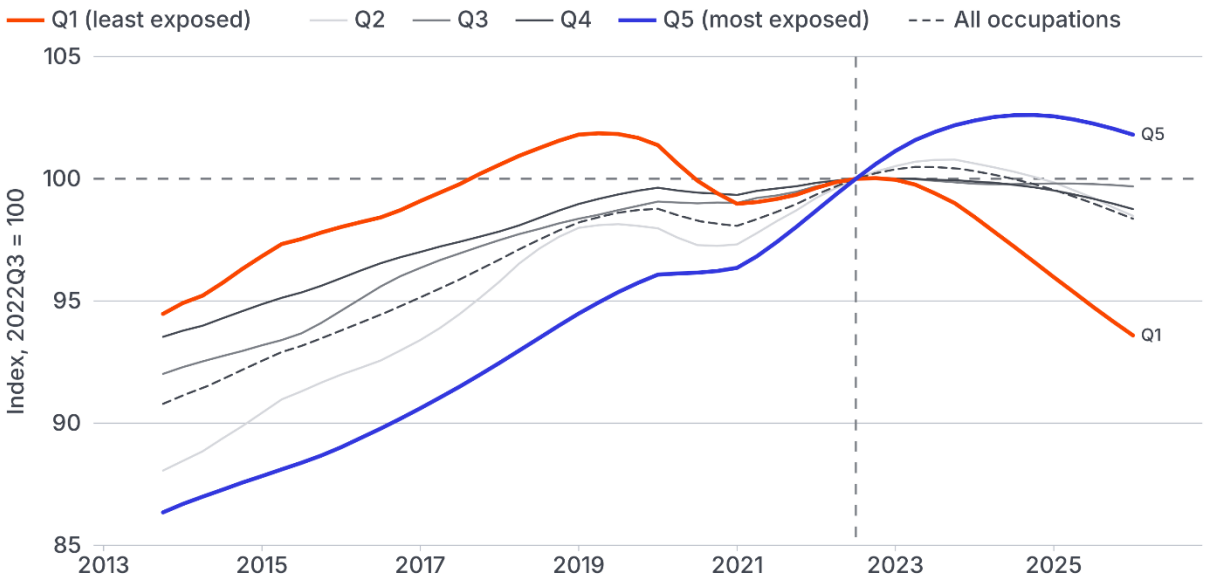
We begin with Germany, where administrative employment statistics of the Federal Employment Agency cover all employees subject to social security contributions. Our sample of full-time employees aged 20 to 64 comprises about 22 million workers in 140 occupations. As these data are a full count of all employees rather than a sample, they allow us to track even small occupations and their age composition precisely. We use quarterly data from 2013Q1 to 2026Q1, which provide a nine-year baseline before the release of ChatGPT against which to compare later developments. We exclude apprentices, as their main activity is training rather than work.

Figure 1 divides occupations into five quintiles by AI exposure and shows the number of employees in each, indexed to 100 in the third quarter of 2022 (2022Q3), the last quarter before ChatGPT's release.[3] There is no sign of economy-wide job losses in exposed occupations after its introduction in 2022Q4. If anything, employment in the most exposed quintile grew steadily from late 2013 until late 2024 and stood 1.8 percent above its 2022Q3 level in early 2026, despite a 1.6 percent decline in overall full-time employment over the same period. This is consistent with recent evidence that employment in AI-exposed jobs has not declined broadly (e.g., Brynjolfsson, Chandar and Chen 2026; Chandar and Klein Teeselink 2026). By contrast, employment in the least exposed quintile peaked in 2019, fell during the COVID-19 pandemic and has declined further since 2023, to 6.4 percent below its 2022Q3 level in early 2026. Part of this divergence was already under way before and likely reflects broader digitalization and structural change, but the gap has widened since the introduction of ChatGPT. Employment in the intermediate quintiles has stayed within 1.5 percent of its 2022Q3 level, close to overall employment across all occupations. The divergence is thus concentrated at the two ends of the exposure distribution, but it is also visible between the most exposed occupations and overall employment.

[3] Series are four-quarter moving averages to remove seasonal fluctuations.

Figure 1

Germany: Employment by AI Exposure Quintile



Note: Full-time employees aged 20–64, excluding apprentices; 140 KldB 3-digit occupations; 2013Q1–2026Q1; four-quarter moving average; index 2022Q3 = 100.
Source: Bundesagentur für Arbeit; Eloundou et al. (2024); own calculations. © ifo Institute

However, these aggregate patterns may conceal differences by age. If AI substitutes most readily for the codified tasks typically performed by entrants, the effects should appear first among young workers. Panel A of **Figure 2** thus plots the employment gap between the most and the least exposed quintile for each age group. Looking at the gap filters out general trends that affect an age group in both the most and the least exposed occupations. Employment of the youngest workers, for instance, has fallen across all exposure groups, which may reflect supply-side factors, such as demographic change or later labor market entry after longer spells in education following the COVID-19 pandemic.

