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Alexander Bick, Adam Blandin, David Deming, Nicola Fuchs-Schündeln and Jonas Jessen

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Centre for Economic Policy Research
187 boulevard Saint-Germain, 75007 Paris, France
2 Coldbath Square, London EC1R 5HL
Tel: +44 (0)20 7183 8801
www.cepr.org

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MIND THE GAP: AI ADOPTION IN EUROPE AND THE US

Abstract

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JEL Classification: J24, M16, O14, O33

Keywords: Generative AI

Alexander Bick - alexander.bick@mailbox.org
Federal Reserve Bank of St. Louis and CEPR

Adam Blandin - adam.blandin@vanderbilt.edu
Vanderbilt University

David Deming - david_deming@harvard.edu
Harvard University

Nicola Fuchs-Schündeln - nicola.fuchs@wzb.eu
WZB Berlin Social Science Center & Goethe University Frankfurt and CEPR

Jonas Jessen - jonas.jessen@wzb.eu
WZB Berlin Social Science Center & IAB

Mind the Gap: AI Adoption in Europe and the US*

ALEXANDER BICK
St. Louis Fed & CEPR

ADAM BLANDIN
Vanderbilt University

DAVID J. DEMING
Harvard University & NBER

NICOLA FUCHS-SCHÜNDELN
WZB & Goethe University & CEPR

JONAS JESSEN
WZB & IAB

March 2026

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1 Introduction

Since the mid 1990s, productivity growth in the US has outpaced growth in Europe. Figure 1 shows that between 1995 and 2025 output per hour increased by 85% in the US versus 29% in Europe, reversing much of the convergence that had occurred in previous decades. Prior research has linked this divergence to greater production and diffusion of information and communication technologies (ICT) in the US (Ark et al. 2008; Oliner and Sichel 2000; Oliner et al. 2007).

Today, recent advances in artificial intelligence (AI) represent a new cluster of technologies that could potentially drive productivity growth in the coming years. As with the prior ICT revolution, the economic impact of AI will depend on the speed and breadth of adoption by workers and firms. An important open question, therefore, is whether a similar "AI gap" will exacerbate existing productivity differences between the US and Europe, or whether this time is different (Acemoglu 2025; Bontadini et al. 2025; Chui et al. 2023; Draghi 2024; Filippucci et al. 2024).

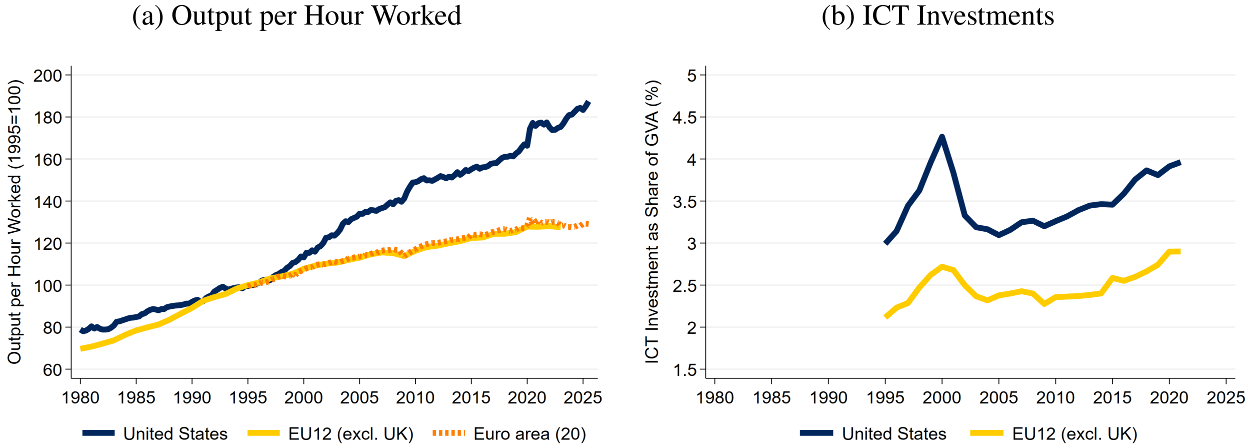
To address this question, we leverage several data sources to document cross-country gaps in AI adoption, investigate the causes of gaps in adoption, and gauge potential economic consequences. We primarily rely on two sources of data. First, we fielded two rounds of nationally representative and internationally comparable worker-level surveys focusing on generative AI adoption. The first survey round was fielded in May-June of 2025 and collected roughly 5,000 responses per country; the second round was fielded in January-February 2026 and collected roughly 3,000 responses per country. Each round covered seven countries: the US, the four largest European economies (Germany, UK, France, Italy), and two of the leading countries in the European Commission's Digital Economy and Society Index (DESI), Sweden and the Netherlands.

Second, we draw on the US Census Business Trends and Outlook Survey (BTOS) and the European Union's "ICT Usage and E-Commerce in Enterprises" Survey (EU-ICT-Firm). These surveys have been fielded repeatedly in recent years and contain broadly comparable information on AI adoption at the firm level. A key benefit of the European survey is that it contains data for 32 countries (all 27 EU countries and 5 non-EU countries) and more detailed information than the BTOS. While the underlying firm-level micro data are not available, we can observe outcomes at the country-industry level. To the best of our knowledge, the AI module of the EU-ICT-Firm survey has not yet been used in academic work.

Our first contribution is to document differences in AI adoption across countries.[1] To compare adoption in Europe and the US, we use two measures available for both regions. First, in 2026 we find that 43% of US workers use AI for their job compared with 32% among European workers in our surveys. Second, both the BTOS and the EU-ICT-Firm surveys ask firms whether they use AI "for the

1. Related work by Liu and Wang (2026) compares generative AI engagement across countries in 2024 using web traffic and Google Trends data.

Figure 1: Output per Hour Worked and ICT Investments in Europe and the United States



Notes: Panel (a) shows quarterly output per hour worked for the US (data from Bureau of Labor Statistics) and for the Euro Area 20 countries (data from European Central Bank since 1995). European data before 1995 are annual output per hour worked for the EU12 countries, excluding UK (data from the Penn World Tables). EU12 excl. UK: Belgium, Denmark, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain. Euro area (20): EU 12 excluding Denmark and the UK, plus Austria, Croatia, Cyprus, Estonia, Finland, Latvia, Lithuania, Malta, Slovakia, and Slovenia. Panel (b) shows annual ICT investments (sum of computing and communications equipment and software and databases) as a share of gross value added, in the EUKLEMS & INTANProd database (Bontadini et al. 2023). Appendix Figure D.1 shows investment from each of the three components as share of gross value added individually and the resulting evolution of the respective real capital stocks relative to 1995 levels.

production of goods or services." In 2025, 7% of US firms use AI for production versus 4% of EU firms. We conclude that AI adoption by US firms and workers exceeds that of Europe overall.

AI adoption rates also vary substantially within Europe. Among European countries that we survey, worker adoption rates in 2026 range from 36% in the UK to 26% in Italy. Among European firms in 2025, the share of firms using AI for the production of goods and services ranges from 9% in Sweden to less than 1% in Serbia. Broadly, the Nordic countries, Benelux countries, Germany, Austria, and the UK have fairly high rates of adoption, while France, Southern Europe, and Eastern Europe have much lower rates of adoption. This result holds both in worker- and firm-level adoption data: in general, AI adoption by workers is highly correlated with AI adoption by firms across countries and industries.

In addition to covering a wide sample of countries, the EU-ICT-Firm survey also covers AI adoption for a broader set of purposes than just the production of goods and services. On average, the share of European firms using AI for any business purpose is five times larger than the share of firms using AI for production. This result is important in light of several recent papers documenting low rates of firm adoption relative to worker adoption in the US (Bick et al. 2026; Bonney et al. 2024; McElheran et al. 2024). Once we include all AI uses by firms, we find more similar adoption rates between European firms and workers. This suggests that the BTOS's focus on AI adoption in the production of goods and services is key to interpreting its low measured adoption rate prior to November 2025. While the BTOS updated its AI questions in November 2025, we argue that the updated question likely continues to under-count AI adoption relative to the EU-ICT-Firm survey.

The EU-ICT-Firm survey, which contains comparable data on AI adoption extending back to 2021, reveals a sharp uptick in adoption in recent years. From 2021 to 2023, AI adoption by European firms was roughly stable. Since 2023, adoption has more than doubled, with early adoption leaders tending to pull further ahead of early laggards. We also observe an increase in AI adoption by workers between the 2025 and 2026 waves of our surveys.

Our second contribution is to assess potential explanations as to why AI adoption varies across countries. We begin by documenting systematic differences in adoption by age, education, occupation, industry, and firm size and ask whether compositional differences across countries can statistically account for differences in aggregate adoption rates. An Oaxaca-Blinder decomposition attributes 55% of average of adoption differences relative to the US to these compositional effects, with occupation, industry, and firm size playing a more important role than demographics. However, an important share of the overall US-European adoption gap remains unexplained by these factors.

We then investigate the role of another potential driver of AI adoption gaps: cross-country differences in firm management practices. A previous literature found that ICT investment and the returns to ICT investment appear intimately linked to the management and internal organization of firms (Bresnahan et al. 2002; Garicano and Heaton 2010; Milgrom and Roberts 1990). Moreover, Bloom et al. (2012) found that different management practices by US firms account for a majority of the higher ICT investment and investment returns by US firms relative to Europe in the 1990s and 2000s.

We find robust evidence that management practices are strongly associated with AI adoption. A country's average management index, as measured by firm interviews in the World Management Survey (WMS), is strongly predictive of country-level adoption rates. We adapt personnel management questions from the WMS to construct a worker-level index capturing the management practices of their firm and show that this relationship also holds within countries. Workers in firms with higher personnel management indices report higher rates of AI adoption, even after controlling for country, demographics, and firm characteristics. These firms are also more likely to encourage their workers to use AI for their job, to provide access to AI tools, and to provide AI training. AI encouragement and AI tool provision are strongly predictive of worker-level AI adoption, while AI training is not. Strikingly, an augmented Oaxaca-Blinder decomposition that includes differences in AI encouragement by firms statistically accounts for nearly all of the US-Europe adoption gap.

Our final contribution is to quantitatively assess the potential economic implications of cross-country gaps in AI adoption. We review a rapidly expanding literature that finds sizable productivity gains from AI in experimental micro data. However, a priori it is unclear whether these micro-level effects will translate to meaningful aggregate productivity gains. To investigate this question, we conduct two complementary analyses.

First, our worker surveys ask AI users to estimate the time that AI saved them in their job in the past week. Reported time savings among AI users are broadly in line with experimental micro estimates, providing some assurance that worker reports are plausible. Aggregated time savings at the country level (including non-users, who save zero time by construction) imply aggregate time savings of 2.3% among all workers in the US. We estimate lower aggregate time savings of between 1.0% and 1.8% in the European countries that we survey. These estimates suggest that as of 2026 AI adoption by workers is associated with an increase of US labor productivity by 0.5 – 1.3 percentage points relative to European countries.

Second, we examine the relationship between AI adoption and measured productivity growth in national statistics. Using AI adoption rates from the EU-ICT-Firm survey, we analyze industry-level productivity growth across 29 European countries with available productivity data, controlling for country and industry fixed effects. We consider three time periods: 2015-2019 (which serves as a placebo check), 2019-2024, and 2022-2024. We find a small and insignificant coefficient during the placebo period, but positive and typically statistically significant coefficients during the later periods. Our estimates imply that a 10-percentage-point increase in AI adoption is associated with 2 - 5 percentage points of additional cumulative productivity growth for the periods ending in 2024.

We then run a similar regression for the US, where productivity data extend through the third quarter of 2025. In this specification we cannot include industry fixed effects; instead, we analyze industry productivity growth relative to each industry's pre-2020 trend. We continue to find a positive cross-industry association. Our estimates imply that a 10-percentage-point increase in worker AI adoption is associated with 3.7 percentage points of additional cumulative productivity growth relative to trend from 2019-2025, and 2.9 percentage points of additional growth from 2022-2025, similar to our European estimates. We emphasize that these estimates are not causal and should be interpreted cautiously, particularly given the short time horizon over which AI has been widely adopted. Nonetheless, the similar findings across methods and geographies are consistent with a positive productivity impact from AI that is broad-based enough to be reflected in national statistics. Finally, we conduct similar analyses investigating whether industry-level AI adoption is associated with changes in employment. We find no clear evidence that recent AI adoption is associated with systematic changes in industry employment in either Europe or the US.

The remainder of the paper proceeds as follows. Section 2 introduces our primary data sources and describes how we measure AI adoption. Section 3 documents AI adoption rates in Europe and the US. Section 4 investigates potential drivers of variation in AI adoption. Section 5 assesses the potential consequences of differential AI adoption patterns for productivity and employment. Section 6 concludes.

2 Data and Measurement

2.1 Worker Surveys

Our primary source for worker-level data is a set of surveys that we fielded simultaneously in the US and six European countries: the four largest European economies (Germany, the UK, France, and Italy) and two leading countries in the European Union's Digital Economy and Society Index (Sweden and the Netherlands). In addition, we also draw on a household survey about ICT use administered by Eurostat, covering all EU countries and several other European countries.

2.1.1 An International Real-Time Population Survey

We model our worker surveys after the Real-Time Population Survey (RPS), an online labor market survey of US adults aged 18–64. The RPS has been fielded repeatedly in the US since April 2020 (Bick and Blandin 2023), and since June 2024 it has included a module measuring AI use (Bick et al. 2026). The RPS is designed to mirror the US's primary household labor market survey, the Current Population Survey (CPS). The RPS matches questions on demographics and labor market outcomes in the basic CPS and CPS Outgoing Rotation Group, using the same word-for-word phrasing when possible and following the intricate sequence of questions necessary to elicit labor market outcomes in a manner consistent with the CPS (US Census Bureau 2015). Replicating key portions of an existing high-quality survey ensures that survey concepts are comparable, which allows researchers to validate RPS outcomes against a widely used benchmark with a larger sample size and to construct sample weights.

We adapt the RPS so that it can be fielded internationally and include novel questions related to AI. In May-June 2025 and January-February 2026 we administered the survey simultaneously in the US and six European countries. Following the RPS strategy, we replicate portions of each country's national labor force survey to assign employment status to respondents. Since the main objective of our paper is to assess workers' AI use in the last week, we focus on the questions that determine whether or not an individual is "employed, at work" in the previous week. Respondents who were either not employed or absent from work do not proceed with the survey.

Samples and Weighting We fielded the 2025 and 2026 survey waves using Bilendi, an international commercial survey provider. Bilendi charges us 1.74 US$ to 3.89 US$ (€2.06 to €4.61 at the time) per completed survey. The Bilendi panel of potential respondents are recruited online. This panel is not necessarily a random sample of each country's population. However, Bilendi can target survey invitations to specific demographic groups. Our survey samples were designed to be nationally representative of each country's "employed, at work" population across key demographics. We also include measures to filter out low-quality responses. Details on sampling and data quality procedures can be found in Appendix A.

Our survey population was adults age 18 to 67 who were employed and at work in the previous week. (In France, our maximum age was 63, which is the statutory retirement age.) The 2025 surveys collected roughly 5,000 respondents per country and were fielded between May 21 and June 18. The 2026 surveys collected roughly 3,000 respondents per country and were fielded between January 19 and February 2. Appendix Figure A.1 compares the unweighted and weighted sample composition between our surveys and government surveys of workers. Our surveys yield very similar population shares to their government survey analogues.

Our survey samples do not match our demographic quotas exactly, and they may not match interactions of demographic cells.[2] To address remaining discrepancies in observable characteristics, we construct sample weights using the raking algorithm by Deming and Stephan (1940), ensuring that the weighted sample proportions align with a rich set of demographic targets. Details on weighting can be found in Appendix A.2. We use weights in our analysis throughout to ensure the representativeness of the survey population.

Despite being representative based on observable characteristics, our survey samples could still potentially suffer from selection on unobservable characteristics correlated with our variables of interest. However, for the US Bick and Blandin (2023) and Bick et al. (2025a, 2025b) show that the RPS closely aligns with government household surveys on employment, hours worked, earnings, industry composition, employee tenure, and work from home, none of which were targeted by our sampling scheme. Bick et al. (2026) show that ChatGPT adoption in the RPS closely aligns with estimates from other surveys (Fletcher and Nielsen 2024; McClain 2024). In particular, the latter estimates are derived from a survey using traditional random address-based sampling and includes respondents without internet access. For Europe, Appendix A.3 shows that industry composition in our surveys, not targeted during sampling, is similar to government surveys. Section 3.3 shows that worker AI adoption rates in our surveys are similar to the EU-ICT-Household survey, which we discuss below.

How the Worker Surveys Measure AI Adoption The core RPS AI module, which we use in our surveys, begins with a definition of AI:

> *Generative AI is a type of artificial intelligence that creates text, images, audio, or video in response to prompts. Some examples of Generative AI include ChatGPT, Gemini, and Midjourney.*

2. For example, our unweighted sample may have the correct share of male respondents and college-educated respondents, but this does not guarantee that we match the share of respondents who are male and college educated.

We included examples of popular AI products because some respondents may be more familiar with those product names than with the broader concept of AI. After defining AI, respondents were then asked about AI use at work:

> *Do you use Generative AI for your job? (No/Yes)*

This question is designed to mirror the analogous computer use question from the CPS Computer and Internet Use Supplement, which was asked every few years between 1984 and 2003.

The survey asks several follow-up questions to AI users regarding which products they used, how intensively they used them, and how much time they saved by using them. Non-users are asked about their reasons for not using AI. We also ask respondents similar questions about their AI usage outside their job.

An important caveat regarding our measurement approach is that it will only capture AI use that respondents are aware of. For example, while typing prompts into ChatGPT is an obvious case of using AI, AI-generated search summaries such as Google's "AI Overview" are a more subtle case that respondents may not consider. Because our estimates may not detect some passive or embedded uses of the technology, we interpret our estimates as a lower bound on the extent of AI adoption.

2.1.2 The EU-ICT Household Survey

The Eurostat Community Survey on ICT Usage in Households and by Individuals (EU-ICT-HH) is an annual technology adoption survey coordinated by Eurostat and carried out by national statistical agencies. The survey has been conducted annually since 2002 and includes all EU member states and some other European countries who participate in Eurostat data collection. The sample covers individuals aged 16-74. The survey gathers data on internet connectivity, digital activities (e-government, e-commerce, social media), digital skills, online privacy, and emerging technologies and in most countries is conducted in the second quarter of each year.

In 2025, the EU-ICT-HH added three questions focused on generative AI usage. Similar to our survey, it first provides a definition of generative AI:

> *Generative Artificial Intelligence (AI) can create new content, such as text, images, programming code, videos, or other data, based on available information and patterns it has learned from existing examples. To generate this content, it requires input or a prompt by the user, such as asking it a question or providing instructions or a topic to focus on.*

After defining AI, respondents were then asked about AI use:

Have you used any generative AI tools (e.g. ChatGPT, Copilot, Gemini, LLaMA, Midjourney, DALL-E) to create content like text, images, programming code, or videos in the last 3 months? (Yes/No)

Anyone answering "Yes" to the previous question was asked:

What was the purpose of using generative AI tools in the last 3 months? (tick all that apply)

- *For private purposes*
- *For professional (work) purposes*
- *For formal education (e.g. school or university)*

The third question, which we do not explore in our analysis, asks about the reasons for not using AI. Currently, the micro data from this survey are not available. However, Eurostat publishes aggregates by age group, educational attainment, and employment status.

2.2 Firm Surveys

To measure AI adoption by firms, we primarily rely on the Eurostat Community Survey on ICT Usage and E-Commerce in Enterprises (EU-ICT-Firm) and the US Business Trends and Outlook Survey (BTOS). Although the underlying firm-level micro data are not available for either source, we can observe estimates of the share of firms (not weighted by employment) who adopt AI at the country, country-industry, and country-firm-size level. Unlike our worker surveys, which focus on generative AI adoption, these firm estimates capture a broader concept of AI, as detailed below.

2.2.1 The EU-ICT Firm Survey

Like the EU-ICT-HH survey, the EU-ICT-Firm survey is an annual technology adoption survey coordinated by Eurostat and carried out by national statistical agencies. The survey covers all sectors with the exception of agriculture, mining, and public services. Its sample frame consists of firms in these sectors with at least 10 employees. In the latest survey round in 2025, 157,000 firms were surveyed. Data collection occurs in the first quarter of a year. The targeted respondent for the survey is a decision maker with major responsibility for ICT-related issues in the enterprise.[3]

A module on firms' AI use was added in 2021 and has been fielded annually since 2023. It asks:

3. The exact phrasing in the Model Questionnaire provided by Eurostat to the national statistic agencies is: "*Target respondent: A decision maker with major responsibility for ICT-related issues in the enterprise (the ICT manager or a senior professional in the ICT department). In smaller enterprises, the respondent should be someone at the level of managing director or the owner. In any case the respondent should not be someone with responsibilities only in accounting.*"

Does your enterprise use any of the following AI technologies? Select all that apply

1. *AI technologies performing analysis of written language (e.g. text mining)*
2. *AI technologies converting spoken language into machine-readable format (e.g. speech recognition)*
3. *AI technologies generating written language, spoken language or programming code (e.g. natural language generation, speech synthesis)*
4. *AI technologies identifying objects or person based on images (e.g. image recognition, image processing)*
5. *Machine learning (e.g. deep learning) for data analysis*
6. *AI technologies automating different workflows or assisting in decision-making (e.g. AI based software robotic process automation)*
7. *AI technologies enabling physical movement of machines via autonomous decisions based on observation of surroundings (e.g. autonomous robots, self-driving vehicles, autonomous drones)*
8. *AI Technologies generating pictures, videos, sound/audio* (added in 2025)

We refer to the firm AI adoption rate as the share of firms using at least one of these technologies. An advantage of asking about a concrete list of technologies is that it reduces ambiguity about what is meant by "AI". However, this also means that some technologies that are not listed but might plausibly be considered "AI" will not be captured. For example, before category 8 was added to the list in 2025, a firm using generative media technologies could be classified as a non-adopter.

Firms using AI were also asked follow-up questions about which business functions AI assisted. The survey asked: *Does your enterprise use AI software or systems for [business function]?* The business functions covered were: marketing or sales; production or service processes; organization of business administration processes or management; logistics; ICT security; accounting, controlling, or finance management; and research and development (R&D) or innovation activity. For each function, the questionnaire provides examples. For example, in the case of "production or service processes": *Examples may include: Predictive maintenance or process optimisation based on machine learning; Tools to classify products or find defects in products based on computer vision; Autonomous drones for production surveillance, security or inspection tasks; Assembly works performed by autonomous robots*.

2.2.2 US BTOS Survey

The BTOS is a biweekly survey administered by the US Census Bureau. Its sampling frame comprises roughly 1.2 million non-farm employers in the US. This sample is organized into six rotating panels, each containing about 200,000 employers. Each panel is surveyed once every 12 weeks, and data are released every two weeks. The BTOS asks a set of core questions covering recent business conditions and expectations. In contrast to the EU-ICT-Firm survey, the BTOS does not specify a target respondent. However, the core questions, covering topics such as changes in revenues and employment, operating capacity, and expectations about future business conditions, require detailed knowledge of the firm's operations, suggesting that the survey is intended to be completed by someone with broad managerial oversight of the business.

In September 2023 the Census introduced a question asking whether the employer used AI to produce goods or services:

> *Between MM/DD – MM/DD, did this business use Artificial Intelligence (AI) in producing goods or services? (Examples of AI: machine learning, natural language processing, virtual agents, voice recognition, etc.)*   *(No/Yes/Do not know)*

Importantly, this question phrasing does not include AI use for other business functions (e.g., logistics, marketing or sales). As a result, when comparing the US and Europe we can only assess AI adoption for producing goods and services, which we often abbreviate as "production processes" or just "production".