The pattern from **Figure 1** differs markedly across age groups. For workers aged 25 and over, the employment gap between the most and least exposed occupations matches the aggregate divergence in **Figure 1** and widens by 8 to 10 log points (roughly 8 to 10 percent) between 2022Q3 and early 2026. For the youngest workers (20–24), the gap tracks the older age groups until 2022. However, it reverses after the introduction of ChatGPT and stands 4.6 log points below its 2022Q3 value by early 2026. Thus, young workers' employment in the most exposed occupations is falling relative to that in the least exposed occupations,[4] as the entry-level hypothesis predicts and in line with recent evidence from the United States (Brynjolfsson, Chandar and Chen 2026).

Panel B compares young and older workers more formally, using an event-study design.[5] For each year relative to 2022, the triple-difference estimates show how much more the employment of young workers (aged 20 to 24) relative to older workers (aged 25 to 64) has changed in more exposed occupations than

[4] As a robustness check, we compare employment in the most exposed quintile (Q5) with the pooled employment of the four remaining quintiles (Q1–Q4) instead of the least exposed quintile only. Because part of the Q5–Q1 gap stems from the decline of Q1 rather than growth of Q5, this comparison narrows the gap for most groups (in early 2026, for workers aged 25–34 from 9.6 to 2.8 log points). However, the reversal for workers aged 20–24 persists: their gap stands 7.6 log points below its 2022Q3 value, whereas it increases for all older age groups.

[5] Following Brynjolfsson, Chandar and Chen (2026), we estimate Poisson regressions, which yield relative effects on employment counts and can handle small cells and cells with zero employment. Unlike them, we compare age groups within occupations rather than exposure groups within firms, as neither data set contains firm identifiers. The regressions include fixed effects for occupation × year, age group × year and occupation × age group; exposure is standardized across occupations, and standard errors are clustered by occupation.

in less exposed ones (ChatGPT was released at the end of 2022).[6] The estimates compare age groups within the same occupation to filter out anything that affects all workers in an occupation, such as rising demand for software developers or the pandemic's toll on hospitality. In addition, comparing the same age group across occupations filters out economy-wide shifts in youth employment, such as those stemming from demographic change or business cycles. The estimates also absorb persistent differences in age structure across occupations, for instance between occupations with longer training periods, such as physicians, and those that young people enter early, such as medical assistants. Finally, they exploit the full range of exposure rather than only comparing the top and bottom quintiles.

Before 2022, the estimates are small and not statistically different from zero: the employment gap between young and older workers developed similarly in more and less exposed occupations. From 2023 onward, they turn negative and statistically significant. By 2025, young workers' employment relative to older workers has fallen by 4.5 percent more in an occupation whose exposure is one standard deviation higher. In the first quarter of 2026, this shortfall reaches 5.5 percent. One standard deviation corresponds roughly to the difference in exposure between retail sales workers, whose work is mostly in-person and hands-on, and human resources staff, whose work is largely desk-based and more exposed to large language models. Typical occupations in the top and bottom exposure quintiles are about 2.5 standard deviations apart. Between them, the ratio of young to older workers has thus fallen by around 11 percent more in the most exposed occupations.