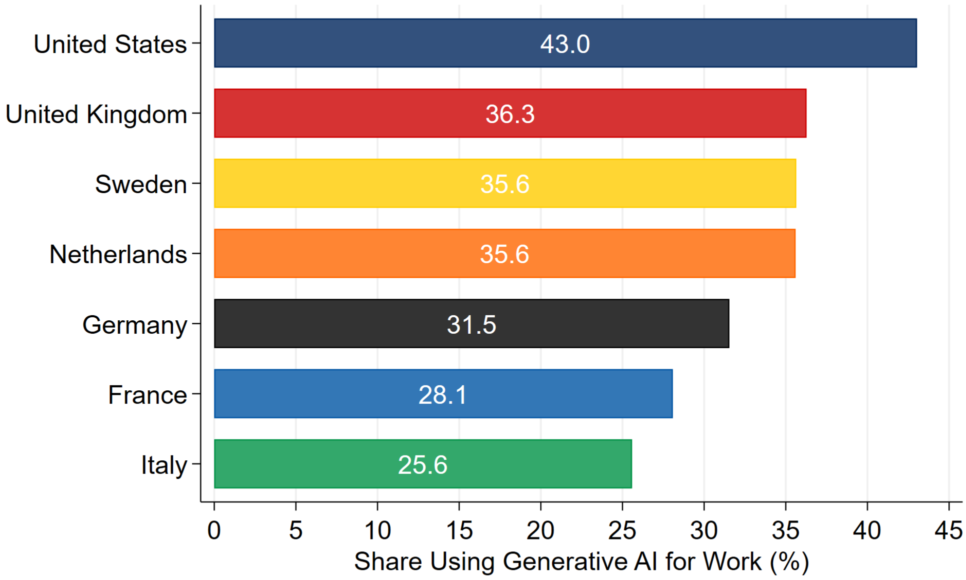
In November 2025, the BTOS broadened the phrasing of its AI adoption question, replacing "producing goods and services" with "any of its business functions."[4] The BTOS also ran two AI supplements, one between December 2023 and February 2024 and one between December 2025 and February 2026. The first supplement asked about 18 different AI technologies used in producing goods and services, while the second asked about AI usage across 15 different business functions, in each case covering the prior six months. Appendices B.2 and B.3 list the exact questions and answer options. Our primary analysis uses BTOS data prior to the change in question phrasing in November 2025, which allows us to compare the evolution of AI adoption in the US over time.

2.2.3 Key Differences Between the BTOS and EU-ICT-Firm Survey

We briefly summarize the key differences between the EU-ICT-Firm and BTOS surveys, which are important for interpreting comparisons between surveys. First, the framing of the adoption question differs. The EU-ICT-Firm survey asks about usage of a specified set of concrete AI technologies and, in a follow-up question, about the business functions for which AI is used. The BTOS, in contrast, asks

4. US Census Bureau (2025) discusses the update of the question, suggesting that the intent of the original question was to capture AI adoption more broadly than for "producing goods and services". However, the expert feedback and testing they cite are consistent with our narrower interpretation of the question, which prompted the change in phrasing in November 2025.

Figure 2: Share of Workers Using Generative AI in 2026



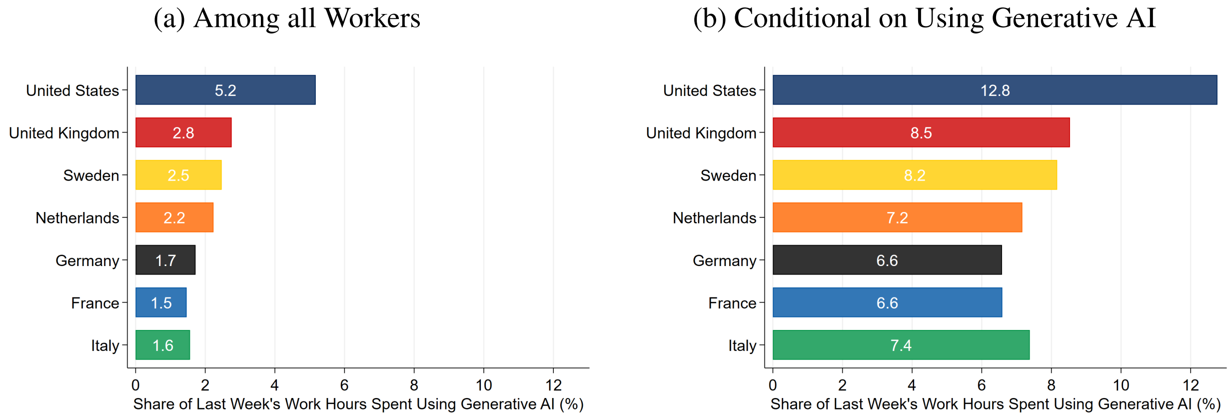
Notes: Figure shows the share of survey respondents who use Generative AI for work. Data source: Authors' own survey run in January-February 2026. $N = 20,916$

directly about usage in a specific business function (producing goods or services) prior to November 2025. Second, the reference period differs. The EU-ICT-Firm survey asks whether firms currently use an AI technology, whereas the BTOS asks about usage in the last two weeks, which respondents may interpret more restrictively. Third, the target respondent differs. The EU-ICT-Firm survey explicitly requires the respondent to be a decision maker with major responsibility for ICT-related issues. The BTOS does not specify a target respondent, though the scope of the questions suggests it is intended for someone with broad managerial oversight. Finally, the EU-ICT-Firm survey covers only firms with at least 10 employees, while the BTOS covers all firm sizes. Since firms with fewer than 10 employees constitute a large share of all firms in both Europe and the US, this difference will impact comparisons if AI adoption varies systematically with firm size.

3 AI Adoption in Europe and the US

This section documents the extent of AI adoption in Europe and the US. We first examine reported AI adoption by workers in the US and the six European countries covered by our worker surveys. Next, we document AI adoption by firms in the US and all European countries covered by the EU-ICT-Firm survey. We then ask whether countries with higher reported rates of worker adoption also report higher rates of firm adoption.

Figure 3: Share of Work Hours using Generative AI in 2026



Notes: Panel (a) reports the share of last week's working hours that was spent using Generative AI. For daily usage, respondents could indicate i) no usage, ii) less than 15 minutes, iii) 15-60 minutes, iv) 1-4 hours, v) more than 4 hours. To obtain the total minutes spent using Generative AI, we assume daily usage of 0, 7.5 minutes, 37.5 minutes, 2.5 hours, and 4 hours for each option, respectively. Weekly usage is calculated by combining daily usage with the reported number of days used. If respondents report using Generative AI on "some days" (rather than one or all days), we assume they used it on half of their working days. For non-users, the share of work hours using Gen AI is mechanically 0. Panel (b) reports the share of work hours using Gen AI conditional on AI usage. Data source: Authors' own survey run in January-February 2026. $N = 19,764$ (all workers) and $N = 5,367$ (Generative AI users)

3.1 What Share of Workers Use AI?

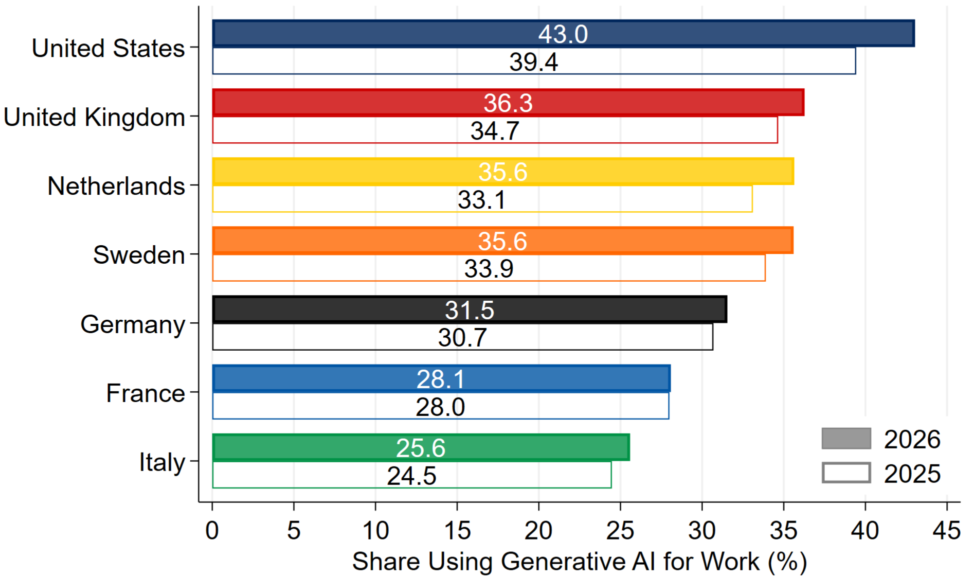
Figure 2 displays the share of workers who report using AI for work in January and February 2026. The top bar shows that 43% of US workers report using AI for their jobs. This exceeds AI adoption in the six European countries covered by our worker surveys, which range from 25.6% (Italy) to 36.3% (United Kingdom). In relative terms, US worker adoption is between 18% and 68% higher than worker adoption in European countries.[5]

Figure 2 does not distinguish between occasional and intensive AI use. To incorporate the intensity of AI use, our surveys asked AI users how many days and how many hours per day they used AI in the past week.[6] We combine these answers with information on days worked last week and weekly hours worked to estimate the share of work hours that each respondent spent using AI in the past week. Figure 3a shows that in 2026, 5.2% of total work hours in the US were spent using AI (see the figure notes for details). This statistic includes non-adopters, who spend 0% of their work hours using AI by construction. The US rate is roughly double the rate in the UK, Sweden, and the Netherlands and more than triple the rate in Germany, France, and Italy. The US-Europe gap in AI work hours is larger than the gap in the share of workers adopting AI because, conditional on using AI, US workers use it

5. Appendix Figure D.2 shows that non-work adoption and work adoption are highly correlated across countries (0.91). Averaging across all countries in our worker surveys, non-work adoption rates are 51% higher than work adoption rates (51% versus 34%). In percentage terms, cross-country variation in non-work adoption is smaller than for work adoption. For example, US non-work adoption is 11-41% higher than in European countries, versus 18-68% for work adoption.

6. In Appendix Figure D.3 we report the share of workers using AI for every work day last week, on more than one day per week or only one day per week. Workers in countries with higher adoption rates tend to use AI on more days. Appendix Figure D.4 summarizes time spent using AI per workday. AI users who use it on more days also spend more hours per workday using AI.

Figure 4: Share of Workers using Generative AI in 2025 and 2026



Notes: Figure reports the share of survey respondents who use Generative AI for work in 2025 and 2026. Data source: Authors' own survey run in May-June 2025 and January-February 2026. $N = 55,415$ ($N = 34,499$ in 2025 and $N = 20,916$ in 2026)

more intensively (see Figure 3b).

Figure 4 shows that adoption rates increased in all countries between our two survey waves, in May-June 2025 and January-February 2026. The share of workers adopting AI increased most in the US, by 3.6 percentage points. In the three countries with the lowest adoption rates (Germany, France, and Italy), adoption rates increased by only 0.1 to 1.1 percentage points, leading to a divergence in AI adoption rates across countries.

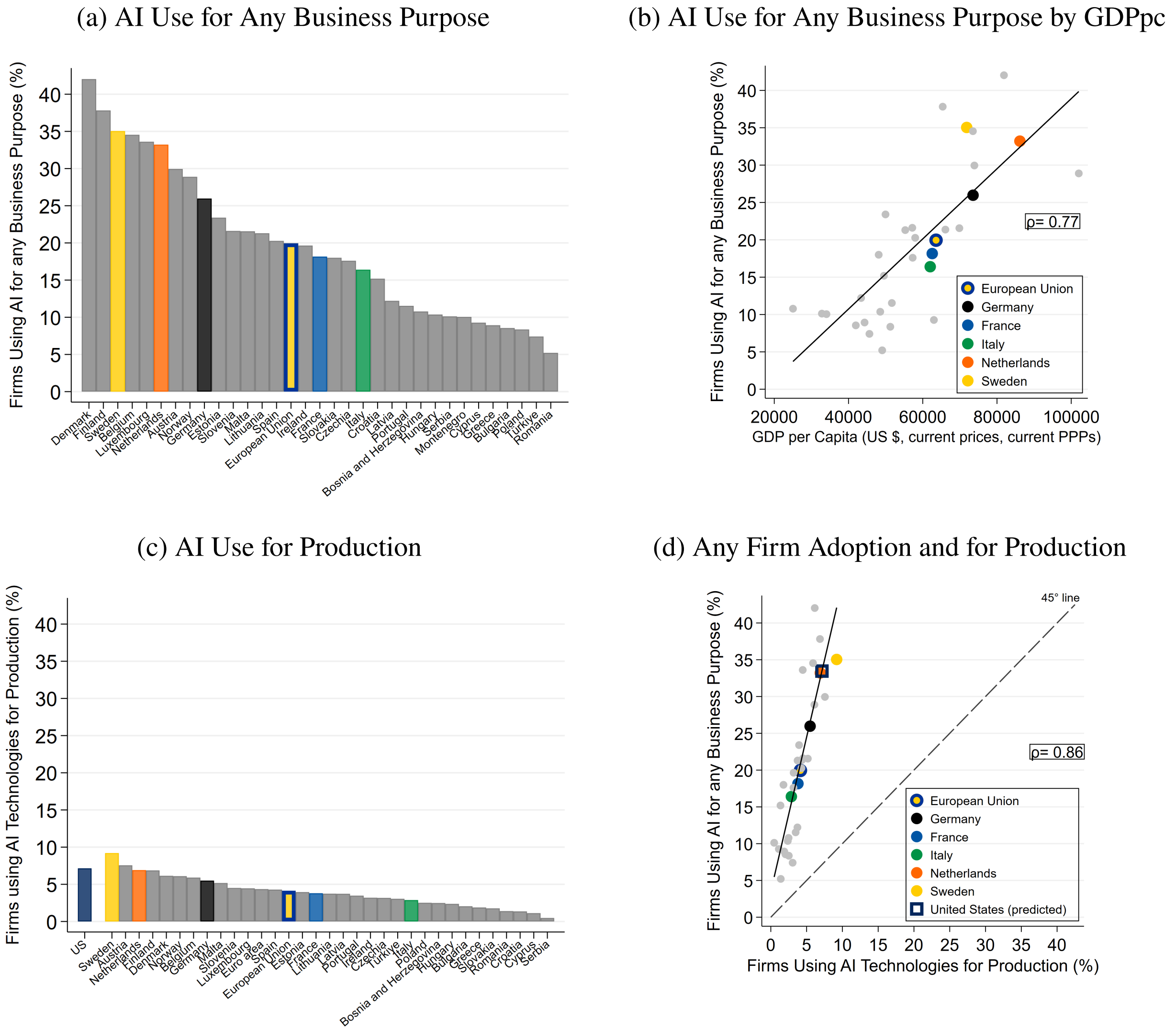
To maximize our sample size, in the remainder of the paper we pool observations from our 2025 and 2026 worker surveys, except where otherwise noted.

3.2 What Share of Firms Use AI?

Another valuable metric of AI adoption is the firm adoption rate. AI adoption rates at the firm level may differ from adoption rates at the worker level for several reasons. For example, some worker adoption may occur without the firm's knowledge or direction. Alternatively, among firms who adopt AI, some employees may not directly interact with the technology. Finally, as explained in Section 2, the worker and firm surveys do not measure AI adoption in exactly the same way.

Figure 5a displays the share of firms in early 2025 who report using at least one AI technology for any business purpose. The US is excluded because the BTOS only measured AI use for the production

Figure 5: Share of Firms using AI in 2025



Notes: Panel (a) reports the share of firms using at least one of eight specified AI technologies: 1) text mining, 2) speech recognition, 3) natural language generation, 4) image recognition and processing, 5) machine learning for data analysis, 6) AI based software robotic process automation, 7) autonomous robots or drones, self-driving vehicles, 8) generating pictures, videos, sound/audio. Appendix Figure D.5a shows the adoption rates for each AI technology individually and Appendix Figure D.5b for the separate business purposes pooled across countries in the European Union. Panel (b) correlates firms' AI use with 2024 GDP per capita (PPP, current international $). We exclude Ireland and Luxembourg since their GDP per capita exceeds GDP per capita of Norway, the country with third highest GDP per capita in our sample, by around 30% and 50%, respectively. The adoption rate is 20% for Ireland and 34% for Luxembourg. Panel (c) shows the share of firms using AI for production processes (no information available for France). For the United States, the survey asks whether businesses have used AI for producing goods or services in the past two weeks. US data collected from December 30, 2024, to April 6, 2025. EU data collected in the first quarter of 2025 for firms with at least 10 employees and which are not in the financial sector, agriculture, and mining. Data sources: 2025 EU-ICT-Firm Survey, US BTOS Survey, World Bank Open Data

of goods and services. On average, 20% of firms in the European Union report using at least one AI technology. On the high end, more than 35% of firms report using AI in Denmark, Finland, and Sweden. On the low end, less than 10% of firms report using AI in Cyprus, Greece, Bulgaria, Poland, Turkey, and Romania. This pattern aligns with evidence from Aldasoro et al. (2026), who document firm adoption of big data analytics using the European Investment Bank Investment Survey. Figure 5b provides a simple way of summarizing this pattern: richer countries tend to have higher AI adoption rates. This is consistent with Comin and Hobijn (2004), who shows that a wide range of past technologies were adopted first in richer countries and subsequently in poorer countries.

To compare firm adoption in Europe and the US, Figure 5c displays the share of firms in 2025 who report using AI to produce goods or services (the closest comparable question across the two firm surveys). The US data refer to the average of the first quarter of 2025, when data were collected in the EU-ICT-Firm survey. The left-most bar indicates that 7% of US firms use AI for production. This is higher than all but two European countries (Sweden and Austria) and almost double the 4% EU average.

Figure 5d shows that, among European countries, the share of firms using AI for any purpose is substantially higher than the share of firms who use AI specifically for the production of goods and services. At the same time, the share of firms using AI for production is highly predictive of the share using AI for any purpose ($\rho = 0.86$). We can use this relationship to project the share of US firms that adopt AI for any purpose, which we do not observe in the BTOS prior to November 2025, based on the US adoption rate for production processes, which we do observe. The projected rate of firm adoption for any purpose in the US is 34% (hollow square), nearly identical to that of the Netherlands, and would place it among the highest adoption rates in Europe.

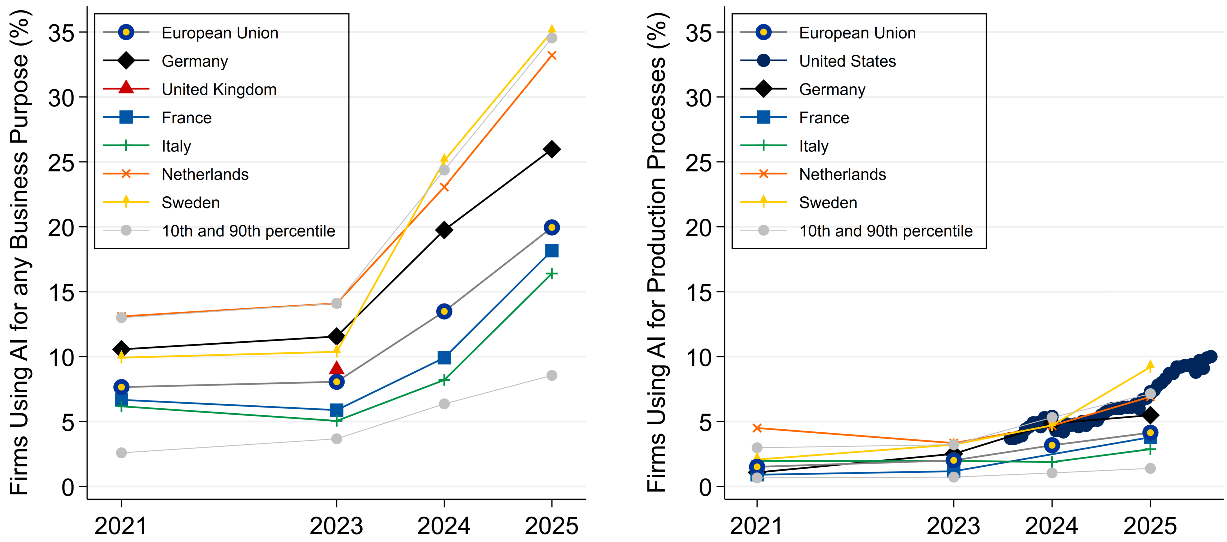
This 34% projected US rate is double the 17% adoption rate reported in the November 2025 BTOS, when the broader AI adoption question was first introduced. Several survey design differences may help explain this gap. First, the EU-ICT-Firm survey excludes firms with fewer than 10 employees. However, Appendix B.1 shows that similar gaps remain even after restricting the BTOS sample to firms with at least 10 employees.

Second, question framing differs across surveys. The BTOS relies on a single, general question with a small set of examples, whereas the EU-ICT-Firm survey asks about the use of eight specific AI technologies (see Section 2). This difference may cause the BTOS to miss a substantial share of AI adoption as defined by the EU-ICT-Firm survey. Consistent with this interpretation, the first BTOS AI supplement, which asked about a detailed list of specific AI technologies, reported higher adoption rates than the standard question (see Appendix B.2).

Third, the surveys may differ in respondent characteristics: the EU-ICT-Firm survey targets ICT decision-makers, whereas the BTOS does not impose comparable respondent requirements. Yotzov et al. (2026) survey senior executives about firm AI use in the US, UK, Germany, and Australia and report substantially higher adoption rates than government surveys: for example, 65% for Germany and 78% for the US, compared with 26% for Germany in the EU-ICT-Firm survey and a projected 34% for the US. They speculate that BTOS respondents may not be as informed about firm-wide AI use as senior executives, which could help account for the stark adoption gap between their survey and the BTOS. However, this explanation is less compelling when applied to the EU-ICT-Firm survey,

Figure 6: Share of Firms Using AI Over Time

(a) AI Use for Any Business Purpose (b) AI Use for Production



Notes: Panel (a) shows the share of firms using at least one of eight specified AI technologies, with the exception of the United Kingdom, where the survey generally asks whether they use AI technologies. Panel (b) reports the share of firms using AI for production processes. The data in the EU-ICT-Firm survey refer to the first quarter of a given year. To ensure comparability, the biweekly US observations are temporally aligned such that the mid-quarter data points correspond with the annual figures from the EU-ICT-Firm survey. Gray lines represent the 10th and 90th percentiles among all countries covered in the EU-ICT-Firm survey in each year. Data sources: 2021, 2023, 2024, and 2025 EU-ICT-Firm Survey, 2023 UK Management and Expectations Survey (MES), US BTOS Survey.

which explicitly targets ICT decision-makers who should be well positioned to assess firm AI use. [7]

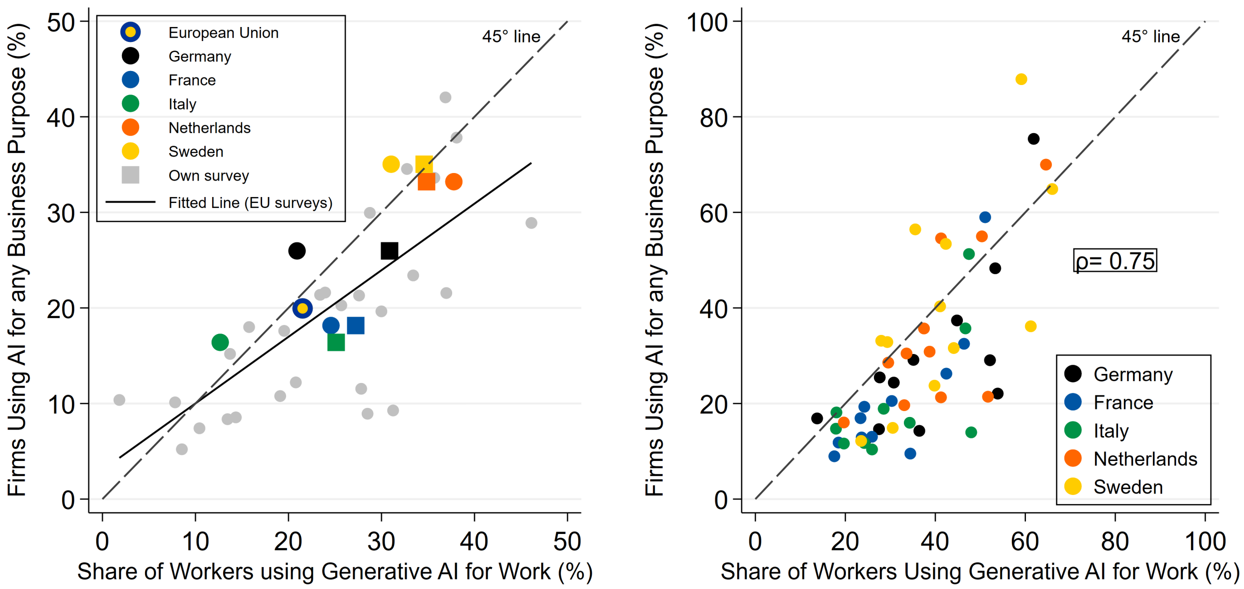
Despite these challenges in comparing adoption levels across surveys and countries, both datasets reveal a clear upward trajectory in AI adoption over time. Figure 6a shows that the pace of AI adoption by firms has quickened in recent years. To simplify the figures, we only display time series for the countries covered by our worker surveys alongside the EU average, as well as the 10^{th} percentile and 90^{th} percentiles of the EU in each year. Across the EU, 8% of firms used AI for any purpose in 2021. This remained approximately constant in 2023, but then increased to 14% in 2024 and 20% in 2025.[8]

7. The adoption question in Yotzov et al. (2026) closely resembles that of the EU-ICT-Firm survey (see Appendix C), allowing comparison across similar AI technology categories for Germany; Appendix Table C.4 shows large gaps in all comparable categories. Although their estimates are employment-weighted, the quantitative impact appears modest: using the same US data (the Survey of Business Uncertainty), Meyer et al. (2025) show that the adoption rate declines from 78% to 69% without weights. Two additional features may help explain their higher estimates. First, large firms appear to be overrepresented in their sample, at least for the US. For example, the documentation of the Survey of Business Uncertainty reports that roughly 30% of firms in the sample have at least 100 employees (Altig et al. 2025), compared with roughly 2% in the 2023 Business Dynamics Statistics. Second, the survey asks about executives' personal AI use before asking about firm-level use (see Appendix C), which may prime responses and blur the distinction between personal and firm adoption. Additional research, such as reweighting the sample to match the firm size distribution or removing the personal-use question, could help assess the importance of these two features.