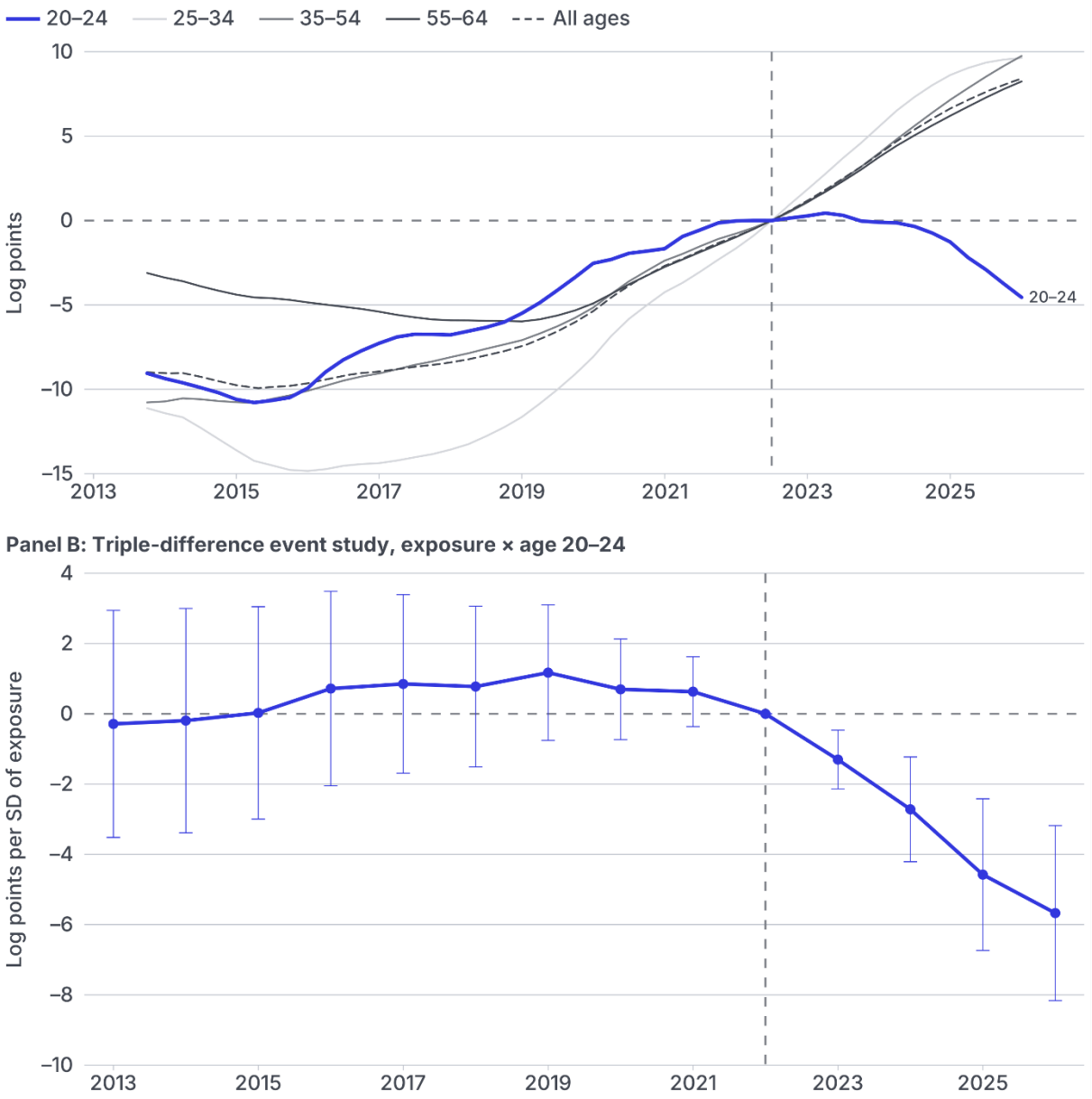
In absolute terms, full-time employment of the youngest workers in Germany's most AI-exposed occupations fell by about 40,000 between mid-2022 and early 2026, from about 279,000 to 239,000, a drop of 14 percent. Over the same period, the number of older workers in these occupations rose slightly. Employment of the youngest workers also declined relative to older workers in the least exposed occupations, but by much less. Even after accounting for this general decline, the most exposed occupations employ roughly 34,000 fewer young full-time workers than would otherwise be expected.[7]

[6] Using German administrative employment data, Arntz, Dinelli and Schlenker (2026) estimate difference-in-differences models by age group and find a negative but statistically insignificant association for workers aged 20–29. Our triple-difference estimates, by contrast, compare younger and older workers within the same occupation, thereby netting out occupation-wide trends.

[7] Counterfactual: employment of the youngest workers in the most exposed quintile if the ratio of young to older workers had changed as in the least exposed quintile (Q1) between 2022Q3 and 2026Q1. Using the four remaining quintiles (Q1–Q4) as the comparison yields about 33,000.

Figure 2

Germany: Employment of Young Workers by AI Exposure



Note: Full-time employees aged 20–64, excluding apprentices; 2013Q1–2026Q1. Panel A: Q5–Q1 gap, four-quarter moving average, log points, 2022Q3 = 0. Panel B: triple difference (exposure × age 20–24 × year), workers aged 20–24 relative to 25–64, log points per standard deviation of exposure, reference year 2022, 95 percent confidence intervals; 2026 covers the first quarter only.
Source: Bundesagentur für Arbeit; Eloundou et al. (2024); own calculations.
© ifo Institute

The shift to remote work coincided with the spread of generative AI and may increase the cost of mentoring and supervising early-career workers, which can also weaken entry-level hiring and employment (e.g., Emanuel, Harrington and Pallais 2026; Lambert and Schindler 2026). However, the decline for young workers persists when we account for whether jobs can be done remotely or for differences between broad occupational groups. By contrast, median wages of young full-time workers in exposed occupations

show no relative decline, consistent with firms adjusting through hiring rather than pay (Brynjolfsson, Chandar and Chen 2026).