8. As discussed in Section 2.2.1, between 2024 and 2025 the EU-ICT-Firm survey added an eighth AI technology category: "generating pictures, videos, sound/audio". A firm who used only this type of technology would be classified as not adopting in 2024, but adopting in 2025. On the one hand, this suggests that some of the increase in adoption between 2024 and 2025 could be due to this expanded definition of AI. On the other hand, the capabilities of AI in generating

Figure 7: Correlation of AI Adoption by Workers and Firms

(a) By Country (b) By Country × Industry



Notes: Panels correlate AI adoption by workers and firms. Panel (a) considers firms' usage of any AI technology and correlates this with AI adoption rates of workers based on the EU-ICT Household survey (circles) and our own survey (squares). To ensure comparability, both the EU-ICT Household survey and our own survey is restricted to workers aged 25-64. Appendix Figure D.7 compares for each survey adoption rates for the respective full age range with the age range 25-64. The differences are negligible. Panel (b) differentiates by 12 sectors and focuses on firms' usage of any AI technology and our own survey. Data sources: Authors' own survey run in May-June 2025 and January-February 2026, 2025 EU-ICT Firms Survey, 2025 EU-ICT Household survey, US BTOS Survey

Countries with early leads in AI tended to maintain their lead in subsequent years: the rank correlation over time of country-level adoption rates is above 0.8 for all years between 2021 and 2025. Moreover, countries with early leads tended to see adoption increase more rapidly than early AI laggards, causing cross-country differences to widen over time. For example, the standard deviation of any-purpose AI adoption rates increased from 4.9% in 2021 to 10.0% in 2025. Figure 6b reveals similar patterns for AI use in production, which includes the biweekly data from the US. Appendix Figure D.6c shows similar trends when restricting to firms with at least 10 employees (as in the EU-ICT-Firm survey) and when using the broader any-purpose measure from November 2025 onward.

3.3 Worker Adoption vs. Firm Adoption

Figure 7a compares AI adoption in our worker surveys and the EU-ICT-Firm survey. To expand the set of countries for which we can make worker-firm comparisons, we also include data from the EU-ICT-HH survey. We highlight two main takeaways.

First, worker and firm adoption rates are highly correlated. The correlation between worker and

visual and audio context expanded greatly between early 2024 and early 2025. While this category was the second most common AI category in 2025, it is not obvious that it was similarly common in 2024.

firm adoption in the five EU countries we surveyed is 0.99; using the 33 countries covered by the EU-ICT surveys, the correlation is 0.73. Figure 7b shows that the correlation between worker adoption in our surveys and firm adoption at the country-sector level is 0.75.

The correlation between AI adoption in our worker surveys and the EU-ICT-HH survey is 0.88. Differences in adoption levels between the two surveys may reflect differences in question phrasing and reference periods. Our surveys ask "Do you use Generative AI for your job?", while the EU-ICT-HH survey asks "Have you used any generative AI tools in the last 3 months?", with one option being "For work purposes." France, Sweden, and the Netherlands exhibit small differences in adoption rates between surveys (between 2.7 and 3.6 percentage points), with larger differences for Germany and Italy (9.9 and 12.5 percentage points, respectively). In particular, the EU-ICT-HH adoption rate in Italy also appears low relative to estimates from the Italian Survey of Consumer Expectations (Gambacorta et al. 2025).[9]

The second main takeaway from Figure 7 is that the difference in adoption rates by workers and firms is much smaller than previous research has suggested: on average, worker adoption rates in our worker surveys exceed firm adoption rates by only 4 percentage points. Earlier papers studying the US have highlighted very low rates of firm adoption in the BTOS relative to worker adoption in household surveys (Bick et al. 2026; Bonney et al. 2024; McElheran et al. 2024). There are several potential explanations for this disconnect, including measurement issues in worker surveys and workers adopting AI ahead of or without the knowledge of their employers. However, as we discuss in Section 3.2, another likely factor is that prior to November 2025 the BTOS only asked about AI use for the production of goods or services. On average, the share of European firms using AI for any purpose is five times the share using AI for production. This suggests that prior BTOS data understate overall US firm adoption, reducing apparent gaps between firm and worker adoption rates.

3.4 Summary

In this section, we found that AI adoption is currently higher in the US than in Europe: in the US, more workers use AI for their jobs, they use it for a larger fraction of their work week, and a larger share of firms use AI for production. However, we also find substantial variation in AI adoption among European countries. The Nordic countries, Benelux countries, Germany, Austria, and the UK have fairly high rates of adoption, approaching or slightly exceeding the US along some margins, while France, Southern Europe, and Eastern Europe have much lower rates of adoption.

9. Gambacorta et al. (2025) estimate an AI adoption rate in the Italian Survey of Consumer Expectations (April 2024, population age 18-75). They find that 36.7% of individuals used AI in the last 12 months (for either work or non-work purposes) and 20.1% used it in the last month. Roughly one year later, the EU-ICT-HH survey estimates that 19.9% of individuals used AI within the last three months. Given that adoption rates have increased over time, the EU-ICT-HH estimate appears low relative to the Italian Survey of Consumer Expectations. Loschiavo et al. (2026) estimate an AI adoption rate in Italy of 31.0% (August/September 2024, population ages 18+). They do not report a monthly usage rate.

We also find that cross-country differences in AI adoption have widened in recent years. In particular, US adoption is pulling farther ahead of the European average, and within Europe the early leaders are pulling further ahead of the early laggards.

4 Explaining Cross-Country Differences in AI Adoption

AI products are available in Europe and the US at similar prices.[10] Why, then, do we observe such large differences in the shares of workers adopting AI across countries?

4.1 Demographics, Occupation, and Industry Composition

We begin by investigating the extent to which cross-country differences in demographics, occupation, industry, and firm size can account for differences in AI adoption.

Figure 8 displays AI adoption rates by worker education, age, and sex in the seven countries covered by our worker surveys. Overall, we observe striking similarities in adoption patterns across countries. On average, AI adoption by university-educated workers is 25 percentage points higher than for other workers (see also Aldasoro et al. 2024a; Bick et al. 2026). AI adoption by workers up to age 45 is on average 14 percentage points higher than for workers age 46 and over. One margin along which we observe smaller differences is sex. Male adoption is higher in all countries except for Germany, but the average magnitude of the difference is only 4 percentage points. This gender gap is smaller than that documented by Humlum and Vestergaard (2025b) and Aldasoro et al. (2024b) based on earlier surveys conducted in 2023 and 2024.

Figures 9a and 9b display the share of workers adopting AI by occupation and industry. We continue to observe similar patterns across countries. For example, all countries have adoption rates below 27% in Personal Services occupations and above 50% in Computer / Math. Similarly, all countries have adoption rates below 33% in Hotels & Food Services and above 48% in Information and Communication industries.

Figure 9c displays the share of workers adopting AI by firm size, measured by the number of employees at the local establishment. In all countries, larger firms tend to have higher adoption rates. For example, in the US, 53% of workers adopt AI in establishments with more than 250 employees, versus 26% of workers in establishments with fewer than 10 employees. Countries with higher aggregate AI adoption tend to have steeper adoption gradients with firm size (US, UK, Netherlands, Sweden), while countries with lower aggregate adoption rates have flatter gradients

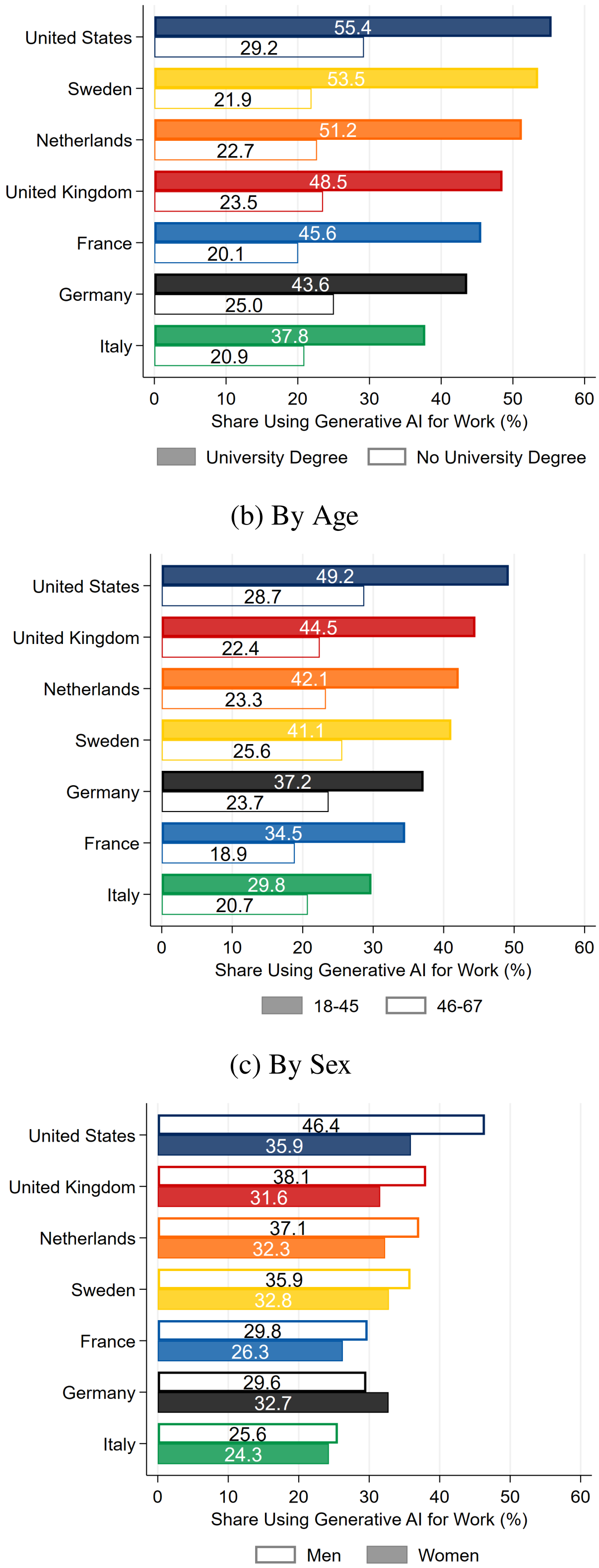
10. For example, at the time of writing, a monthly subscription to ChatGPT plus costs $20 in the US and is about €20 Europe plus the value added tax. Moreover, the basic versions of ChatGPT or Gemini, the second most widely used tool in our survey, are freely available in all countries we consider.

Figure 8: Worker AI Adoption By Education, Age, and Sex

(a) By Educational Attainment

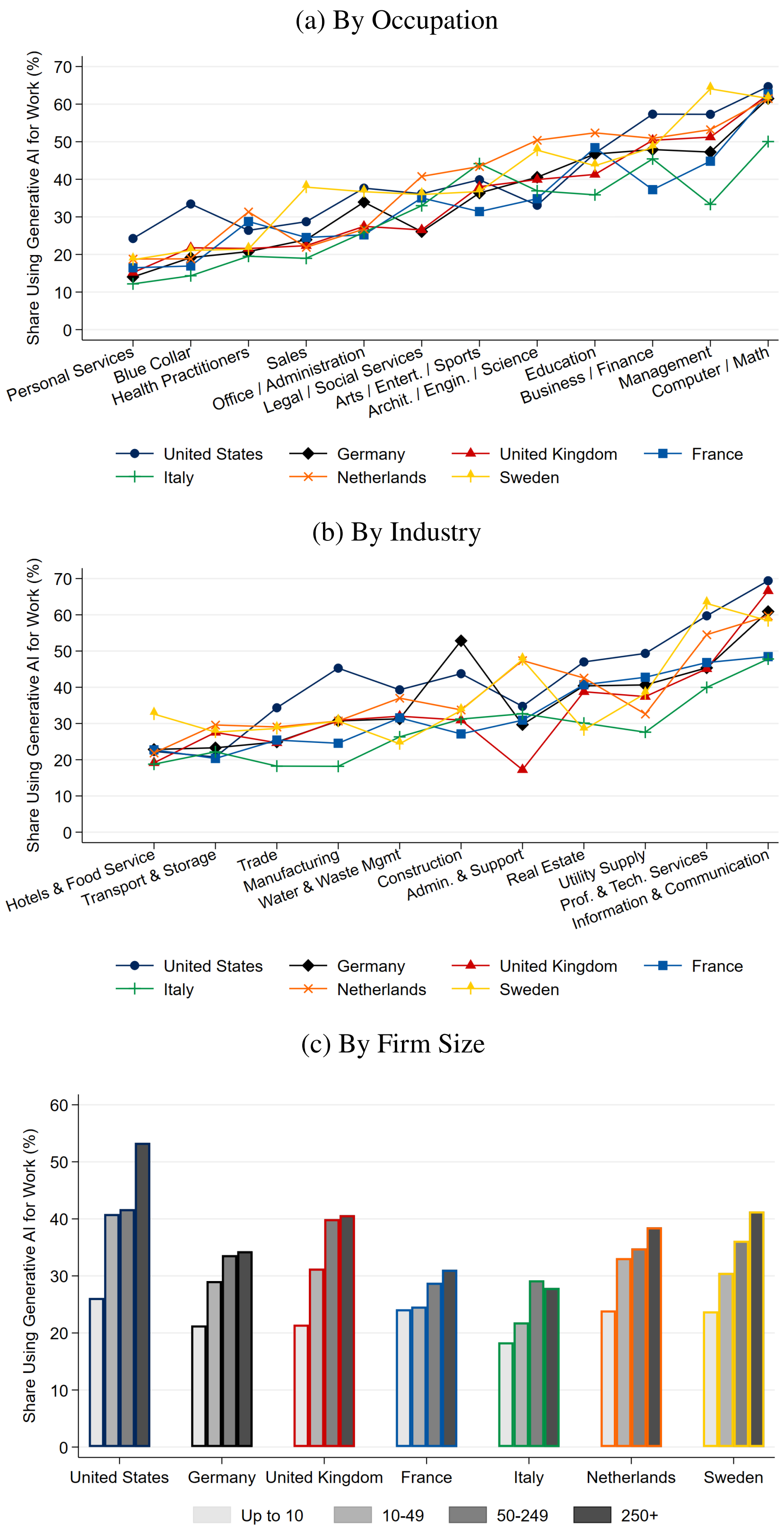
(b) By Age

(c) By Sex



Notes: Figure shows heterogeneity in Generative AI use at work by worker characteristics. Panel (a) distinguishes by educational attainment; to ensure comparability across countries with different education systems, we distinguish by whether respondents have a university degree (bachelor's degree or higher). Data source: Authors' own survey on Generative AI adoption of workers in May-June 2025 and January-February 2026

Figure 9: Worker AI Adoption by Occupation, Industry, and Firm Size



Notes: Appendix Figure D.8 shows AI adoption of firms by industry and firm size. Data source: Authors' own survey on Generative AI adoption of workers in May-June 2025 and January-February 2026

(Germany, France, Italy). Interestingly, we only observe higher US adoption for workers in firms with more than 10 employees; US adoption in the smallest establishments is not systematically higher than in other countries.

4.1.1 A Formal Decomposition

These systematic patterns by demographics, occupation, industry, and firm size suggest that cross-country differences in aggregate AI adoption rates could potentially be driven by differences in the composition of workers and firms. For example, Bick et al. (2019) show that a majority of the gap in aggregate hours worked between the US and Southern Europe can be accounted for by higher rates of education in the US. Similarly, higher rates of education in the US might account for some of the US-Europe gap in aggregate AI adoption. To quantify the importance of these channels, we conduct the following Oaxaca-Blinder decomposition (Blinder 1973; Oaxaca 1973).

Define A_c as the overall AI adoption rate in country c, and let $\mathbf{X}_c$ denote a vector of worker and firm characteristics (education, age, sex, occupation, industry, and firm size) measured as population shares (these are shown in Appendix Figure D.9). Let $\boldsymbol{\beta}_c$ be the associated coefficients from a linear probability model of individual-level AI adoption estimated separately for each country. For each country c, we decompose its adoption gap relative to the US as:

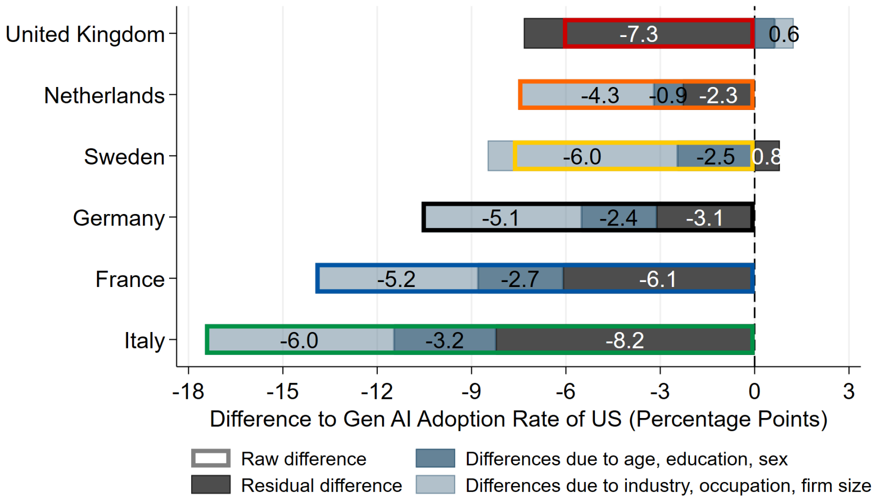
$$A_c - A_{\text{US}} = \underbrace{(\mathbf{X}_c - \mathbf{X}_{\text{US}})\,\boldsymbol{\beta}_{\text{US}}}_{\text{Explained (composition)}} + \underbrace{\mathbf{X}_{\text{US}}\,(\boldsymbol{\beta}_c - \boldsymbol{\beta}_{\text{US}})}_{\text{Unexplained (remaining differences)}} .$$

The explained component measures how much of the adoption gap (relative to the US) is due to compositional differences in observable characteristics, holding coefficients fixed at US levels. The unexplained component captures residual differences in adoption.

Figure 10 summarizes the results of this decomposition. Among the six European countries we survey, the average AI adoption gap is 10.9 percentage points. In all countries besides the UK, demographic and firm composition partially account for low AI adoption relative to the US. On average, composition effects account for 6.1 percentage points of the US adoption gap, or 55% of the average gap. Compositional differences in the industry, occupation, and firm size structure are more important than demographics: on average they account for 67% of the explained component while demographic differences in age, education, and sex together account for 33% of the explained component. Appendix Figure D.11 shows that demographic and firm composition also statistically explain an important share of variation of AI adoption between European countries.

The share of the US-Europe adoption gap that is explained by demographic and firm composition varies substantially across countries. For example, in Sweden the explained component statistically

Figure 10: Decomposition of Differences in AI Adoption vs. the US



Notes: Figure shows an Oaxaca-Blinder decomposition of Generative AI adoption rates of workers in European countries relative to the US. Colored fringes report the raw differences. Dark gray represents the residual difference not accounted for by demographics, industry, occupation, and firm size. Figure 15 shows the same decomposition, but additionally accounts for firm encouragement. The sample is restricted to workers in dependent employment (private or public sector). source: Authors' own survey on Generative AI adoption of workers in in May-June 2025 and January-February 2026

accounts for the entire adoption gap. The exercise suggests that if Sweden had the same demographic and firm composition as the US, they would have nearly identical aggregate AI adoption rates. In the other direction, the exercise suggests that the UK would have an even lower adoption rate if it had the demographic and firm composition of the US.

We conclude that demographic and firm composition statistically explain an important share of differences in AI adoption between the US and Europe and between European countries. However, roughly half of the gap remains unexplained by these variables.