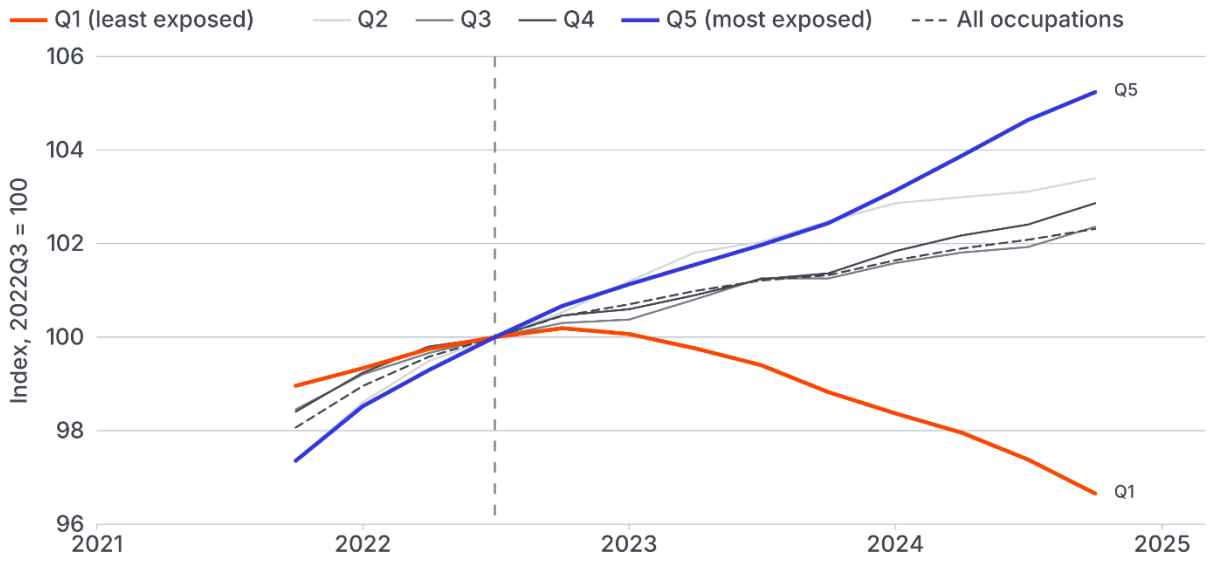
EU-27: Fewer Early-Career Hires Where AI Can Automate

We extend the analysis to the EU-27 using Eurostat's EU Labour Force Survey. Its coverage is broader, but the data come from a harmonized household survey rather than administrative records. Because the survey methodology changed in 2021, we restrict the analysis to 2021Q1–2024Q4. Compared with the German data, this leaves a shorter period both before and after the release of ChatGPT.[8] The sample covers full-time employees aged 20 to 64 who are not in education.[9]

Figure 3 shows employment by exposure quintile over time. As in **Figure 1** for Germany, the gap between the most and the least exposed quintile widens after the introduction of ChatGPT in 2022Q4. By the end of 2024, employment in the most exposed quintile stands 5.2 percent above its 2022Q3 level, while employment in the least exposed quintile is 3.3 percent below it. As in Germany, part of this divergence likely reflects broader digitalization and structural change that predate ChatGPT, rather than AI alone.

Figure 3

EU-27: Employment by AI Exposure Quintile



Note: Full-time employees aged 20–64 not in education; 118 ISCO 3-digit occupations; 2021Q1–2024Q4; four-quarter moving average; index 2022Q3 = 100.
Source: Eurostat, EU Labour Force Survey; Eloundou et al. (2024); own calculations. © ifo Institute

Panel A of **Figure 4** again plots the gap between the most and least exposed quintiles by age. For employment, the gap widens for every age group. It widens least for the youngest, but overall there is no substantial employment penalty for young workers in the EU-27. The EU-LFS also records when respondents started working for their current employer, which allows us to identify new hires, defined as employees who joined their current employer within the past twelve months. Firms tend to adjust by hiring fewer entrants rather than dismissing employees, so changes in hiring show up in overall employment only gradually. Young entrants also tend to have the least on-the-job experience, and their tasks are often those

[8] The change reflects the introduction of the Integrated European Social Statistics (IESS) framework; see Eurostat (2025).
[9] For Malta, Slovenia and Bulgaria, occupations are available only at the ISCO two-digit level; excluding these countries does not change the results.