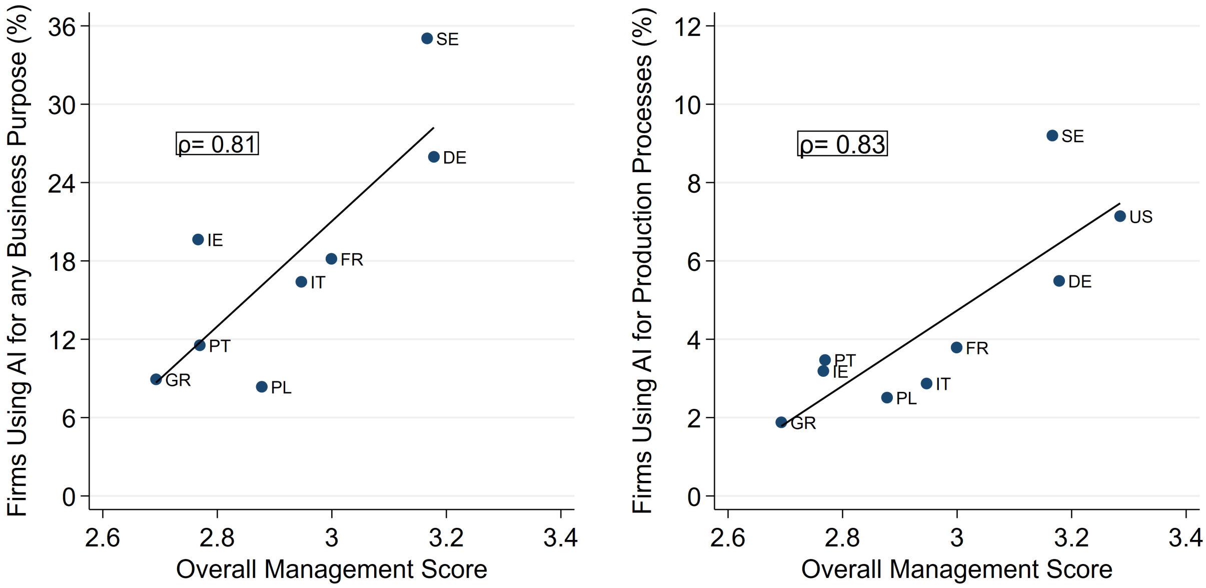
4.2 Management Practices

What explains the remaining sizable gaps in AI adoption after controlling for demographics, firm size, and industry? A previous literature on the adoption of information and communication technologies (ICT) suggests one possible explanation: differences in firm management practices. This literature found that US firms invested more intensively in ICT capital and obtained greater productivity gains from a given investment in ICT capital. It also found that US firms, including multinational establishments owned by US firms but operating in Europe, score higher on several indices of management quality, and that these higher management scores account for a majority of the higher returns to ICT investment (Bloom et al. 2012). Higher-scoring management practices may yield greater ICT returns and lead to greater ICT investment because the returns from ICT appear intimately linked to the

Figure 11: Management Practices and AI Adoption

(a) Firm Adoption: Any Business Purpose

(b) Firm Adoption: Production



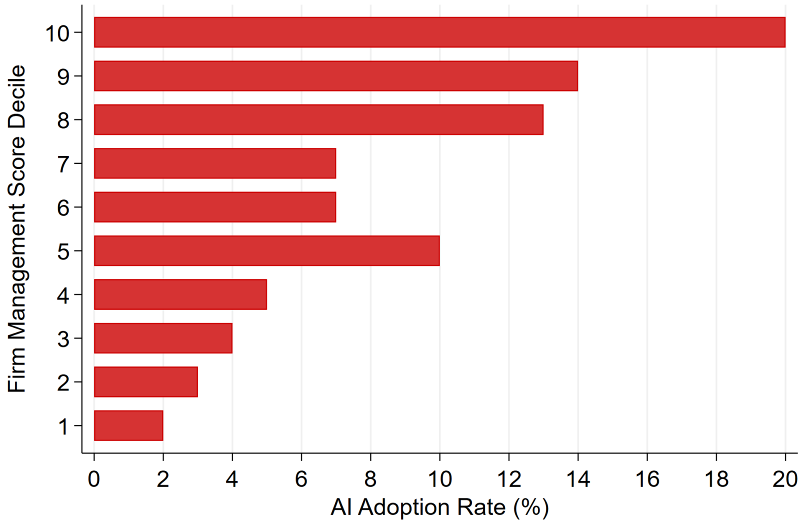
Notes: Panel (a) plots country-level firm management scores against the share of firms adopting AI for any purpose. Panel (b) plots firm management scores against the share of firms adopting AI for production processes. Firm-level AI adoption measures are from the 2025 EU-ICT-Firm Survey (Europe) and the 2025 Business Trends and Outlook Survey (BTOS) (US). Worker-level AI adoption measures are from worker surveys conducted by the authors in 2025.

internal organization, or reorganization, of firms in which management plays a key role (Milgrom and Roberts 1990). For example, Bresnahan et al. (2002) argue that ICT raises productivity primarily when paired with organizational changes such as increased decentralization and skill upgrading. Relatedly, Garicano and Heaton (2010) provide evidence that technology reshapes information flows inside firms, and firms with higher-quality management are more capable of reorganizing tasks and hierarchies to exploit these improved information flows.

Figure 11 displays correlations between country-level firm AI adoption rates and management scores from the World Management Survey (WMS), an international firm-level survey of management practices (Bloom et al. 2021).[11] Figure 11a plots overall country management scores against AI adoption for any purpose for 8 countries that have both management and adoption data. We find a correlation of $\rho = 0.81$. Figure 11b plots overall country management scores against AI adoption for production processes for 9 countries with sufficient data, which allows us to include the US ($\rho = 0.83$). These results indicate that differences in management scores are strongly associated with differences in AI adoption rates across countries.

11. The survey is conducted through interviews with firm managers. We use data on manufacturing firms from the 2013-2014 survey waves, which represent the most recent data covering the largest number of countries. This data covers 35 countries, including 10 countries that overlap with our firm-level AI adoption datasets. Management scores in the manufacturing sector are not necessarily representative of management scores for the economy as a whole; however, country scores in manufacturing are correlated with scores in other sectors (Scur et al. 2021).

Figure 12: Management Practices and AI Adoption Among UK Firms



Notes: Figure reproduces results from Table 5 of Office for National Statistics (2024). The figure plots AI adoption rates by firm management score decile among UK firms. Management scores are based on standardized measures of structured management practices from the 2023 UK Management and Expectations Survey (MES) (conducted in November and December of that year) and are grouped into deciles within the UK firm distribution. AI adoption is defined as firm use of artificial intelligence technologies. The sample includes private-sector firms with at least 10 employees. The MES sample excludes firms in section A (Agriculture, Forestry and Fishing), and section K (Financial and Insurance Activities), and results are weighted to reflect the population of firms. Data source: UK Management and Expectations Survey (MES).

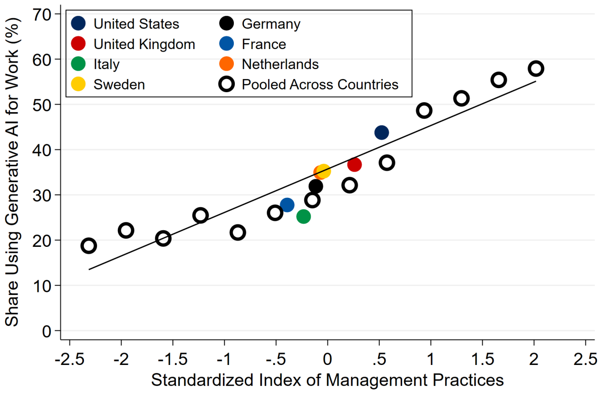
While these results are consistent with the notion that differences in management practices might lead to variation in AI adoption, the correlation between management scores and AI adoption may be driven by other forces that are correlated with these variables. Furthermore, the number of country observations is small.

To address these concerns, we now turn to within-country evidence on the link between management practices and AI adoption. One useful data source is the UK Management and Expectations Survey (MES), which collects information on firm management practices and technology adoption.[12] While we do not have access to the underlying micro data, a report using data from the 2023 survey summarizes the relationship between firm AI adoption and firm management scores, which are measured using a similar framework to the WMS (Office for National Statistics 2024). Figure 12 plots 2023 firm AI adoption rates by management score decile in the UK. UK firms with higher management scores are more likely to adopt AI. For example, only 2% of firms in the bottom management decile adopt AI, compared with 20% in the top decile. The MES report documents a similar relationship between management scores and AI adoption after controlling for potential confounding factors such as firm age, firm size, industry, and geographic region.

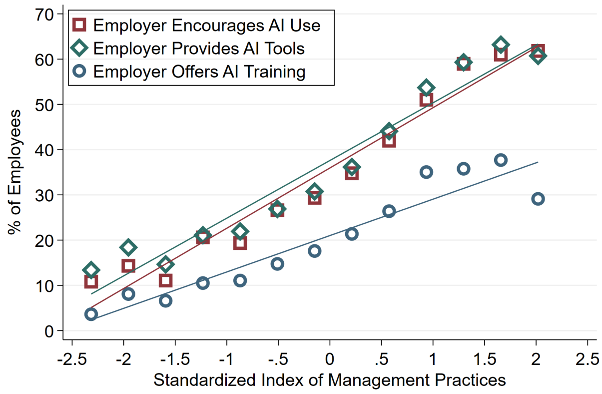
12. The MES is a large-scale survey administered by the UK Office for National Statistics (ONS). The sampling frame covers private-sector firms in the UK with at least 10 employees, drawing on the Inter-Departmental Business Register. The MES sample excludes firms in section A (Agriculture, Forestry and Fishing), and section K (Financial and Insurance Activities), and results are weighted to reflect the population of firms. We use the most recent wave of the MES, conducted in November and December 2023.

Figure 13: Worker-Level Data on Management Practices and AI Adoption, Encouragement, Provision of AI Tools and Training

(a) GenAI Adoption



(b) GenAI Encouragement, Training and Provision



Notes: The index of management practices is based on three management-related questions on incentives at work. A higher value indicates that performance is more incentivized. The index is standardized across countries. Panel (a) correlates management practices with AI adoption rates. Panel (b) correlates management practices with three measures of how employers motivate AI use by their employees. AI provision means that employers either provide a license / subscription to an off-the-shelf AI product or that AI tools are used that are developed or customized for the employer. The sample is restricted to workers in dependent employment (private or public sector). Data source: Author's own survey on Generative AI adoption of workers in January-February 2026

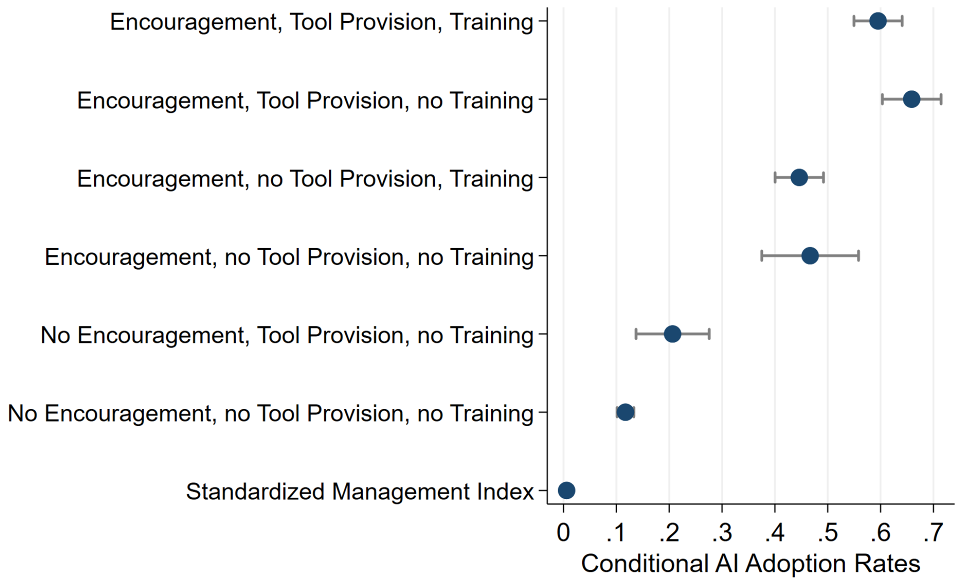
We can expand the analysis beyond the UK using several management-related questions from our worker surveys. To begin, we asked each worker three questions about their employer's personnel management, which we adapted from the WMS. The questions elicited the extent to which employees felt that performance was rewarded, promotions were based on performance, and poor performance was addressed.[13] For each worker we create a personnel management index by taking the average of their answers to these three questions and then standardize the index. A higher value denotes that performance is more incentivized.

Figure 13a shows that AI adoption is strongly increasing in workers' personnel management index. Hollow circles indicate mean adoption rates by management score index, pooling all countries. In our pooled data, the estimated slope between a worker's management index and their adoption choice indicates that a 1-SD increase in a worker's management index is associated with a 9.6-percentage-point-higher adoption rate. This relationship is approximately linear. Figure 13a also shows that a similar relationship holds at the country level (solid circles). In particular, the US has the highest mean management index, and countries with higher management indices tend to have higher adoption rates.

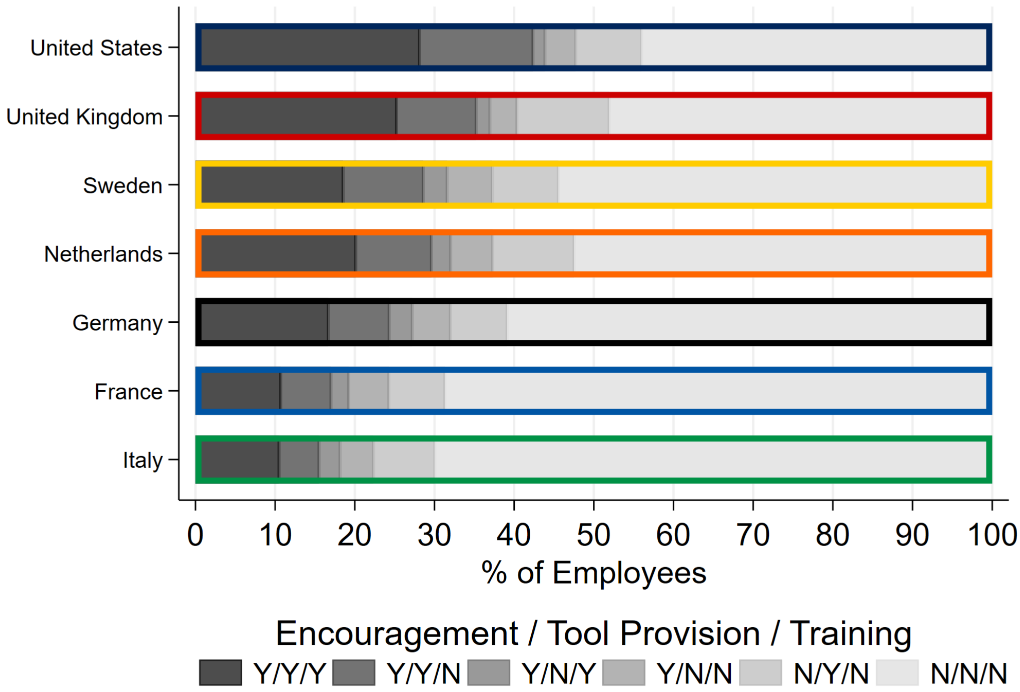
13. These questions are only contained in the second survey wave fielded in January-February 2026. The questions read as follows: *Please indicate whether you agree with the following statements*: 1) *Where I work, rewards (pay, bonuses, promotions, recognition) are linked to individual performance*. 2) *Where I work, promotions are based on performance rather than how long someone has worked here*. 3) *Where I work, action is taken when someone consistently performs poorly in their job*. For each item, respondents could indicate their assessment on a 5-point Likert ranging from "Strongly Disagree" to "Strongly Agree". Appendix Figure D.10 shows that our worker-based measures are positively correlated at the country level with the richer WMS measures, which are constructed from double-blind interviews with managers.

Figure 14: Employer Encouragement, Training, Tool Provision and AI Adoption

(a) Regression: Predictors of AI Adoption by Workers



(b) Share of Employees Receiving AI Encouragement, AI Tool Provision, and AI Training



Notes: Panel (a) shows coefficients and 95% confidence intervals from a regression of AI adoption on combinations of employer encouragement, training, and tool provision. The regression controls for country fixed effects, demographics (age, education, and gender), industry, occupation, and firm size. Panel (b) reports the share of employees who report: whether the employer encourages AI use; whether the employer provides AI training; and whether the employer provides AI tools, meaning either a license / subscription for an off-the-shelf AI product or access to an AI tools that was developed or customized for the employer. The sample is restricted to workers in dependent employment (private or public sector). Data source: Authors' own survey on Generative AI adoption of workers in January-February 2026.

Why do workers with higher management indices adopt AI at higher rates? Additional questions in our worker surveys asked whether the worker's firm encouraged them to use AI, whether it provided AI training, and whether it provided access to at least one AI tool to assist their work. Figure 13b shows that firms with higher management indices were much more likely to encourage their workers to use AI and to provide AI tools and training.

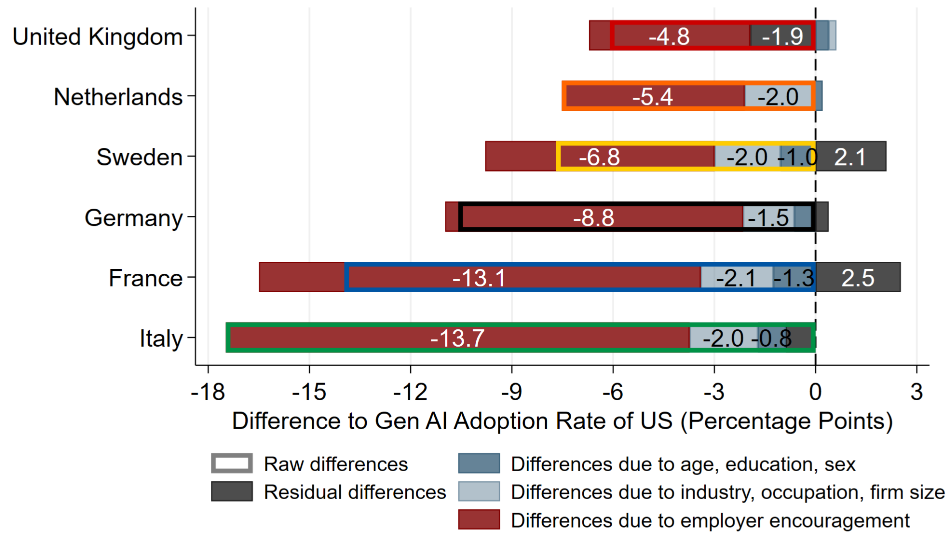
To disentangle the relationship between firm management scores, AI encouragement, AI tool provision, and AI training, we regress AI adoption on these variables, as well as controls for worker demographics and occupation, firm industry, and country fixed effects. The estimated coefficients for the management-related variables are displayed in Figure 14a.

We highlight four main takeaways. First, AI encouragement is the strongest predictor of AI adoption. For example, among workers who did not receive AI training or tools, 47% adopted AI if they received encouragement from their employer, versus 10% of workers who were not encouraged. Second, AI tool provision predicts higher adoption after controlling for encouragement and training, though the effect is smaller than for encouragement. For example, among workers who did not receive encouragement or training, 21% adopted AI if they were provided AI tools, versus 10% of workers who were not provided tools. Third, AI training does not predict higher adoption once we control for encouragement and tool provision. Fourth, the worker's management index does not predict higher adoption once we control for AI encouragement, tool provision, and training, suggesting that the positive association between management and adoption operates primarily through firms' AI encouragement and tool provision rather than other channels.

Figure 14b displays cross-country variation in the combination of employer supports that workers receive. The US exhibits the highest share of workers receiving both encouragement and tool provision simultaneously (the sum of the two darkest bars: 42%), while France and Italy have the lowest shares (17% and 16%, respectively). The US also exhibits the lowest share of workers receiving none of the three supports we consider (44%, versus 69% in France and 70% in Italy).

Given the regression evidence that encouragement and tool provision are strong predictors of adoption, the results in Figure 14b suggest that cross-country variation in encouragement and tool provision may help explain the remaining adoption gaps between countries. Figure 15 displays results from an expanded Oaxaca-Blinder decomposition, which adds employer AI encouragement to the set of demographic and industry composition terms from Section 4.1.1. (We do not include tool provision in the decomposition because these data were not collected in our 2025 surveys.) Almost all of the US-Europe adoption gap is accounted for in the Oaxaca-Blinder decomposition once firm encouragement is taken into account. In five of the six European countries, more than 95% of the US adoption gap is statistically explained by these variables (67% for the UK). Appendix Figure D.11 shows a similar result for differences in AI adoption between European countries.

Figure 15: Decomposition of Differences in AI Adoption vs. the US—Including Firm Encouragement



Notes: Figure shows an Oaxaca-Blinder decomposition of Generative AI adoption rates of workers in European countries relative to the US. Colored fringes report the raw differences. Dark gray represents the residual difference not accounted for by demographics, industry, occupation, firm size, and employer encouragement. The sample is restricted to workers in dependent employment (private or public sector). Figure 10 shows the same decomposition, but excludes firm encouragement. Data Source: Author's own survey on Generative AI adoption of workers in May-June 2025 and January-February 2026.

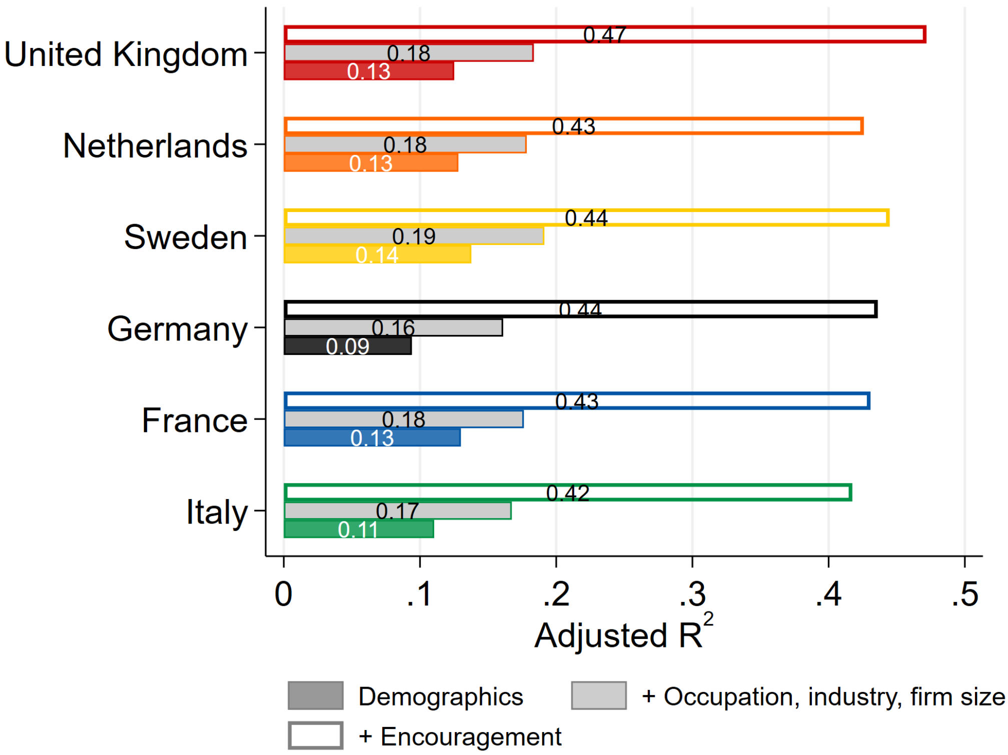
Firm encouragement alone accounts for 80% of the overall average gap. This is in line with Bick et al. (2026) who show that, in the US, firm encouragement is by far the best predictor of worker AI adoption.[14] Figure 16 compares the R^2 from country-specific regressions of AI usage on (i) demographics, (ii) demographics, occupation, industry, and firm size dummies, and (iii) all of the prior variables and firm encouragement. The country-specific R^2 for regression (i) range from 9% to 14% and increase to the range of 16% to 19% for regression (ii). Adding firm encouragement in (iii) substantially increases the country-specific R^2 to between 42% and 47%.

Discussion We have shown that firms who reward and promote high performers (and address poor performers) also tend to encourage their workers to use AI, to provide them with access to AI tools, and to provide AI training. These workers are in turn more likely to adopt AI. While our evidence is correlational, not causal, it is robust to controlling for a host of other worker and firm characteristics.

One hypothesis for why AI adoption is higher in firms with performance-focused personnel management is that performance incentives induce workers to independently seek out productivity-enhancing technologies. Relatedly, performance-focused firms may attract workers who are more willing or able to seek out new technologies on their own. However, this interpretation is in tension with our finding that a worker's personnel management index does not predict AI adoption once we control for AI encouragement and tool provision. Rather than setting performance-based incentives

14. A survey of employees in Germany in 2024 also documented that workers are almost twice as likely to use AI-supported programs if these were formally introduced by their firm (Arntz et al. 2026).

Figure 16: R^2 of Regressing AI Usage on Various Sets of Regressors



Notes: Figure reports the adjusted R^2 of regressions of AI adoption on various explanatory variables based on country-by-country estimation. The sample is restricted to workers in dependent employment (private or public sector). Data source: Author's own survey on Generative AI adoption of workers in May-June 2025 and January-February 2026.

and letting workers choose to adopt AI on their own, firms appear to increase adoption by explicitly subsidizing and encouraging its use.

What does "encouragement" concretely involve? Figure D.12 suggests one possibility. In the US, workers are less likely to report that they do not use AI because they have not heard of it or because it is not useful for their job. This could reflect encouragement operating by increasing awareness, highlighting practical use cases, or creating space for experimentation. More broadly, whether performance-focused management directly causes firms to promote AI adoption or whether both reflect some deeper organizational trait is an important question for future research.

5 Potential Consequences of AI Adoption Gaps

Since 1995, output per hour in the US has outpaced growth in Europe (Figure 1a). Prior research has linked this divergence to greater production and diffusion of ICT technologies in the US (Ark et al. 2008; Bloom et al. 2012). The gap in AI adoption between the US and Europe raises the question: will AI perpetuate these differences in the coming years?