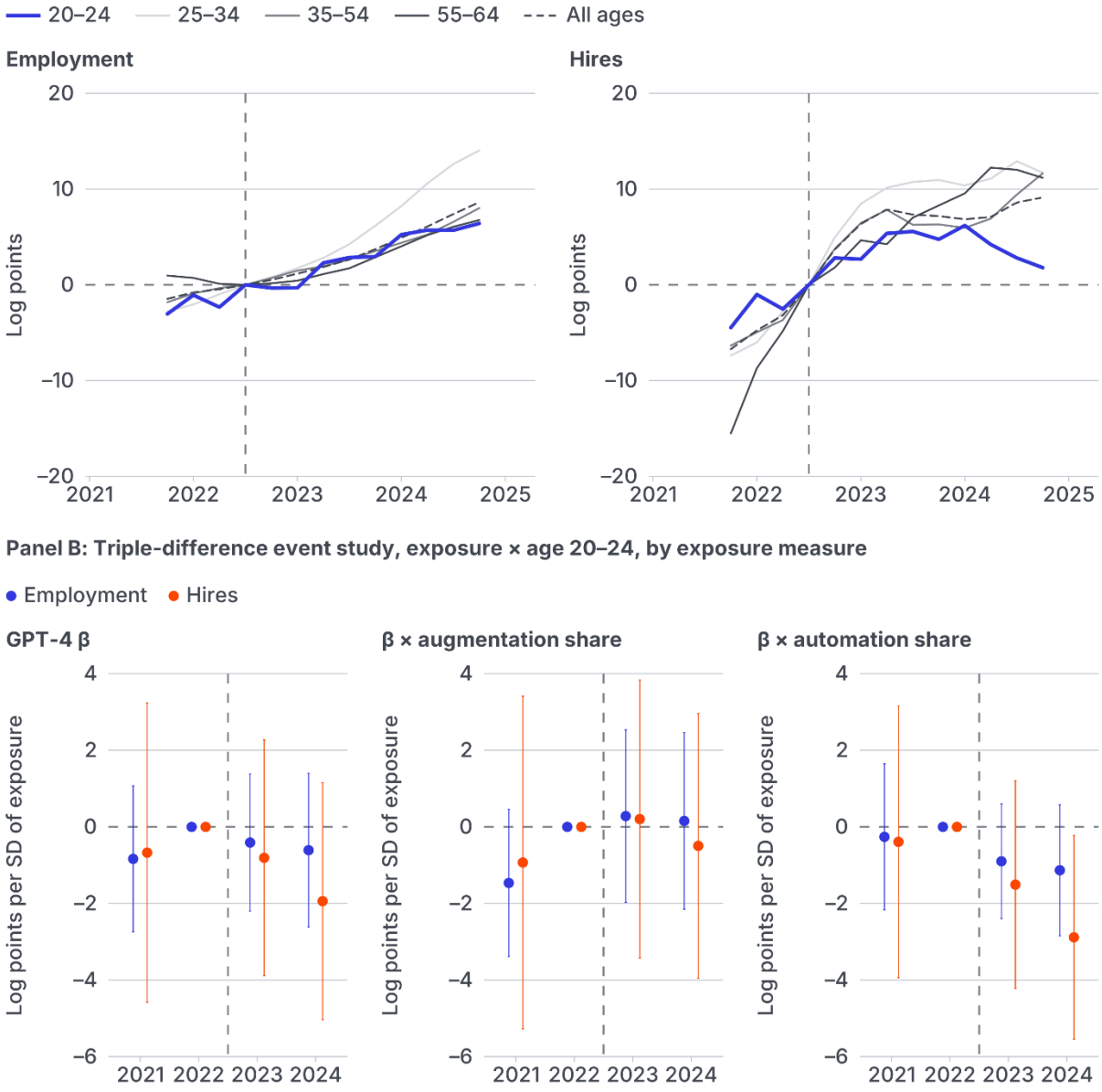
that AI can most readily take over. Consistent with this, Brynjolfsson, Chandar and Chen (2026) find that, in the United States, the decline in young workers' employment stems mainly from reduced hiring.

Indeed, the right-hand side of Panel A shows that from 2024 onward, the youngest workers begin to diverge from older workers in terms of new hires, while the hiring gaps for older groups continue to widen.

Panel B applies the event-study design used for Germany (**Figure 2**, Panel B) separately to employment and hires and to different types of AI exposure. The baseline exposure measure by Eloundou et al. (2024) captures overall exposure to AI, but not whether AI complements workers or automates their tasks. We therefore also weight exposure by the share of AI use that automates or augments tasks, drawing on usage data from the AI assistant Claude (Handa et al. 2025). With the baseline exposure measure, the employment coefficients for young workers are in line with Panel A and remain close to zero. By contrast, the hiring estimate is about −1.9 percent per standard deviation of exposure in 2024. This pattern appears to be driven by exposure to AI automation. By 2024, young workers' hiring relative to older workers is 2.9 percent lower per standard deviation of automation-weighted exposure but shows no association with augmentation-weighted exposure. The estimates are imprecise, and only the automation-weighted hiring estimate for 2024 is statistically significant. The evidence is therefore suggestive, but it points in the same direction as in the United States, where employment declines among young workers are concentrated in occupations in which AI use is predominantly automation-oriented (Brynjolfsson, Chandar and Chen 2026).

Figure 4

EU-27: Employment and Hiring of Young Workers by AI Exposure



Note: Full-time employees aged 20–64 not in education; 2021Q1–2024Q4; hire = job tenure under 12 months. Panel A: Q5–Q1 gap, four-quarter moving average, log points, 2022Q3 = 0. Panel B: triple difference (exposure × age 20–24 × year), workers aged 20–24 relative to 25–64, log points per standard deviation of exposure, reference year 2022, 95 percent confidence intervals. β × augmentation/automation share: GPT-4 β (Eloundou et al. 2024) weighted by the share of AI use that is augmentation/automation (Handa et al. 2025).
Source: Eurostat, EU Labour Force Survey; Eloundou et al. (2024); Handa et al. (2025); own calculations. © ifo Institute

Conclusion: Early Signals at the Entry Level

In the first years after the release of ChatGPT, labor market data from Germany and the EU-27 show no economy-wide job losses in AI-exposed occupations so far. Employment in the most exposed occupations has held up or grown, while the least exposed occupations have lost ground. This divergence began before generative AI became widely available and likely reflects broader structural change. However, the youngest workers are the exception. In Germany, employment of 20- to 24-year-olds has fallen relative to older workers, especially in highly exposed occupations. In the EU-27, there are signs of a similar pattern in hiring, which is concentrated in occupations in which AI is mainly used to automate tasks.

Figure 5 indicates where automation and augmentation are likely to matter most. It ranks occupations by AI exposure (Eloundou et al. 2024) weighted by the share of AI use that augments or automates tasks (Handa et al. 2025). Augmentation-weighted exposure is highest in professional occupations, such as journalists or legal professionals, while automation-weighted exposure is highest in clerical support and IT occupations, such as secretaries or ICT support technicians. The ranking rests on how people use a single AI system and should be read as indicative, not as a forecast of job losses. Nevertheless, clerical and IT support jobs have in the past offered young workers relatively well-paid entry points into the labor market. This may no longer hold as AI takes over more of the tasks typically performed by entrants.

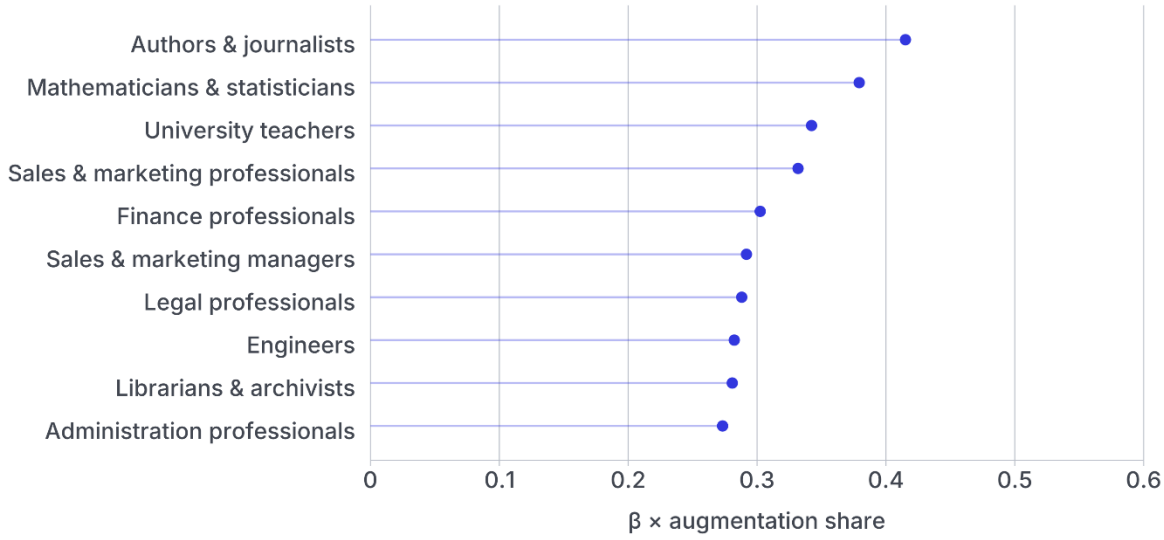
The patterns we document are descriptive and do not establish that AI caused the decline in hiring and employment of the youngest workers in exposed occupations. Demographic change, longer spells in education after the pandemic, cyclical shifts in labor demand, or the spread of remote work also affect young workers' employment and coincide with the arrival of generative AI. Nevertheless, like the findings of Brynjolfsson, Chandar and Chen (2026) for the United States, they provide an early indicator for Europe, one that is available long before any productivity effects show up in national accounts.