In this section, we examine preliminary evidence on this question. Macroeconomic productivity ultimately reflects the accumulation of changes across millions of workers and firms, so we begin with micro-level evidence of productivity gains from AI before turning to more aggregate data. We also examine whether AI adoption is associated with changes in employment.

5.1 Micro Evidence on the Productivity Impact of AI

5.1.1 Experimental Evidence

A rapidly growing body of experimental and quasi-experimental research provides some early evidence on how AI tools affect worker productivity in a variety of work contexts. Several studies find that AI substantially increases worker productivity. Peng et al. (2023) find that software developers who were randomly provided access to GitHub Copilot completed coding tasks 55% faster than those without. Cui et al. (2026) confirm this pattern in large-scale field experiments at three large companies involving nearly 5,000 developers: AI access increased task completion by 26%. Noy and Zhang (2023) conduct a randomized experiment that asked college-educated professionals to complete incentivized writing tasks. Participants who received access to ChatGPT completed tasks 40% more quickly while increasing output quality by 18%. Dell'Acqua et al. (2026) find a similar pattern in a pre-registered experiment among Boston Consulting Group (BCG) consultants who were assigned tasks that were designed to be within the capabilities of GPT-4. Consultants assigned GPT-4 access completed 12% more tasks with a 40% increase in quality. Choi et al. (2024) find that law students randomly assigned GPT-4 reduced the time to complete legal tasks by 12-32%, depending on the task, with no reduction in average quality. Goldsmith-Pinkham et al. (2026) study radiologists who receive access to an AI diagnosing tool. They report that access to AI roughly doubles per-radiologist monthly scan volumes while holding processing times and mortality rates constant. Other studies document similar gains among less-educated workers. Brynjolfsson et al. (2025) find that customer support agents who receive access to an AI conversational assistant increased issues resolved per hour by 15%. Kanazawa et al. (2025) find that taxi drivers using AI-powered route recommendations saw productivity gains of 5% on average. In all of these studies except one (Goldsmith-Pinkham et al. 2026), improvements tended to be larger for less-experienced or less-skilled workers.

Alongside evidence of productivity gains, other results suggest more nuanced effects. The same BCG study by Dell'Acqua et al. (2026) finds that access to AI reduced output quality for tasks that were designed to be outside AI's competency (such as combining quantitative analysis with business judgment). Otis et al. (2024) run a field experiment that randomly assigned some Kenyan entrepreneurs a GPT-4-powered business advisor. They find that AI increased revenues by 15% for high-performing entrepreneurs, while AI reduced revenues by 10% for low performers. The authors attribute this divergence not to differences in the advice received but to which recommendations entrepreneurs chose to implement. These findings suggest that, at least in some settings, successfully utilizing AI may require complementary skills, such as judging the quality of AI output and deciding when or how to use its suggestions.

5.1.2 Observational Survey Evidence on the Productivity Impact of AI

While experimental studies provide cleanly identified evidence on the causal effects of AI in specific work contexts, they are not designed to be representative of the labor market as a whole. For example, researchers may selectively study contexts where productivity gains seem most plausible, and experiments with null findings may go unpublished. It is therefore an open question whether these micro-level effects will translate to meaningful productivity gains in the aggregate. To investigate this question, we now turn to nationally representative evidence from our worker surveys.

Our surveys asked workers who used AI in the previous week to estimate how much time AI saved them in the past week:

> *You indicated that LAST WEEK you worked __X__ hours and that you used Generative AI for your job. Now, imagine that LAST WEEK you did not have access to Generative AI. How many additional hours of work would you have needed to complete the same amount of work? [For X we fill in the respondent's reported hours worked last week.]*

The answer options were: Less than 1 hour, 1 hour, 2 hours, 3 hours, 4 hours, More than 4 hours. For respondents who selected "less than 1 hour," we assume that AI saved zero hours of work. For respondents who selected "more than 4 hours," we assume that AI saved 5 hours of work. These assumptions are conservative in the sense that they reflect a lower bound of time savings.

Pooling all countries, we find that, among AI users, 22% reported saving less than 1 hour per week, 21% saved 1 hour per week, 40% saved 2 to 3 hours per week, and 17% saved 4 hours or more (see Appendix Figure D.13). Reported time savings were higher for workers who used AI every workday compared with those who used it only during some workdays. For instance, 29% of every-day users report time savings of 4 hours or more per week, while the share is 17.1% for those using AI on several but not all days and only 6% for workers using AI one day a week.

Appendix Figure D.5c provides context for where these time savings occur. We asked AI users to indicate which broad work activities they used AI for and, if multiple were selected, which of these tasks they find AI most useful for. The most common activity was Writing Communications, which 55% of AI users selected as a task and 21% as the most useful task. This is followed by Searching for Facts of Information (51%, 13% as most useful) Interpreting, Translating, or Summarizing (46%, 12% as most useful). On average, AI users indicated they used AI for four of the listed tasks.

Comparing Survey Evidence with Experimental Micro Evidence Data based on self-reported time savings is subject to measurement error and is not derived from exogenous variation in access to AI. One way to assess the plausibility of these estimates is to compare them with the existing experimental and quasi-experimental estimates discussed in the previous section.

To make this comparison, we note that the experimental evidence in the previous section found productivity gains ranging from 5% to 96 %, with a mean of 31% across studies.[15] When we pool all countries covered by our surveys, the mean time savings among AI users is 5.8%. For example, an AI user who works 40 hours per week would have needed to work 2.3 additional hours to complete the same work without AI. Alternatively, we can ask how much time workers save per hour that they spend using AI. Pooling across all surveyed countries, we find that on average AI users spent 3.19 hours per week using AI with reported time savings of 1.92 hours per week, implying that each hour spent using AI saved workers 0.6 hours of additional work. We conclude that our mean time savings estimates of 5.8% per user, or 60% per hour spent using AI, are broadly in line with existing experimental estimates.

Cross-Country Differences in Reported Time Savings Figure 17a reports mean time savings among all workers by country (non-users have zero time savings by construction). On average, workers in the US report saving 2.3% of work hours. This reflects an average time savings of 6.1% of work hours among the 37.1% of US workers who used AI in the previous week and zero time savings among the 62.9% of workers who did not use AI in that week. Time savings from AI in the US exceeds time savings in each of the six European countries covered by our worker surveys, which range from 1% (France) to 1.8% (UK). Averaging across the six European countries surveyed, we arrive at an aggregate time savings of 1.4%, compared with 2.3% in the US.

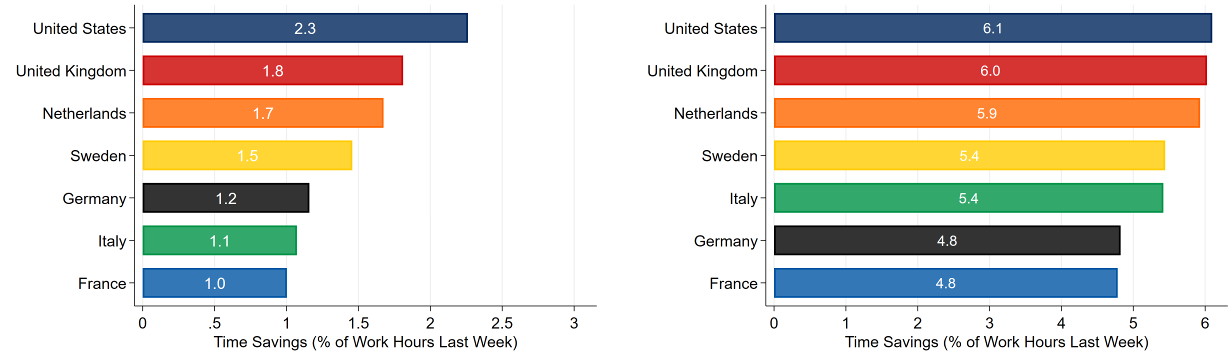
Figure 17b displays mean time savings by country among AI adopters only. AI users tend to report higher time savings in countries with higher adoption rates. However, most of the differences in time savings are accounted for by differences in adoption rather than differences in time savings conditional on adoption. For example, across countries the max / min percent difference in time savings is $2.3/1.0 - 1 = 130\%$, while the analogous difference in time savings among AI users is $6.1/4.8 - 1 = 27\%$. Figure 17c shows that time savings are strongly increasing in adoption rates at the country-industry level. Consistent with the country-level results, Figure 17d shows that AI users in high-adoption industries report modestly higher time savings.

15. Specifically, the reported time savings / productivity gains are: Kanazawa et al. (2025), 5%; Dell'Acqua et al. (2026), 12%; Brynjolfsson et al. (2025), 15%; Noy and Zhang (2023), 18%; Choi et al. (2024), 22%; Cui et al. (2026), 26%; Peng et al. (2023), 55%; Goldsmith-Pinkham et al. (2026), 96%. We do not incorporate quality improvements into these calculations, since it is not obvious how to weight these gains relative to time savings. In most studies, AI improved quality on average, which would tend to increase the quality-adjusted productivity gains.

Figure 17: Worker-Reported Time Savings Due to AI

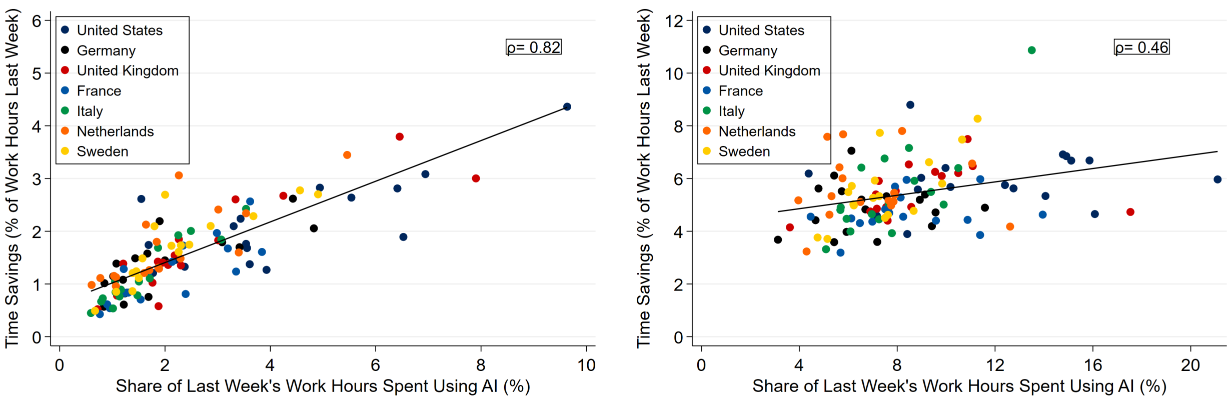
AI Time Savings By Country

(a) All Workers (b) AI Users Only



AI Time & Time Savings By Country-Industry

(c) All Workers (d) AI Users Only



Notes: Time savings from using AI are estimated by survey participants using AI how many more working hours they would have needed in the past week to complete the same tasks. Respondents could indicate i) less than 1 hour, ii) 1 hour, iii) 2 hours, iv) 3 hours, v) 4 hours, vi) more than 4 hours. We conservatively assumed 0 hours saved for option i) and 5 hours for option vi). Time savings are then divided by weekly working hours. Non-users in the last week have been assigned 0% of their work hours using AI and 0% time savings. See notes of Figure 3 for the share of working hours spent using AI is calculated. In panel (d) we drop one outlier: NACE sector R (Arts, entertainment and recreation) from the United Kingdom which has time savings of 11.1% and share of work hours using AI of 30.7%. Data source: Author's own survey run in May-June 2025 and January-February

5.2 Macro Evidence on the Productivity Impact of AI

Figure 17c reveals meaningful variation in reported time savings due to AI across European and US industries. For example, 28 of 118 observations report average time savings exceeding 2%, while 30 observations report time savings below 1%. If these time savings translate into firm-level productivity gains, we should expect to see similar patterns reflected in industry productivity data. However, this analysis faces three related complications. First, productivity is determined by many factors, some of which may be correlated with, but not caused by, AI adoption. Second, mean reported time savings, while nontrivial, are still fairly modest, which could make it difficult to isolate the role of AI amid

Table 1: Regression Summary: Firm AI Adoption Rates and Annualized Productivity Growth

	(1)	(2)	(3)	(4)
Panel A: 2015 / 2019 (placebo)				
AI adoption	0.025	0.021	0.010	0.022
p-value	[0.481]	[0.536]	[0.812]	[0.582]
N	269	264	251	247
Panel B: 2019 / 2024				
AI adoption	0.100	0.074	0.048	0.057
p-value	[0.025]	[0.060]	[0.261]	[0.129]
N	269	261	251	248
Panel C: 2022 / 2024				
AI adoption	0.259	0.108	0.146	0.124
p-value	[0.014]	[0.011]	[0.012]	[0.002]
N	271	246	253	237
Drop outliers		✓		✓
Drop utilities			✓	✓

Notes: The table summarizes the coefficient of firm AI adoption shares in a series of regressions of annualized log productivity growth. The sample includes 29 European countries: All 27 EU countries, plus Norway and Serbia. Some countries do not report data for certain industries. Productivity data and firm AI adoption rates are available for the following 1-digit NACE industries (see Appendix Table A.3): C, D, E, F, G, H, I, J, M, N. Observations are at the country-industry level. All regressions include country and industry fixed effects. An AI coefficient of 0.1 indicates that increasing the firm adoption rate by 0.1 (i.e., 10 percentage points) for that country-industry is associated with an increase in annualized log productivity growth of $0.1 \times 0.1 = 0.01$ (about 1 percentage point). Columns (2) and (4) drop observations in which the absolute value of annualized productivity growth over the reference period exceeded 10% per year. Columns (3) and (4) drop observations in the Utilities industry, which exhibits particularly volatile productivity.

other factors. Third, our sample size is limited by our survey coverage of only 7 countries, which makes it even more difficult to isolate the role of AI.

In light of these complications, we regress country-industry productivity (output per worker) growth on 2025 firm adoption rates for 29 European countries, controlling for country and industry fixed effects. This expands our sample beyond the seven countries in our worker surveys to cover the full EU plus Norway and Serbia, though it does require dropping the US and the UK. Country and industry fixed effects remove country- and industry-specific growth trends that may be correlated with AI adoption. Our dependent variable is annualized log productivity growth for a given country-industry. The industries included in our estimation are listed in the table notes.

Table 1 summarizes the results of our analysis. Panel A shows results for productivity growth from 2015-2019, which we treat as a placebo test. This time period precedes recent developments in AI capabilities, and so it should not return a significant coefficient in the absence of omitted variable problems. Reassuringly, we find a small and statistically insignificant coefficient. Columns (2-4) show that this result is robust to dropping outlier observations and those in the Utilities industry, which exhibit particularly volatile productivity.

Panel B shows results for productivity growth from 2019-2024. 2019 is a natural starting year since it is the most recent year preceding the Covid-19 pandemic, which had large effects on measured productivity (see Figure 1); 2024 is currently the most recent year of productivity data for our sample. In our main specification, we find a coefficient on AI adoption of 0.100. Our estimates range from 0.048 to 0.074 in the alternative specifications of Columns (2-4). These coefficients imply that a 10-percentage point increase in AI adoption is associated with additional productivity growth of roughly 0.48 - 1.00 percentage points per year from 2019-2024, or cumulative productivity growth of roughly 2.40 - 5.00 percentage points over this period. Columns (1) and (2) are statistically significant at the 3% and 7% level, respectively. However, for the two specifications in which we drop observations from the Utilities industry, the coefficient is no longer statistically significant.

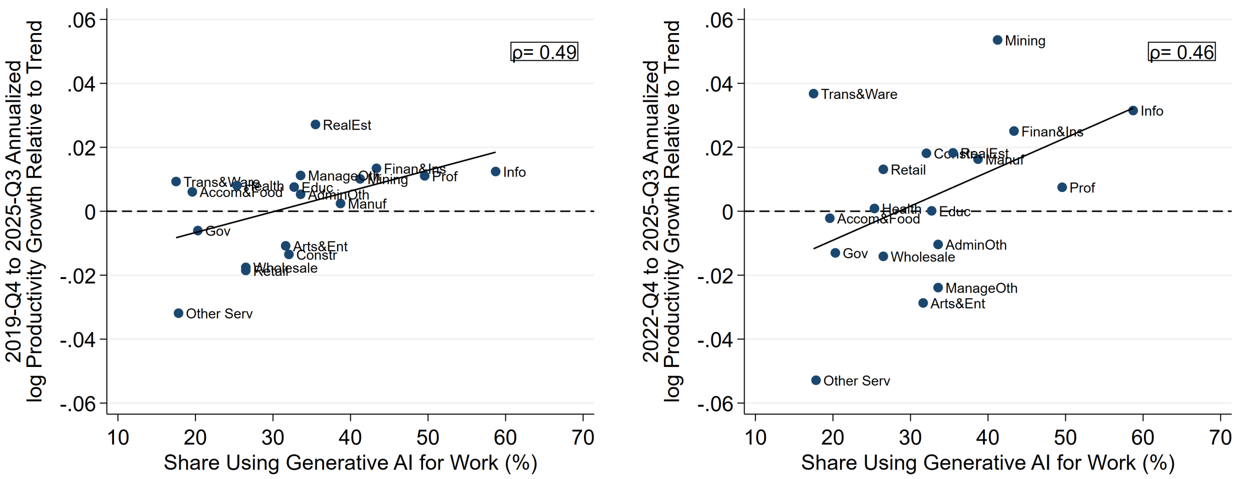
Panel C shows results for productivity growth from 2022 to 2024: 2022 is another reasonable starting point, as it avoids the most turbulent years of the Covid-19 pandemic and is the year in which ChatGPT was released. In the main specification, we find a coefficient of 0.259. Our estimates range from 0.108 to 0.146 in Columns (2-4). These coefficients imply that a 10-percentage point increase in AI adoption is associated with additional productivity growth of roughly 1.08 – 2.59 percentage points per year from 2022-2024, or cumulative productivity growth of roughly 2.16 - 5.18 percentage points over this period. For these years, in all specifications the AI coefficient is statistically significant at the 2% level or lower.

Next, we conduct a similar analysis for the US, whose productivity data extend through 2025-Q3. Because comparable firm-level AI adoption data are not available for the US, we instead use worker AI adoption rates by industry. With only one country and one observation per industry, we cannot include country or industry fixed effects. Instead, we construct an industry-specific productivity pre-trend using annualized log growth in output per worker from 2015-Q4 to 2019-Q4 and subtract this from annualized log productivity growth since 2019-Q4 (or 2022-Q4). This de-trended measure captures the extent to which each industry's post-2019 productivity growth differs from its pre-pandemic trajectory.

Figure 18a plots industry-level worker AI adoption against de-trended productivity growth in the US from 2019-Q4 to 2025-Q3. Industries with higher AI adoption experienced larger deviations from their pre-2019 productivity trends (ρ = 0.49). A 10-percentage-point increase in worker AI adoption is associated with approximately 0.6 percentage points of additional annualized productivity growth per year over 2019–2025, or about 3.7 percentage points cumulatively. This estimate is similar to our European estimates, which imply additional cumulative growth of 2.4–5.0 percentage points from 2019-2024. Figure 18b shows a similar pattern for 2022-Q4 to 2025-Q3 (ρ = 0.46). Over this shorter window, a 10-percentage-point increase in adoption is associated with 1.1 percentage points of additional annualized growth per year, or 2.9 percentage points cumulatively. This estimate is also similar to our European estimates, which imply additional cumulative growth of 2.2–5.2 percentage points from 2022-2024.

Figure 18: US AI Adoption and Productivity Growth Relative to Trend

(a) 2019-Q4 to 2025-Q3 (b) 2022-Q4 to 2025-Q3



Notes: The figure plots worker AI adoption rates versus productivity growth in the US. Observations are at the industry level. Productivity growth is annualized growth of log output per worker from 2019-Q4 / 2022-Q4 to 2025-Q3. Trend productivity growth is annualized growth of log output per worker from 2015-Q4 to 2019-Q4. Productivity growth relative to trend is the difference between productivity growth and trend productivity growth. We drop the Utilities sector because it has a small sample size and the value of its output is highly volatile and particularly dependent on commodities prices.

Our estimates imply that observed differences in AI adoption between the US and Europe are large enough to generate meaningful productivity differences. In our worker surveys, 43% of US workers report using AI, compared with 32% across the European countries we survey—a gap of 11 percentage points. For 2019–2025, our US estimates imply that a 10-percentage-point increase in worker AI adoption is associated with roughly 3.7 percentage points of cumulative productivity growth. Scaling this to an 11-percentage-point gap yields approximately $1.1 \cdot 3.7 = 4.1$ percentage points of additional cumulative productivity growth in the US relative to Europe over this period. For 2022–2025, a 10-percentage-point increase in adoption is associated with 2.9 percentage points of cumulative growth; applying the same scaling implies roughly $1.1 \cdot 2.9 = 3.2$ percentage points of additional cumulative growth since 2022.

Taken together, the micro and macro evidence paint a broadly consistent, if somewhat noisy, picture. Worker surveys suggest that AI generates meaningful time savings, in line with experimental estimates. These aggregated time savings are larger in the US than in Europe, primarily because US workers adopt AI more intensively. Industry-level productivity data reinforce this pattern: higher AI adoption is associated with faster productivity growth in both Europe and the US. While we do not establish causality, the similar findings across methods and geographies are consistent with the notion that AI is contributing to productivity growth, and to a widening productivity gap between the US and Europe.

Table 2: Regression Summary: Firm AI Adoption Rates and Employment Changes

	(1)	(2)	(3)	(4)
Panel A: 2015 / 2019 (placebo)				
AI adoption	0.246	0.143	0.193	0.112
p-value	[0.046]	[0.185]	[0.199]	[0.441]
N	269	263	251	246
Panel B: 2019 / 2025				
AI adoption	-0.189	-0.170	-0.263	-0.222
p-value	[0.116]	[0.160]	[0.158]	[0.234]
N	269	266	251	248
Panel C: 2022 / 2025				
AI adoption	-0.056	-0.130	-0.044	-0.106
p-value	[0.695]	[0.168]	[0.810]	[0.419]
N	273	254	255	239
Drop outliers		✓		✓
Drop utilities			✓	✓

Notes: The table summarizes the coefficient of firm AI adoption shares in a series of regressions of log employment growth. The sample includes 29 European countries: All 27 EU countries, plus Norway and Serbia. Some countries do not report data for certain industries. Productivity data and firm AI adoption rates are available for the following 1-digit NACE industries (see Appendix Table A.3): C, D, E, F, G, H, I, J, M, N. Observations are at the country-industry level. All regressions include country and industry fixed effects. An AI coefficient of 0.1 indicates that increasing the firm adoption rate by 0.1 (i.e., 10 percentage points) for that country-industry is associated with an increase in log employment growth of $0.1 \times 0.1 = 0.01$ (about 1 percentage point). Columns (2) and (4) drop observations in which the absolute value of annualized employment growth over the reference period exceeded 10% per year. Columns (3) and (4) drop observations in the Utilities industry.

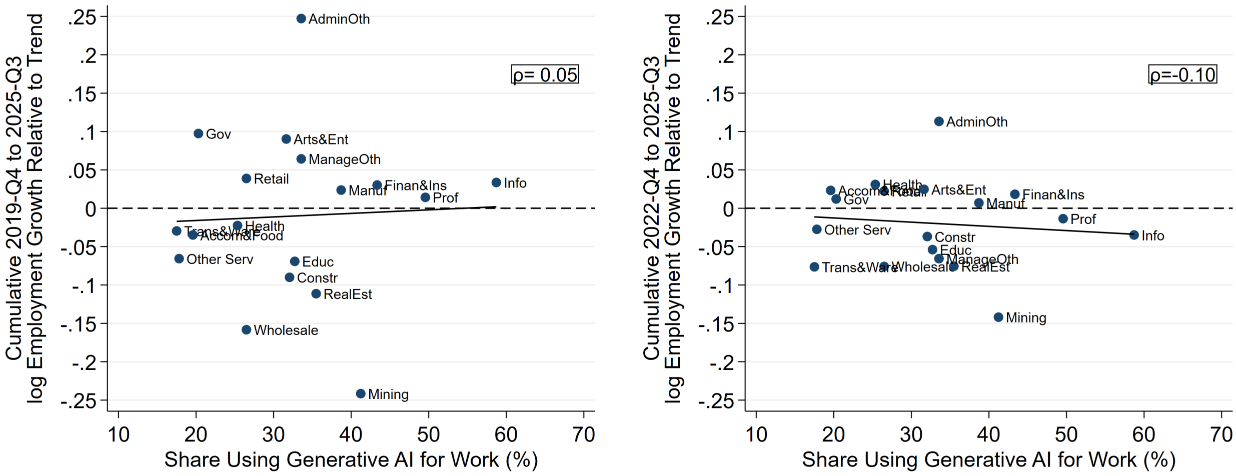
5.3 AI Adoption and Employment

In addition to AI's productivity potential, researchers and policymakers are also interested in whether AI will impact employment rates. Existing research on the relationship between employment and AI provides mixed evidence. Bonfiglioli et al. (2024) find negative effects of AI exposure on employment across US commuting zones between 2000 and 2020. Acemoglu et al. (2022) find no significant effect on employment in more exposed industries and occupations from 2010 to 2018. Albanesi et al. (2025) study 16 European countries from 2011 to 2019. They find that employment shares in more exposed occupations increase, especially in countries with higher rates of education, technology diffusion, and competition. However, all of these studies rely on data from 2020 or earlier, prior to recent advances in generative AI, and rely on AI exposure predictions rather than actual adoption. Using more recent data from Denmark through 2024, Humlum and Vestergaard (2025a) find no meaningful impacts of AI adoption on employment and earnings among workers in a small number of occupations that are particularly exposed to generative AI. In this section, we complement this emerging evidence using direct measures of AI adoption across multiple countries.

Table 2 summarizes a parallel set of regressions of log employment growth on firm AI adoption rates in Europe using the same country–industry framework as in the previous section. The placebo

Figure 19: US AI Adoption and Employment Growth Relative to Trend

(a) 2019-Q4 to 2025-Q3 (b) 2022-Q4 to 2025-Q3



Notes: The figure plots worker AI adoption rates versus employment growth in the US. Observations are at the industry level. Employment growth is cumulative growth of log employment share from 2019-Q4 / 2022-Q4 to 2025-Q3. Trend employment growth is cumulative growth of log employment share from 2015-Q4 to 2019-Q4. Employment growth relative to trend is the difference between employment growth and trend employment growth. We drop the Utilities sector because it has a small sample size and for consistency with our productivity analysis.

panel (Panel A, 2015-2019) returns a positive and significant coefficient in the baseline specification (0.246, p=0.046), though this result becomes insignificant in all alternative specifications that drop outliers and utilities. Turning to the main periods of interest, Panels B and C show negative but statistically insignificant coefficients across all specifications. Overall, we find no robust evidence that industry-level AI adoption is associated with changes in employment growth in Europe.

Figure 19 plots industry-level worker AI adoption against employment share growth relative to trend, using the same specification as our US analysis in the previous section. Consistent with our European results, we find essentially no relationship between AI adoption and employment share growth, either from 2019-2025 or from 2022-2025. Collectively, these results provide no clear evidence that firm-level AI adoption is associated with either employment expansion or contraction at the industry level in recent years.

6 Conclusion

This paper combines evidence from both worker and firm surveys to document a large gap in AI adoption between the US and Europe. An important share of this gap can be accounted for by differences in demographics and firm composition. Adoption is also closely linked to firm personnel management practices and whether firms actively encourage and support AI use by workers. Together, demographics, firm composition, and employer encouragement account for nearly all of the US-Europe gap in most countries.

We then examine whether these differences in AI adoption are reflected in economic outcomes. Micro-level evidence from an existing experimental literature and our worker surveys suggests that AI can generate meaningful time savings for individual workers. At the macro level, we find a positive association between firm AI adoption and industry-level productivity growth in recent years, both in Europe and the US. We find no evidence that AI adoption is associated with changes in employment. Given the brief timeline between recent developments in AI capabilities and our most recent economic indicators, these findings should be interpreted with caution, and revisiting them as more data become available will be essential.

Our findings have important implications for researchers and policymakers attempting to measure the economic impact of AI. On the firm side, the EU-ICT-Firm survey and recent BTOS modules provide a useful foundation for tracking and comparing AI adoption within and across countries. Greater harmonization of these surveys, and the creation of comparable datasets for additional countries, would make cross-country comparisons more reliable and informative. On the worker side, the EU-ICT-HH survey offers broad coverage across European countries and the RPS will continue to collect data for the US on a quarterly frequency. To further strengthen worker-level measurement in the US, AI adoption questions could be incorporated into a special CPS module, analogous to the Computer and Internet Use (CIU) supplement introduced in the 1980s.

As AI technologies continue to advance, measurement efforts will need to adapt as well. Our results suggest that augmenting government surveys with questions on management practices, AI support and encouragement for workers, and how AI is used would improve our understanding of why adoption varies and whether firms are effectively leveraging AI. Beyond surveys, textual analysis of employee CVs, job postings, patents, earnings call transcripts, and AI prompt histories offers a promising approach for tracking AI's diffusion and impact (see, for example, Acemoglu et al. 2022; Babina et al. 2024; Bonfiglioli et al. 2024; Chatterji et al. 2025; Eisfeldt et al. 2025; Hampole et al. 2025; Handa et al. 2025; Hassan et al. 2025; Kalyani 2025; Liu et al. 2025; Schubert 2025). These and other innovative approaches can complement traditional data sources to shed light on the evolving economic impact of AI.

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ONLINE APPENDIX[1]

Mind the Gap:
AI Adoption in Europe and the US

Alexander Bick Adam Blandin David J. Deming
Nicola Fuchs-Schündeln Jonas Jessen

1. *Contact*: alexander.bick@stls.frb.org; adam.blandin@vanderbilt.edu; david_deming@harvard.edu; nicola.fuchs@wzb.eu; jonas.jessen@wzb.eu. The working draft of this paper was presented at the Spring 2026 Brookings Papers on Economic Activity (BPEA) Conference and the final version will be published in the Spring 2026 BPEA volume. The views in this paper are those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of St. Louis or the Federal Reserve System.

A The International RPS: Measurement and Definitions

A.1 Sample Restrictions

The Bilendi panel is not a random sample of the population in each country. However, researchers can instruct Bilendi to target survey invitations to specific demographic groups. The International RPS sample was designed to be nationally representative of each country's "employed, at work last week" population aged 18-67 (if applicable, the upper age limit corresponds to the statutory retirement age in the respective countries) across gender, age, education, income, and (within-country) region of residence. To construct these targets we used the most recently available labor force surveys at the time we fielded the 2025 survey (April 2025 CPS for the US, the 2024 Labour Force Survey for the UK, and the 2023 EU-LFS for the remaining European countries).

Individuals who take the survey too fast (i.e., in less than 120 seconds) or who do not state that they will provide their best answers are automatically dropped from the sample.[2] In addition, we included a captcha question and the Bilendi staff also filtered out any responses that look suspicious. This is the case for 3-8% of responses per country. Appendix Table A.1 shows the number of completed responses per country that fulfill our quality criteria and which we use in our analysis.

Table A.1: Number of Observations per Country

Survey wave:	May-June 2025 (1)	January-February 2026 (2)
United States	4,720	3,001
Germany	4,885	3,077
United Kingdom	4,929	2,922
France	4,907	3,082
Italy	5,203	3,061
Netherlands	4,954	2,703
Sweden	4,901	3,070
Total	34,499	20,916

Notes: Table shows the number of observations per country and survey wave from our own survey on AI adoption. Number of observations correspond to those used in the analysis, i.e., after low-quality responses have been filtered out.

2. The exact phrasing of the screener question is: "We care about the quality of our survey data and hope to receive the most accurate measure of your opinions, so it is important to us that you thoughtfully provide your best answer to each question in the survey. Do you commit to providing your thoughtful and honest answers to the questions in this survey?" with the following three answer options (1) I will provide my best answers, (2) I will not provide my best answers, and (3) I can't promise either way.

A.2 Weighting

As described in the body of the paper, we asked Bilendi to administer the survey in each country to a sample of respondents who match the population along a few broad demographic characteristics: gender, five age bins (18-27, 28-37, 38-47, 48-57, 58-63/67), two education groups (low and medium, high), three income bins for household income (US) or personal net income (in European countries, whereby data for the EU countries is based on statistics provided by EU-SILC) over the past 12 months, and regions. The cut-offs for income and educational attainment were defined country-specific.

Using the iterative proportional fitting (raking) algorithm of Deming and Stephan (1940), we construct sampling weights to ensure the our survey population matches the CPS, EU-LFS and UK-LFS sample proportions for the set of demographic characteristics included in the Bilendi sampling targets for the overall sample. In the 2025 survey, we targeted race/ethnicity in the US and UK, and country of birth in EU countries (born in the country, born in another EU country, born outside the EU). It turned out that race/ethnicity or country of birth cannot be targeted well by Bilendi such that we did not include these quotas in the 2026 survey, but include them in the construction of the weights for both surveys. To construct the sampling weights we use more disaggregated categories for education (see Appendix Table A.2), and we additionally use information on household composition (marital status or whether respondents are living in a household with a partner, and whether children live in the households). All these characteristics are interacted with gender. Appendix Table A.2 states the categories of educational attainment and the income categories use as sampling targets in parentheses. For income, we use the same categories for sampling and for our weighting scheme. For education, we use finer categories and separate them by lines. For example, in the US we use all six categories, while in Germany we combine the two lowest education groups (Kein Abschluss and Allbemeinbildender Abschluss) into one as well as the fourth and fifth (Weiterführender Berufsabschluss and Berufsbezogener Abschluss mit Hochschulzugang) into one such that we use five education categories in our weighting scheme.

Appendix Figure A.1 compares the sample composition between the CPS, EU-LFS or UK-LFS and our survey for each country along the demographics targeted in the sampling procedure pooled for our 2025 (blue) and 2026 (green) surveys. We report both the unweighted demographics in our surveys (circles) and shares using the weights from the raking procedure described above (triangles).

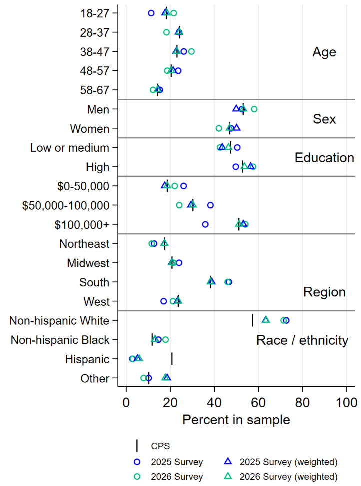
A.2.1 Weighting Adjustment Based on Awareness

In addition to the raking procedure described above to ensure representativeness along demographic characteristics, our weighting scheme incorporates results discussed in Bick et al. (2026) who tested alternative question sequences for measuring genAI awareness and use.

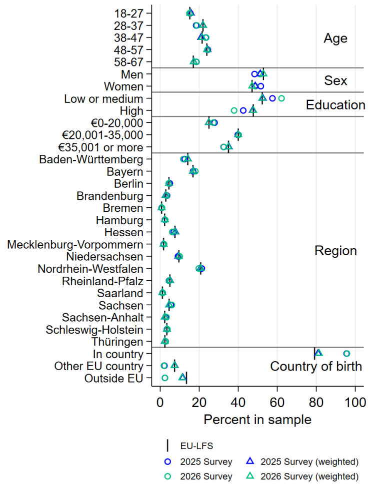
Details. Our May/June 2025 surveys followed the same question sequence as the regular RPS

Figure A.1: Targets and Sample Composition in Survey Population

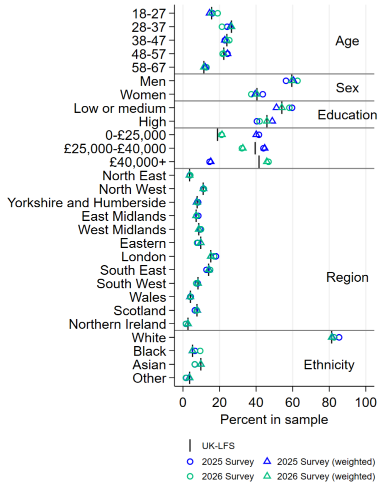
(a) United States



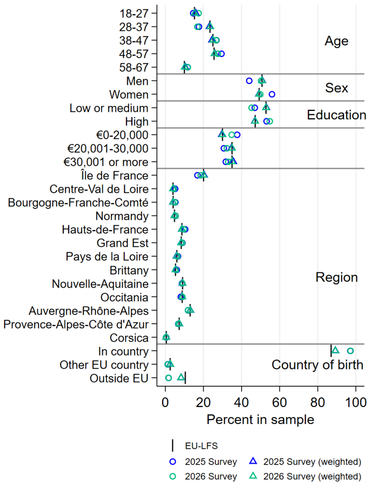
(b) Germany



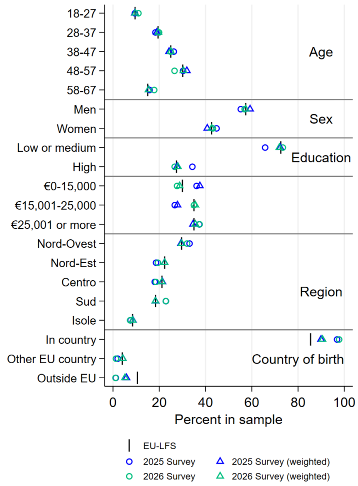
(c) United Kingdom



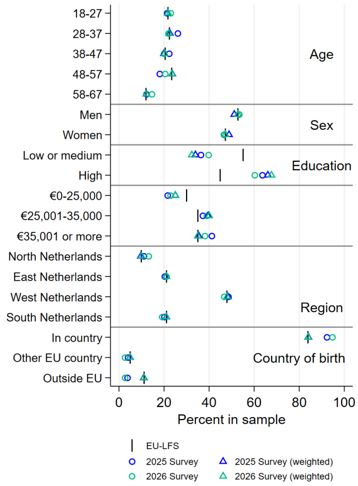
(d) France



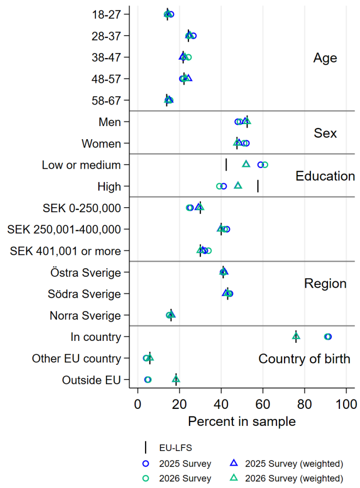
(e) Italy



(f) Netherlands



(g) Sweden



Notes: Figure compares unweighted and weighted sample averages in our survey to the targets calculated using the Current Population Survey (United States), UK Labour Force Survey (UK) and the European Labour Force Survey (other European countries). Data source: Authors' own survey on Generative AI adoption of workers in in May-June 2025 and January-February 2026

Table A.2: Education and Income Thresholds Used as Targets and in the Raking Procedure

	Education (1)	Income (2)
United States	Did not complete 12th grade *(low or medium)*	$0-25,000 *(low)*
	High school graduate or the equivalent *(low or medium)*	$25,001-50,000 *(low)*
	Some college but no degree *(low or medium)*	$50,001-75,000 *(medium)*
	Associate’s degree *(high)*	$75,001-100,000 *(medium)*
	Bachelor’s degree *(high)*	$100,000-125,000 *(high)*
	Graduate degree *(high)*	$125,000-150,000 *(high*
		$150,001 or more *(high)*
Germany	Keinen Abschluss *(low or medium)*	€0-5,000 *(low)*
	Allgemeinbildender Schulabschluss *(low or medium)*	€5,001-10,000 *(low)*
	Abitur, Fachabitur, Berufsausbildung *(low or medium)*	€10,001-15,000 *(low)*
	Weiterführender Berufsabschluss *(low or medium)*	€15,001-20,000 *(low)*
	Berufsbezogener Abschluss mit Hochschulzugang *(low or medium)*	€20,001-25,000 *(medium)*
	Hochschulabschluss *(high)*	€25,001-30,000 *(medium)*
	Weiterführender Hochschulabschluss *(high)*	€30,001-35,000 *(medium)*
		€35,001 or more *(high)*
United Kingdom	No education *(low or medium)*	£0-5,000 *(low)*
	Early Years Foundation Stage *(low or medium)*	£5,001-10,000 *(low)*
	Key Stage 3 and equivalent *(low or medium)*	£10,001-15,000 *(low)*
	Key Stage 4 *(low or medium)*	£15,001-20,000 *(low)*
	Advanced Level Diplomas *(low or medium)*	£20,001-25,000 *(low)*
	Higher National Certificate *(high)*	£25,001-30,000 *(medium)*
	Bachelor’s Degrees *(high)*	£30,001-35,000 *(medium)*
	Master’s Degrees *(high)*	£35,001-40,000 *(medium)*
		£40,001-45,000 *(high)*
		£45,001-50,000 *(high)*
		£50,001 or more *(high)*
France	Pas de diplôme *(low or medium)*	€0-5,000 *(low)*
	Éducation primaire et secondaire générale *(low or medium)*	€5,001-10,000 *(low)*
	Diplôme de fin d’études secondaires *(low or medium)*	€10,001-15,000 *(low)*
	Formation post-secondaire non-tertiaire *(high)*	€15,001-20,000 *(low)*
	Formation professionnelle de niveau supérieur *(high)*	€20,001-25,000 *(medium)*
	Diplôme de l’enseignement supérieur *(high)*	€25,001-30,000 *(medium)*
	Diplôme de deuxième cycle / diplôme de troisième cycle *(high)*	€30,001-35,000 *(high)*
		€35,001 or more *(high)*
Italy	Nessuna istruzione *(low or medium)*	€0-5,000 *(low)*
	Scuola Primaria *(low or medium)*	€5,001-10,000 *(low)*
	Scuola secondaria di I grado *(low or medium)*	€10,001-15,000 *(low)*
	IeFP corsi vocazionali e ITS *(low or medium)*	€15,001-20,000 *(medium)*
	Scuola secondaria di 2 grado *(low or medium)*	€20,001-25,000 *(medium)*
	Laurea Triennale *(high)*	€25,001-30,000 *(high)*
	Laurea Magistrale o Dottorato *(high)*	€30,001-35,000 *(high)*
		€35,001 or more *(high)*
Netherlands	Geen diploma *(low or medium)*	€0-5,000 *(low)*
	Voortgezet onderwijs *(low or medium)*	€5,001-10,000 *(low)*
	Beroepsopleiding tot mbo-niveau 3 *(low or medium)*	€10,001-15,000 *(low)*
	Mbo-niveau 4 *(high)*	€15,001-20,000 *(low)*
	Hoger onderwijs bachelor *(high)*	€20,001-25,000 *(low)*
	Hoger onderwijs master (hbo-master, wo-master, doctoraat) *(high)*	€25,001-30,000 *(medium)*
		€30,001-35,000 *(medium)*
		€35,001 or more *(high)*
Sweden	Har inte avslutat grundskolan *(low or medium)*	SEK 0-50,000 *(low)*
	Avbröt gymnasiet *(low or medium)*	SEK 50,001-100,000 *(low)*
	Gymnasieexamen eller motsvarande *(low or medium)*	SEK 100,001-150,000 *(low)*
	Viss högskoleutbildning, men ingen examen *(high)*	SEK 150,001-200,000 *(low)*
	Kortare högskoleutbildning *(high)*	SEK 200,001-250,000 *(low)*
	Kandidatexamen *(high)*	SEK 250,001-300,000 *(medium)*
	Magister- eller masterexamen, professionell examen eller doktorsexamen *(high)*	SEK 300,001-350,000 *(medium)*
		SEK 350,001-400,000 *(medium)*
		SEK 401,000 or more *(high)*

Notes: Table reports for each country in our survey the categories of educational attainment and income we elicit in the survey. In parentheses we show the quota groups these are assigned to when we construct the targets. Horizontal lines between the education categories show how we summarize the education groups in our raking procedure. For income we target the three groups reported in parentheses. In the US, income refers to the combined family income in the past 12 months. In all European countries, income refers to personal net income in the last year.

AI module for the US through May 2025. In particular, respondents were first asked whether they had heard of generative AI and, conditional on having heard of it, about their usage. To assess whether this structure induced systematic differences in reporting, Bick et al. (2026) introduced a randomized experiment in their August 2025 RPS wave for the US. Respondents were randomly assigned to one of two groups. Group 1 received the original sequential flow, where they were first asked whether they had heard of genAI, and then whether they used it. Alternatively, Group 2 was first asked whether they used genAI, and if they did not use it they were asked why, with one option being that they had not heard of it.

Measurement differences across groups. Bick et al. (2026) found that a larger share of respondents reported having heard of genAI in Group 2. However, across the two groups, a similar share of respondents reported using genAI conditional on having heard of genAI, suggesting that differential awareness reporting was evenly split between genAI users and non-users. The higher awareness rate in Group 2, combined with similar usage rates conditional on awareness between Groups 1 and 2, translated into higher overall usage rates in Group 2. Similar patterns held across employment status and for usage at home and at work. These results indicate that the initial awareness question (for Group 1) generated a downward bias in reported usage rates. One possible explanation for this pattern is that some respondents strategically reported that they had not heard of genAI because they guessed they would receive fewer questions with that answer. We implemented the same randomization in our January-February 2026 survey and found similar results.

Reweighting strategy. In the January-February 2026 surveys, we can adjust for this bias by reweighting Group 1 respondents to match Group 2 usage rates. We constructed adjustment weights across gender, age, education, and usage (at work and at home) using a raking algorithm that increases the weight of Group 1 users relative to non-users while leaving Group 2 weights unchanged. To maintain coverage across demographic–usage cells, we did not incorporate intensity of usage into the adjustment.

We then apply this adjustment to the May/June 2025 survey. Since all respondents in these prior waves received the question sequence of Group 1, we apply the adjustment to all respondents in these waves.

A.3 Definition of Industries and Occupations

Industries in our survey correspond to the Statistical Classification of Economic Activities in the European Community (NACE Rev. 2), but we slightly simplify the titles. We also omit the industries A, B, T, and U (agriculture, mining, activities of households as employees, and armed forces) due to expected low coverage. We also allowed respondent to select “Other” as their industry and then asked them to indicate their industry. We used the free text answer to assign respondents to one of the NACE categories, if possible. The NACE classification allows for data from the EU or the UK, such as the EU ICT enterprise survey, to be directly merged to our survey data. For the US, we map NAICS industries to their corresponding NACE industries and report this in Appendix Table A.3.