With these caveats in mind, our findings point to three implications for monitoring the labor market effects of AI. First, the evidence from both the United States and Europe suggests that monitoring should focus on labor market entry. The adjustment shows up first in the hiring and employment of young workers. Administrative labor market data on hiring by age and detailed occupation, combined with online job postings that track the demand for entry-level positions in near real time, could capture such shifts early. Second, monitoring capacity is best built before any disruption occurs. This requires fine-grained exposure measures that keep pace with the latest AI technologies, linked to timely employment and hiring records across EU countries, as envisaged in a proposed Union-level monitoring framework (Schnitzer et al. 2026). Data on how AI is actually used are particularly valuable. Whether AI automates or augments tasks appears to matter for young workers' employment, and this distinction can only be measured from actual use. Third, beyond policymakers, such indicators should also benefit education providers and firms. If AI takes over the tasks through which entrants gain experience, education and training systems need to equip labor market entrants with skills that AI complements. Technology and labor market foresight can help schools, universities and vocational training providers identify these skills. It can thereby inform curricula that give them more weight while building on a strong foundation of basic skills. Such foresight can also guide firms in designing training that builds the expertise entrants once gained on the job and enables workers and AI to raise each other's productivity. Timely monitoring of the transformation of work can thus support flexible adjustment and help ensure that a shortfall in hiring today does not become a shortage of experts tomorrow.

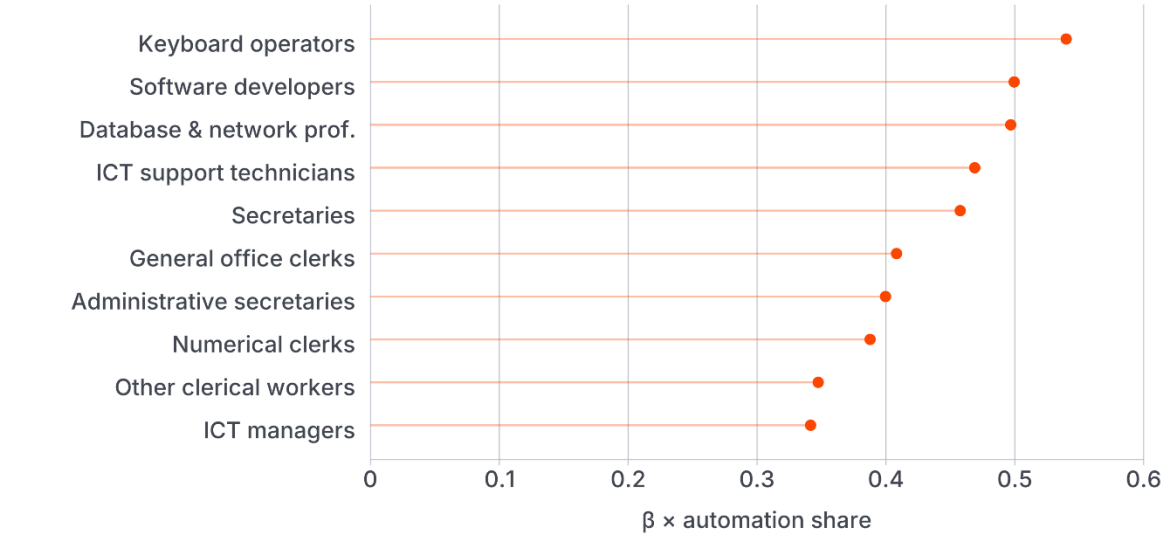
Figure 5

Occupations Most Exposed to Augmentation and Automation

Panel A: High β × augmentation



Panel B: High β × automation



Note: Top 10 ISCO 3-digit occupations by β × augmentation share and by β × automation share. β: GPT-4 exposure (Eloundou et al. 2024); augmentation and automation shares from Claude usage data (Handa et al. 2025).
Source: Eloundou et al. (2024); Handa et al. (2025); own calculations.

© ifo Institute

References

Acemoglu, D. (2024), "The Simple Macroeconomics of AI", Economic Policy 39, 287–326.

Acemoglu, D. and D. Autor (2011), "Skills, Tasks and Technologies: Implications for Employment and Earnings", in O. Ashenfelter and D. Card, eds., Handbook of Labor Economics, Vol. 4B, Elsevier, Amsterdam, 1043–1171.

Aghion, P. and S. Bunel (2024), "AI and Growth: Where Do We Stand?", Mimeo, LSE.

Arntz, M., M. Dinelli, O. Schlenker (2026), *KI als Jobkiller für Berufseinsteiger? Entwarnung mit Vorbehalt*, *IAB-Forum 13th October 2026*, https://iab-forum.de/ki-als-jobkiller-fuer-berufseinsteiger-entwarnung-mit-vorbehalt/ (accessed November 8, 2026).

Autor, D. and N. Thompson (2025), "Expertise", Journal of the European Economic Association 23, 1203–1271.

Bick, A., A. Blandin, and D. Deming (2026), "The Rapid Adoption of Generative AI", Management Science, https://doi.org/10.1287/mnsc.2025.02523.

Brynjolfsson, E., D. Chandar, and R. Chen (2026), "Canaries in the Coal Mine? Six Facts about the Recent Employment Effects of Artificial Intelligence", Stanford Digital Economy Lab.

Chandar, B. and B. Klein Teeselink (2026), "How Does AI Change Labor Demand? Evidence from 41 Countries", Stanford Digital Economy Lab, https://digitaleconomy.stanford.edu/publication/how-does-ai-change-labor-demand (accessed November 2, 2026).

Eloundou, T., S. Manning, P. Mishkin, and D. Rock (2024), "GPTs are GPTs: Labor Market Impact Potential of LLMs", Science 384, 1306–1308.

Emanuel, N., E. Harrington, and A. Pallais (2026), "The Power of Proximity to Coworkers", Quarterly Journal of Economics, https://doi.org/10.1093/qje/qjag027.

Eurostat (2025), EU Labour Force Survey: Reference Metadata (ESMS), https://ec.europa.eu/eurostat/cache/metadata/EN/lfsi_esms.htm (accessed November 2, 2026).

Facius, D. and R. Iacono (2026), "Labor Market Consequences of Generative AI: Early Evidence from Norway", CESifo Working Paper 12752.

Filippucci, F., P. Gal, and M. Schief (2024), "Miracle or Myth? Assessing the Macroeconomic Productivity Gains from Artificial Intelligence", OECD Artificial Intelligence Papers 29.

Handa, K. et al. (2025), "Which Economic Tasks Are Performed with AI? Evidence from Millions of Claude Conversations", Anthropic Economic Index.

Hardy, W., R. Keister, and P. Lewandowski (2018), "Educational Upgrading, Structural Change and the Task Composition of Jobs in Europe", Economics of Transition 26, 201–231.

Humlum, A. and E. Vestergaard (2025), "Large Language Models, Small Labor Market Effects", NBER Working Paper 33777.

Lambert, P. J. and Y. Schindler (2026), "The Broken Ladder: AI, Remote Work, and Early-Career Hiring", CEP Discussion Paper 2193, Centre for Economic Performance, London School of Economics.

Misch, F., B. Park, C. Pizzinelli, and G. Sher (2025), "AI and Productivity in Europe", IMF Working Paper 25/67.

Palladino, M. G., A. Bergeaud, A. Bertheau, S. Bunel, and O. Degos (2026), "Generative AI: The First Changes in the Labour Market Are Affecting Young People", Banque de France Eco Blog 463, https://www.banque-france.fr/en/publications-and-statistics/publications/generative-ai-first-changes-labour-market-are-affecting-young-people (accessed November 2, 2026).

Schnitzer, M. et al. (2026), A Transformative AI Strategy for Europe, https://transformative-ai.eu/ (accessed November 2, 2026).

Authors



Oliver Falck

Oliver Falck is Director of the Center for Innovation Economics and Digital Transformation at the ifo Institute, Co-Director of the LMU–ifo Economics & Business Data Center (EBDC), and Professor of Economics at LMU Munich. He also serves as Scientific Program Director at the CESifo Research Network. He is currently a member of the Scientific Commission of Lower Saxony and was a member of the German Council for Technological Sovereignty from 2022 to 2025. He has been a member of the German Expert Commission on Research and Innovation (EFI) since September 2026.



Clemens Fuest

Clemens Fuest is President of the ifo Institute – Leibniz Institute for Economic Research at the University of Munich, Professor of Economics at LMU Munich, Director of the Center for Economic Studies (CES), and Director of CESifo GmbH. He is, among others, a member of the Scientific Advisory Board at the German Federal Ministry of Finance (since 2003), the European Academy of Sciences and Arts, and the German National Academy of Science and Engineering (acatech). Professor Fuest served as president of the International Institute for Public Finance (IIPF) from 2018 to 2021.



Yuchen Guo

Yuchen Guo is an Economist at the ifo Center for the Economics of Innovation and Digital Transformation. He obtained his PhD in Economics from LMU Munich. His research examines technological change and the labor market. He contributed to this field as a researcher on the EU Horizon 2020 PILLARS project (Pathways to Inclusive Labour Markets). He has also contributed to policy-oriented work on productivity, innovation, and the economic costs of bureaucracy.