Table A.3: Mapping from NACE to NAICS Industry Codes

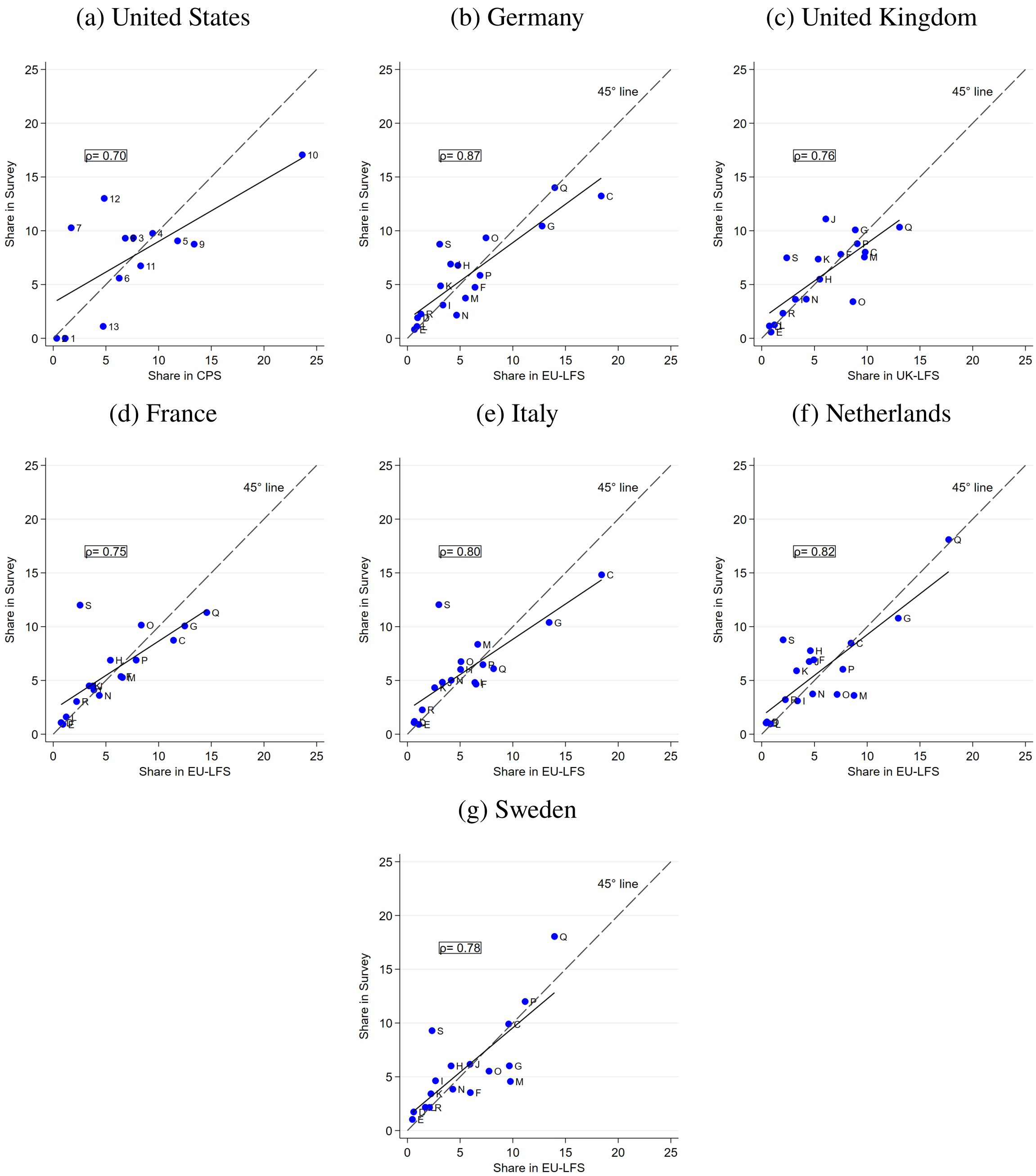
NACE Rev. 2 classification		NAICS classification	
A	Agriculture, forestry and fishing	11	Agriculture, Forestry, Fishing and Hunting
B	Mining and quarrying	21	Mining
C	Manufacturing	31-33	Manufacturing
D	Electricity, gas, steam and air conditioning supply	22	Utilities
E	Water supply; sewerage, waste management and remediation activities		
F	Construction	23	Construction
G	Wholesale and retail trade; repair of motor vehicles and motorcycles	42	Wholesale Trade
G	Wholesale and retail trade; repair of motor vehicles and motorcycles	44-45	Retail Trade
H	Transportation and storage	48-49	Transportation and Warehousing
I	Accommodation and food service activities	72	Accommodation and Food Services
J	Information and communication	51	Information
K	Financial and insurance activities	52	Finance and Insurance
L	Real estate activities	53	Real Estate Rental and Leasing
M	Professional, scientific and technical activities	54	Professional, Scientific, and Technical Services
N	Administrative and support service activities	56	Administrative and Support and Waste Management Services
N	Administrative and support service activities	55	Management of Companies and Enterprises
O	Public administration and defense; compulsory social security	92	Public Administration
P	Education	61	Educational Services
Q	Human health and social work activities	62	Health Care and Social Assistance
R	Arts, entertainment and recreation	71	Arts, Entertainment and Recreation
S	Other service activities	81	Other Services (except Public Administration)
T	Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use		
U	Activities of extraterritorial organizations and bodies		

Notes: Table shows the mapping of the Statistical Classification of Economic Activities in the European Community (NACE Rev. 2 classification) to the North American Industry Classification System (NAICS) that we are using in our analyses.

To validate that the industry distribution in the International RPS sample broadly corresponds to the actual shares in the economies, we correlate the distributions in Appendix Figure A.2. The average correlation coefficient is 0.79, indicating that the survey matches the actual industry compositions quite well.

Occupations in our survey correspond to the 22 major occupations according to the Standard Occupational Classification (SOC) used in the US. The correlation between the occupation distribution in our survey and that of the May 2025 Current Population Survey (CPS) is 0.82, comparable to the correlation for the industry distribution. Since the SOC codes do not map directly into the International Standard Classification of Occupations used in Europe, we cannot conduct a similar analysis for the European countries covered in our survey.

Figure A.2: Industry Shares in AI Survey and CPS / EU-LFS / UK-LFS



Notes: Figure reports the correlation between industry shares in the AI survey to those obtained from national labor force surveys. Data sources: Authors' own survey on Generative AI adoption of workers in in May-June 2025 and January-February 2026, April 2025 CPS, 2023 EU-LFS, 2024 UK Labour Force Survey

B The BTOS

B.1 Adoption Rates Excluding Firms with Fewer than 10 Employees

The EU-ICT-Firm survey excludes firms with fewer than 10 employees, while the BTOS covers all firm sizes. Since firm adoption rates will be pulled down if smaller firms adopt AI less, this difference in coverage could in principle contribute to the gap between the two surveys. Using the 2023 Business Dynamics Statistics and firm adoption rates by firm size, we compute BTOS adoption rates restricted to firms with at least 10 employees. The adjustment is small in both directions. In the first quarter of 2025, the adoption rate for producing goods and services falls slightly from 7.0% to 6.3% when excluding firms with fewer than 10 employees, because firms with 1–4 employees have above-average adoption rates and constitute the largest share of all firms (see Figure D.6a). Using 6.3% to project any-purpose adoption based on the relationship in Figure 5d yields 30.0% rather than 34.0%. In November 2025, the any-purpose adoption rate moves in the opposite direction, rising from 17.3% to 19.4% when restricting to firms with at least 10 employees, because both firms with 1–4 employees and firms with 5–9 employees have below-average adoption rates at that time (see Figure D.6b). In both cases the adjustment is modest, and we conclude that the difference in firm size coverage between the two surveys does not materially affect the comparison.

B.2 1st AI Supplement

The BTOS ran its first AI supplement between December 2023 and February 2024, asking about usage of 18 specific AI technologies in producing goods and services. By providing more concrete examples than the standard question, the supplement appears to make AI adoption more salient to respondents: the adoption rate under the supplement was 8.8% (see Table 4a in Bonney et al. (2024)), compared to 5.0% under the standard question at the same time. This suggests that question framing matters meaningfully for measured adoption rates, though the comparison is not entirely clean since the supplement also changed the reference period from the last two weeks to the last six months.

The exact question wording was as follows:

> *In the last six months, what types or applications of Artificial Intelligence (AI) did this business use in producing goods or services? Select all that apply.*

18 AI technologies plus “None” were provided as possible answer options: Machine learning, Natural language processing, Virtual agents or chat bots, Speech/voice recognition using AI, Recommendation systems based on AI, Large language models, Text analytics using AI, Data analytics using AI, Neural networks, Augmented reality, Decision making systems based on AI, Deep learn-

ing, Image/pattern recognition, Machine/computer vision, Robotics process automation, Biometrics, Marketing automation using AI, None.

B.3 2nd AI Supplement

The BTOS ran its second AI supplement between December 2025 and February 2026. In addition to the standard question about AI usage in any business function cited in the main text, the BTOS asked:

> *In the last six months, did this business use Artificial Intelligence (AI) in any of the following business functions? (Yes/No/Do not know)*

15 categories were provided: Production of goods (e.g., making or assembling products, construction), Provision of services, products, or merchandise (e.g., providing services, products, or merchandise to customers), Strategy and business development, Finance and accounting, Sales and marketing, Customer service, Research and development, Information technology, Human resources, Public relations and communication, Management and administration, Sourcing, supply chains, and purchasing, Quality management and control, Distribution, Legal and compliance.

At the time of writing, results had not yet been released, as data collection had only recently been completed.

C Survey Questions in Yotzov et al. (2026) and Comparison with the EUICT-Firm Survey

The two main questions of interest for our analysis in Yotzov et al. (2026) are the following. The surveys first ask the respondents about their own AI usage.

> *On average, how frequently do you **personally use** A.I. technologies in a **typical working week**?*
>
> – *Note: Among other things, A.I. technologies could include text generation using large language models (e.g. Microsoft Copilot), data or image processing using machine learning, and visual content creation.*
>
> The answer options are: More than 5 hours a week, 1 to 5 hours a week, Up to 1 hour a week, Not at all.

The survey then asks about firm-level AI adoption:

> *Which of the following artificial intelligence (AI) technologies, if any, does your firm currently use? Select all that apply.*
>
> The answer options are: Autonomous vehicles, Data processing using machine learning, Image processing using machine learning, Robotics, Text generation using large language models, Visual content creation, Other, No AI technologies.

Table C.4: Comparison of AI Technology Adoption Rates Use Cases for Germany

EU-ICT-Firm Survey		**Yotzov et al. (2026)**	
Any AI Technology	26%	65%	
Comparable Use Cases			
Generating written language, spoken language or programming code	9%	46%	Text generation using LLMs
Machine learning for data analysis	6%	21%	Data processing using ML
Identifying objects or persons based on images	7%	15%	Image processing using ML
Generating pictures, videos, sound/audio	14%	30%	Visual content creation
Physical movement of machines via autonomous decisions	2%	4% / 3%	Robotics / Autonomous vehicles
Use Cases without a clear counterpart in Yotzov et al. (2026)			
Analysis of written language (text mining)	14%	—	—
Converting spoken language into machine-readable format	11%	—	—
Automating workflows or assisting in decision-making	4%	—	—
Use Cases without a clear counterpart in EU-ICT-Firm Survey			
—	—	20%	Other AI technologies

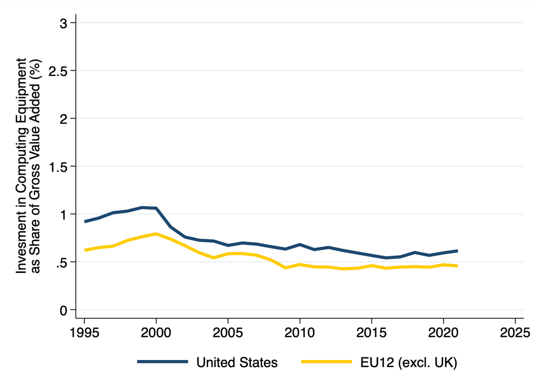
Notes: The table compares AI technology adoption rates for Germany across Yotzov et al. (2026) and the EU-ICT-Firm Survey. Panel A lists categories with a close counterpart in both surveys. Panels B and C list categories that appear in only one of the two surveys. In Yotzov et al. (2026), robotics and autonomous vehicles are listed as separate options; in the EU-ICT-Firm Survey these are combined into a single category. EU-ICT-Firm rates refer to the 2025 survey wave. Yotzov et al. (2026) rates are employment-weighted and refer to the BOP-F survey conducted in January 2026.

D Figures

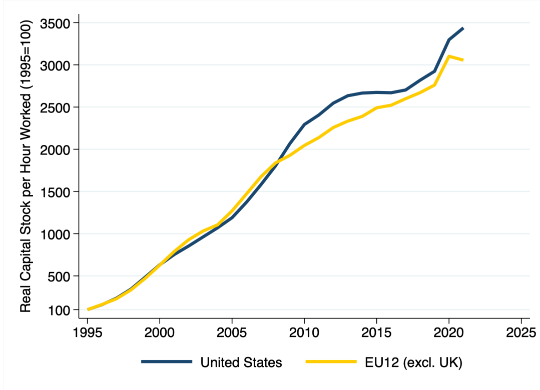
Figure D.1: ICT Investments and Capital Stocks

Computing Equipment

(a) Investment

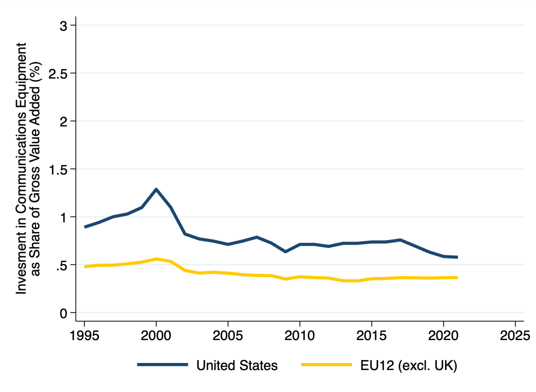


(b) Real Capital Stock

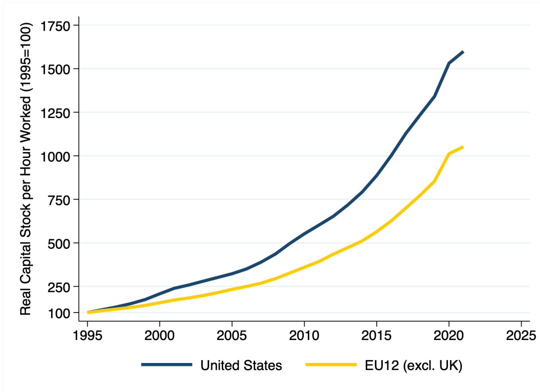


Communications Equipment

(c) Investment

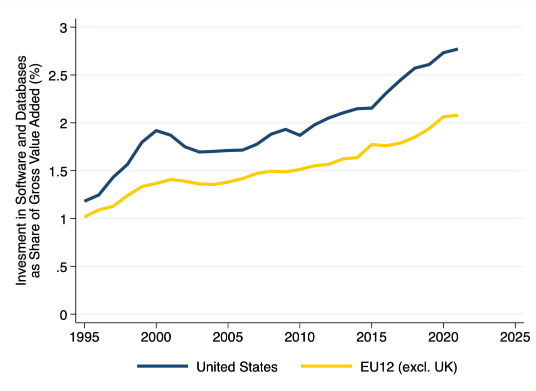


(d) Real Capital Stock

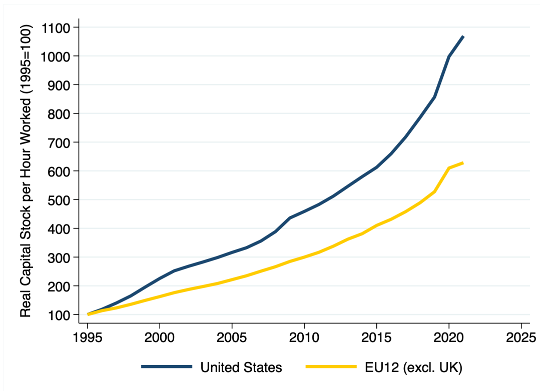


Software and Databases

(e) Investment



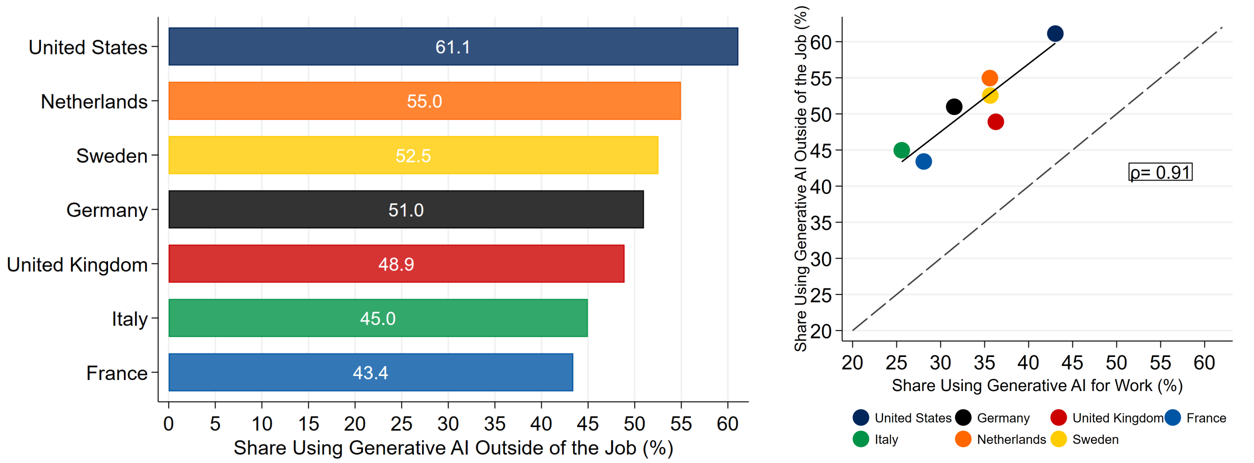
(f) Real Capital Stock



Notes: Figures show ICT investments as share of gross value added and real capital stocks per hour worked (normalized to 100 in 1995) from the EUKLEMS & INTANProd database (Bontadini et al. 2023). We construct real capital stocks using via the perpetual inventory method using real investments. We adjust the price index for each investment category in Europe following Schreyer (2002).

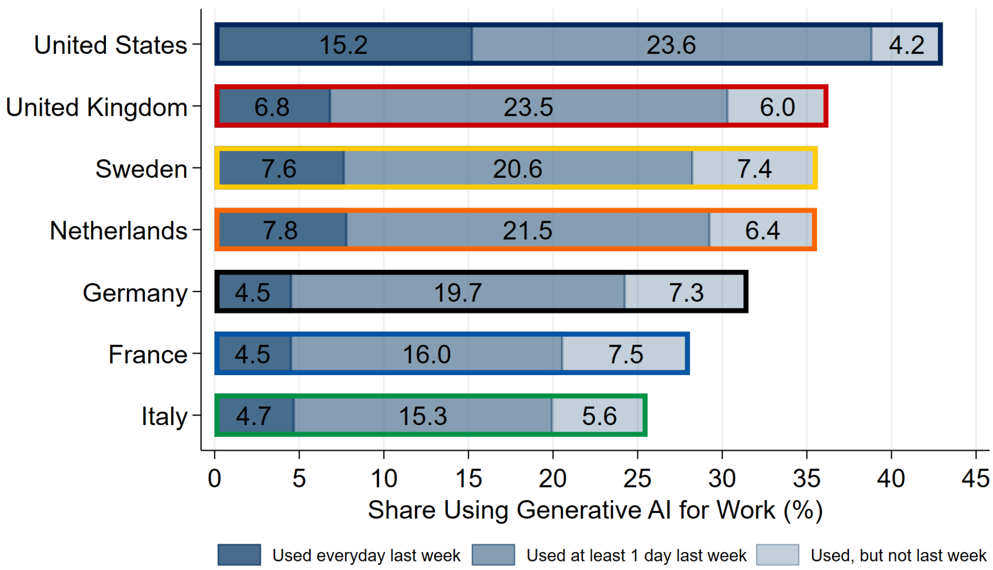
Figure D.2: Generative AI Adoption by Workers Outside of the Job in 2026

(a) Adoption Outside of the Job (b) ... vs. Adoption At Work



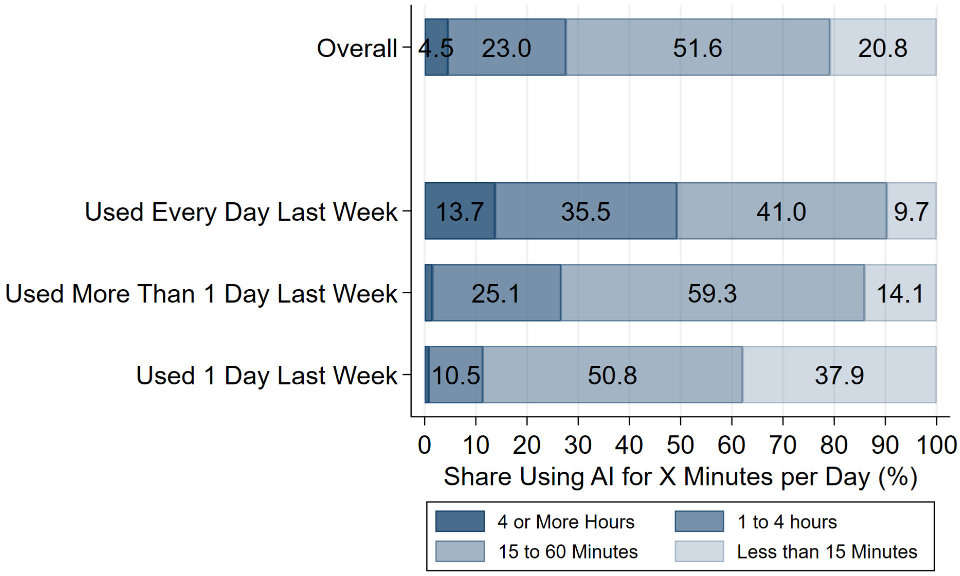
Notes: Panel (a) shows the share of survey respondents who use Generative AI outside of the job. Panel (b) plots panel (a) against the at work adoption rates from Figure 2. Data source: Authors' own survey run in January-February 2026. $N = 20,916$.

Figure D.3: Frequency of Generative AI Use of Workers in 2026



Notes: Figure shows the share of survey respondents who use Generative AI for work distinguishing by the frequency of AI use. Figure 2 reports the AI use for workers pooling the frequencies. Data source: Authors' own survey run in January-February 2026. $N = 20,916$

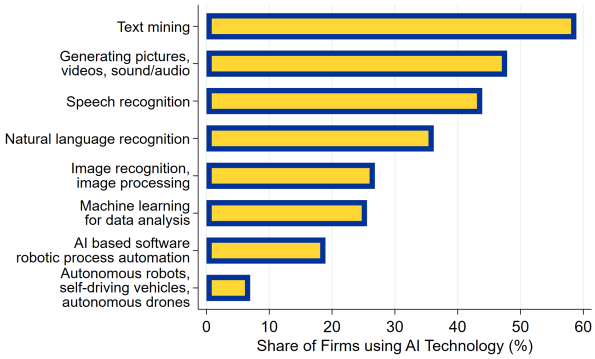
FIGURE D.4: Intensity of Generative AI Use For Work in 2026



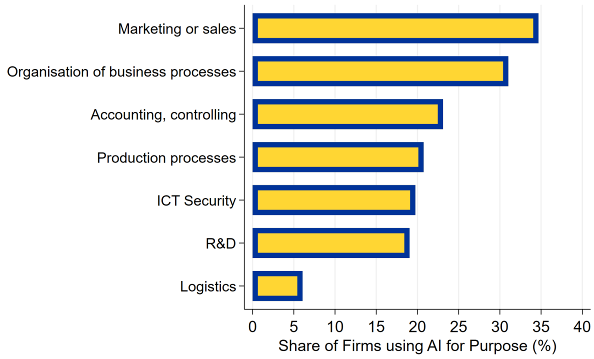
Notes: Figure reports the share of last week's working hours that was spent using Generative AI. Data source: Authors' own survey run in January-February 2026

Figure D.5: AI Technologies and Use Cases

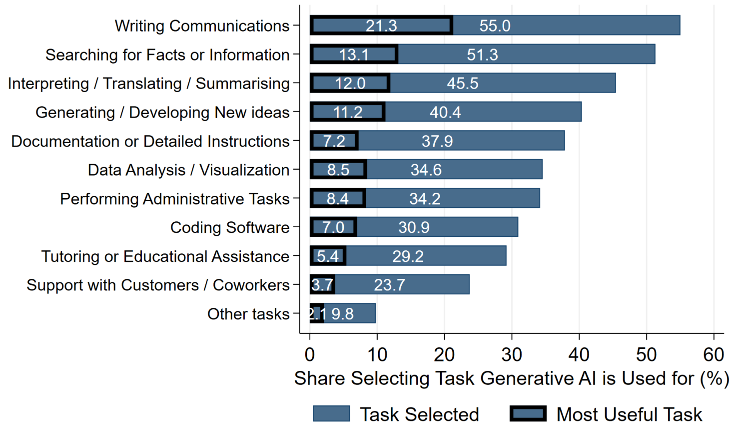
(a) Firms: Which AI Technology?



(b) Firms: AI Use Cases

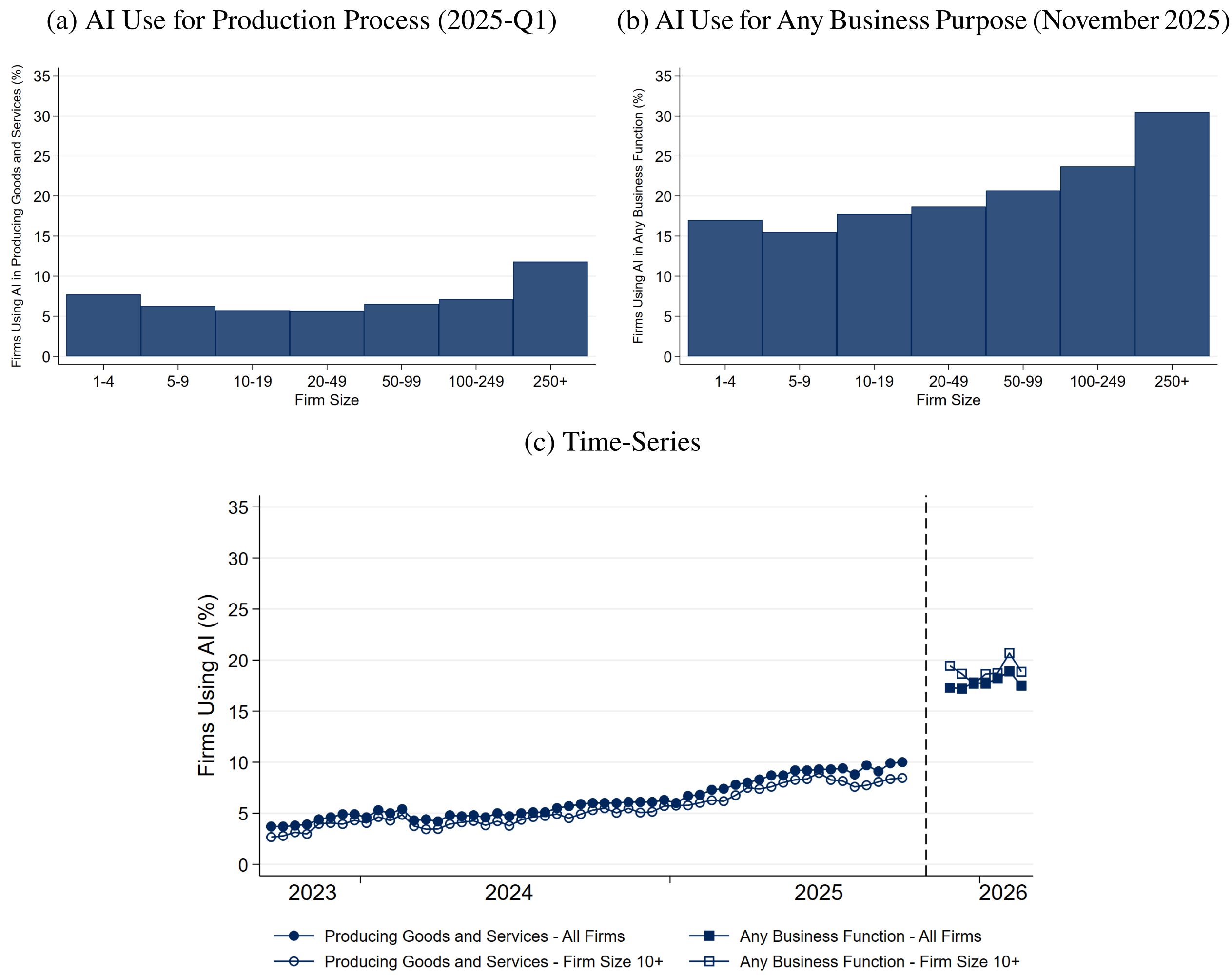


(c) Workers: AI Use Cases



Notes: For both workers and firms the sample is AI users. In the EU-ICT-Firm survey, firms were first asked whether they use one of the eight technologies shown in panel (a). If they responded affirmatively to at least one of these, they were, among other questions, asked about which use cases they used AI for, which is is shown in panel (b). Panels (a) and (b) refer to averages in the European Union. In the worker survey, respondents were presented with the displayed list of AI use cases shown in panel (c). If multiple were selected, a follow-up question elicited the most important use case. Panel (c) pools data from the seven countries covered in our survey. Data source for firm panels: 2025 EU survey on ICT usage in enterprises. Data source for worker panel: Authors' own survey run in May-June 2025 and January-February 2026.

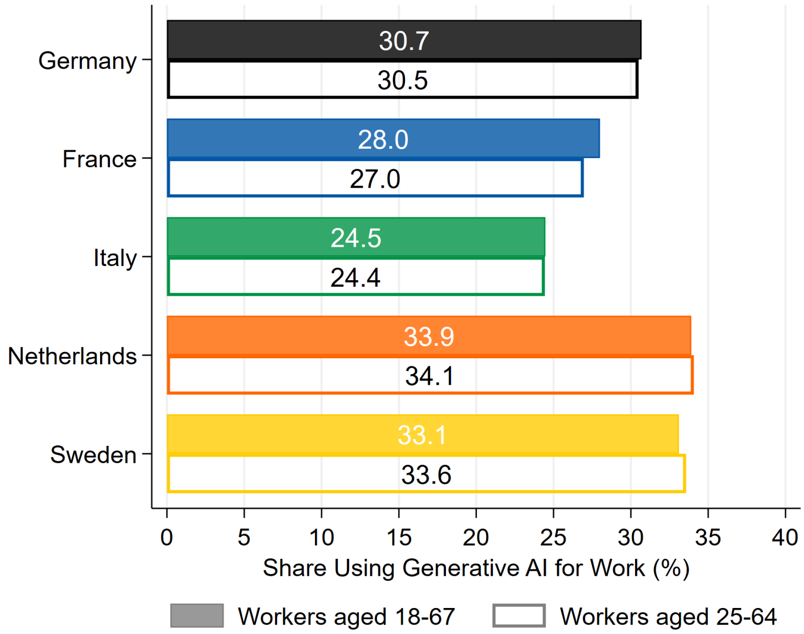
Figure D.6: AI Use by Firms by Firm Size in the US



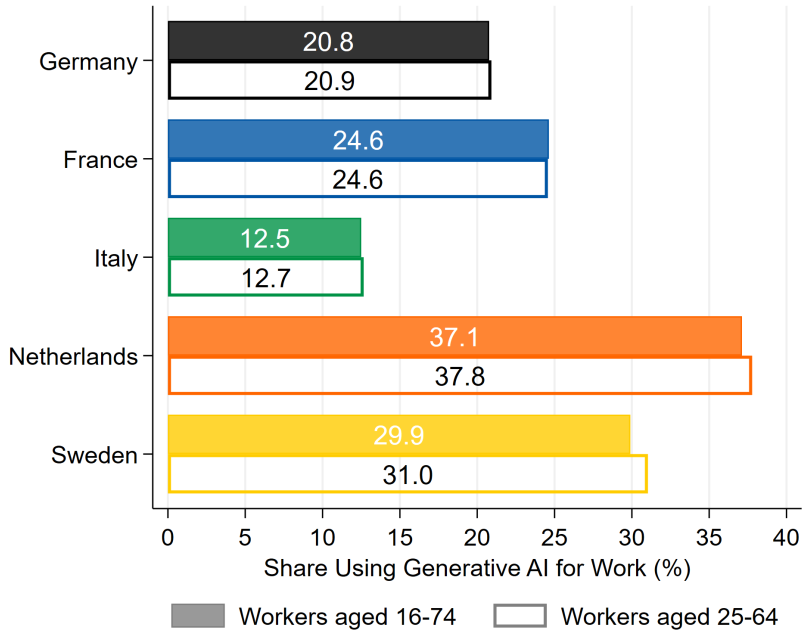
Notes: Figure reports AI Use by firms in the US by firm size. Panel (a) shows the share of firms using AI in producing goods and services averaged over the first quarter of 2025. Panel (b) shows the share of firms using AI in any business function in November 2025. Panel (c) shows the share of firms using AI for producing goods and services (circles) and the share of firms using AI for any business function (squares). The vertical line indicates when the questionnaire in the BTOS changed the way it asked firms about their AI use. Solid symbols report the number for all firms and hollow symbols the AI use rates for firms with at least 10 employees. Source: US BTOS Survey

Figure D.7: Generative AI Adoption in the Worker Surveys by Age

(a) Our Own Survey



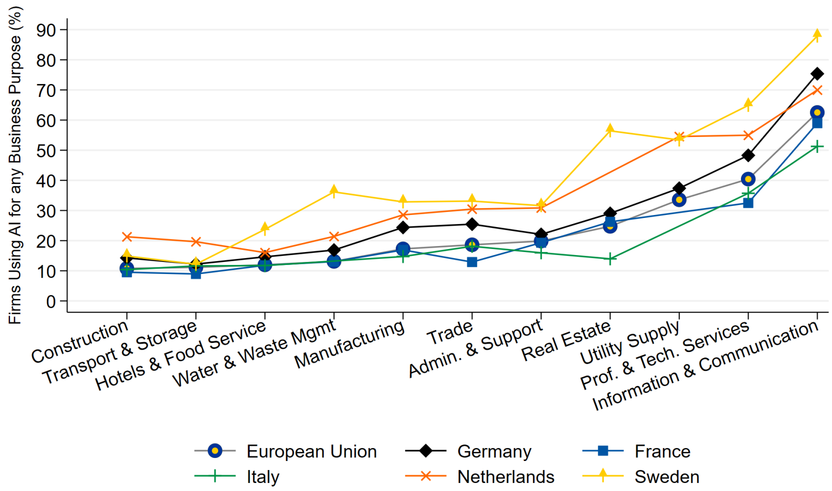
(b) EU-ICT-Household Survey



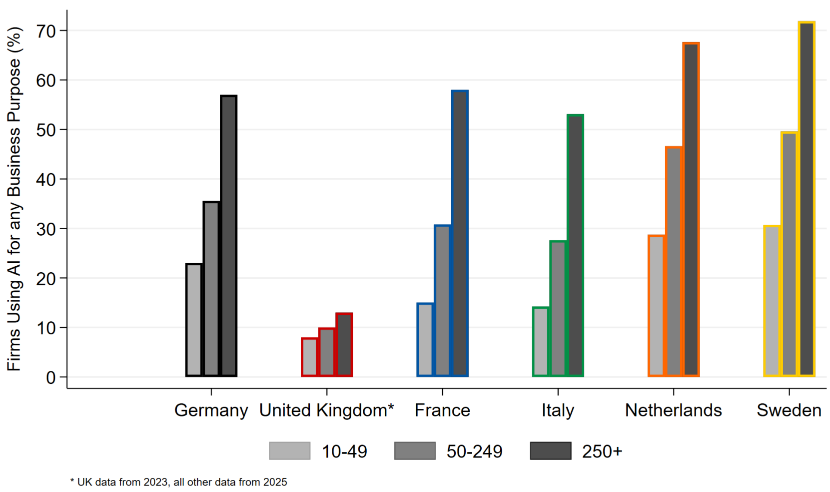
Notes: Data sources: Authors' own survey run in May-June 2025 and 2025 EU-ICT Household survey.

Figure D.8: Firm AI Adoption by Industry, and Firm Size

(a) By Industry



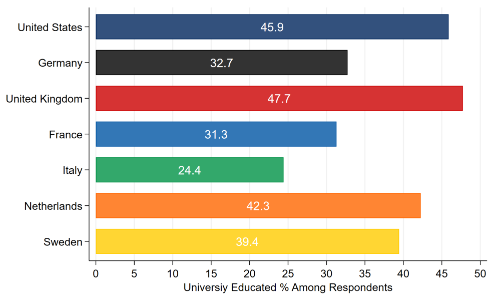
(b) By Firm Size



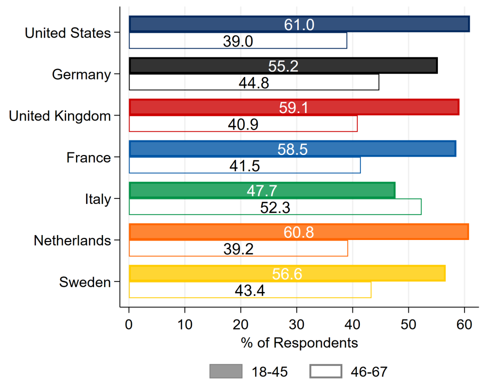
Notes: Data source: EU-ICT-Firm survey 2025 and 2023 UK Management and Expectations Survey (MES)

Figure D.9: Composition of Workers Across Countries

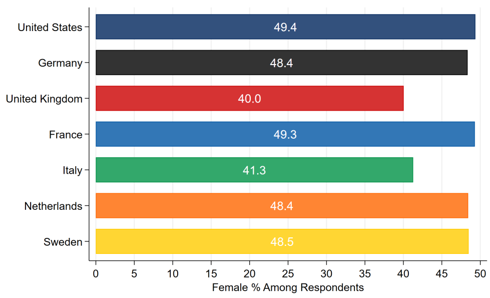
(a) Educational attainment



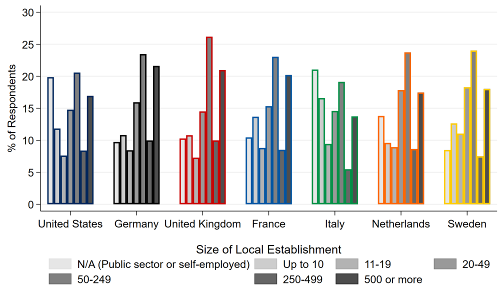
(b) Age



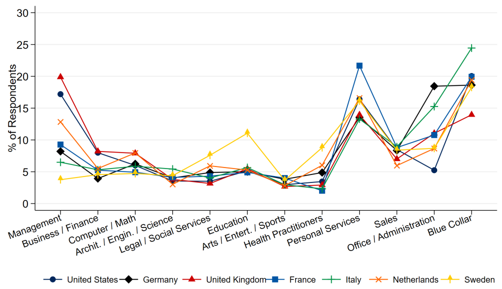
(c) Sex



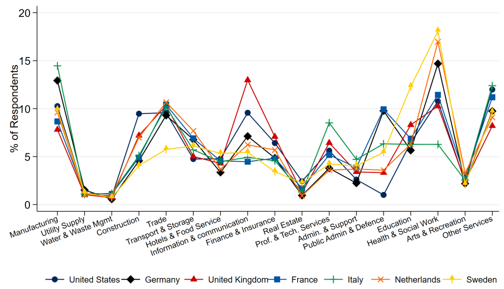
(d) Local firm size



(e) Occupation

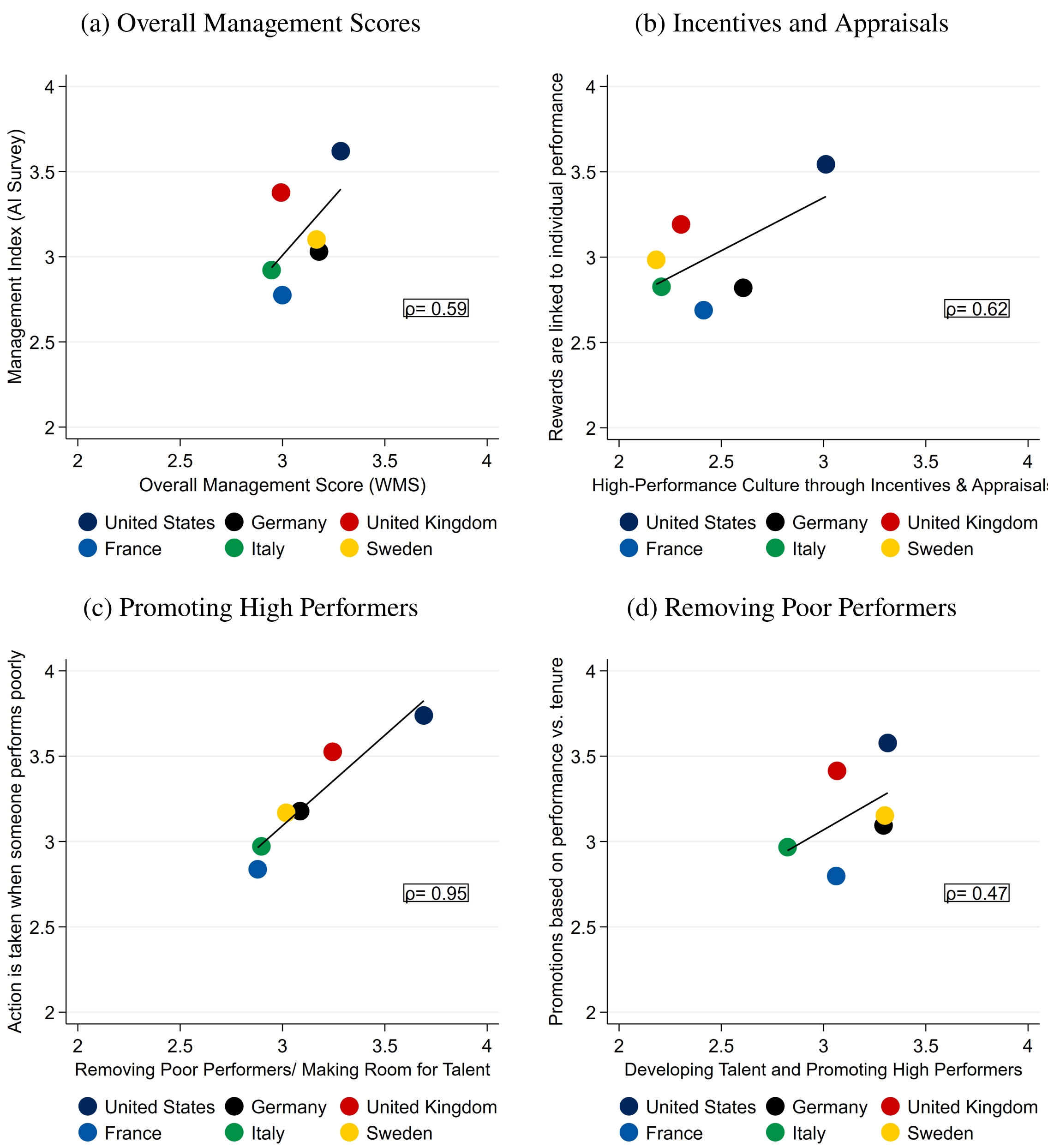


(f) Industry



Notes: Figures reports the distribution of demographics, firm size, occupation and industry of workers in our AI survey across countries. Data source: Authors' own survey on Generative AI adoption of workers in May-June 2025 and January-February 2026

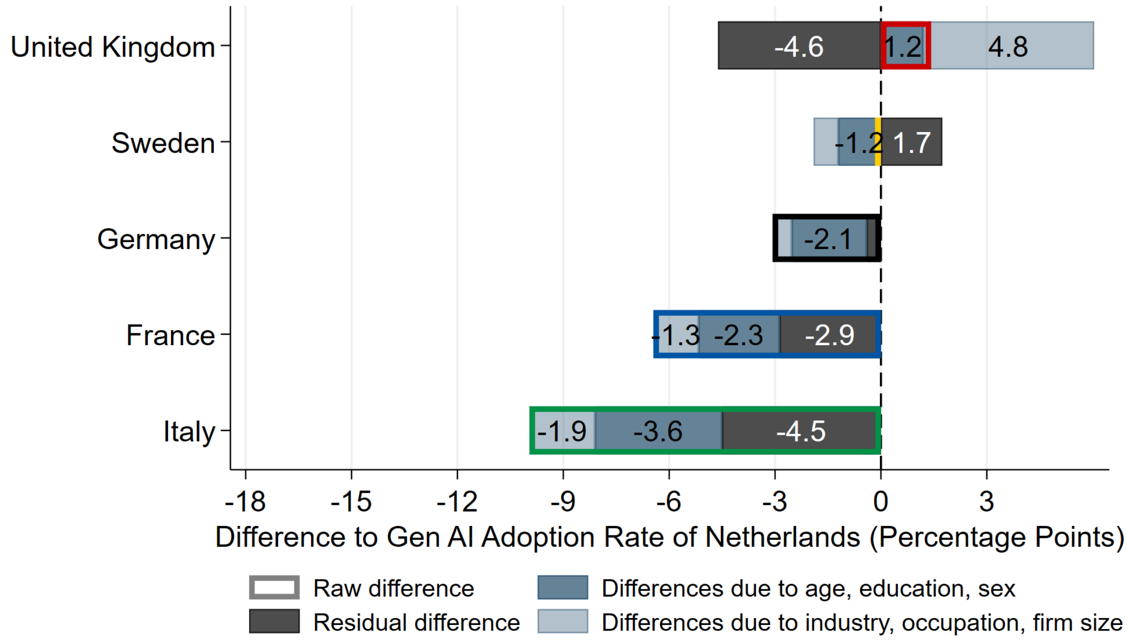
Figure D.10: Comparison of Scores in the WMS and of Management Questions in Our Survey



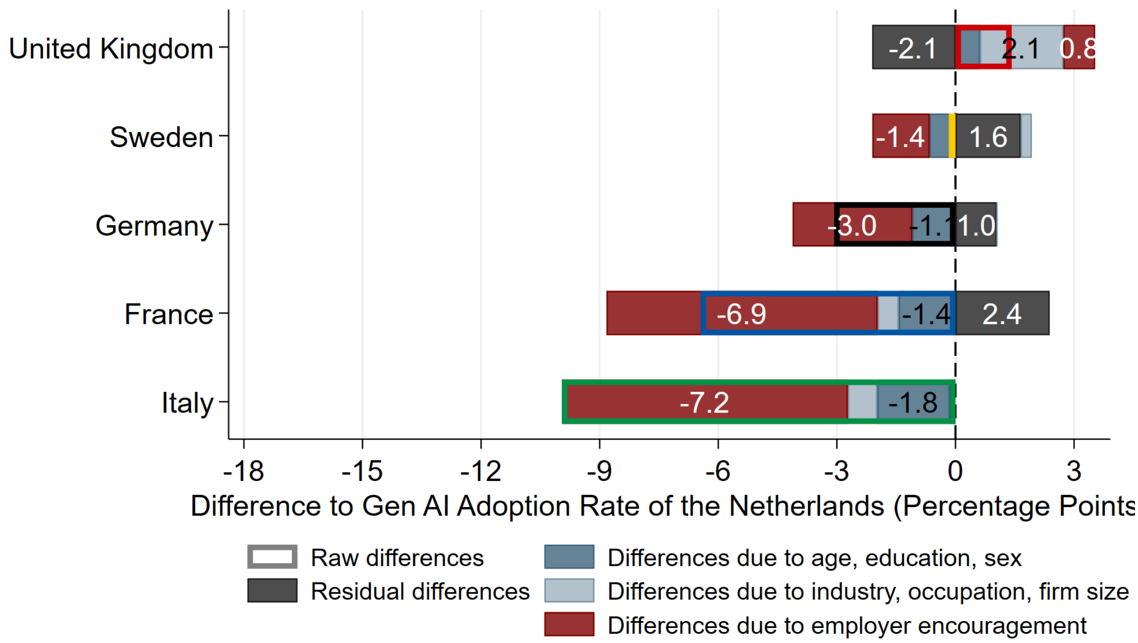
Notes: Figure compares the scores from the WMS with the scores from our worker survey. Scores from the WMS are reported on the vertical axes, scores from our worker survey on the horizontal axes. Panel (a) contains the aggregate management scores, which in our survey is based on three questions. Detailed questions in the WMS are listed in the 2010 Manufacturing Survey Instrument file. The WMS score in panel (b) is based on management question 14 in the questionnaire (*talent2 score* in the data), panel (c) on question 16 (*talent4*) and panel (d) on question 15 (*talent3*). Full wording of our question is shown in footnote 13. Sources: World Management Survey, Authors' own survey on Generative AI adoption of workers in January-February 2026

FIGURE D.11: Decomposition of Differences in AI Adoption within Europe (Netherlands as baseline)

(a) Without employer encouragement



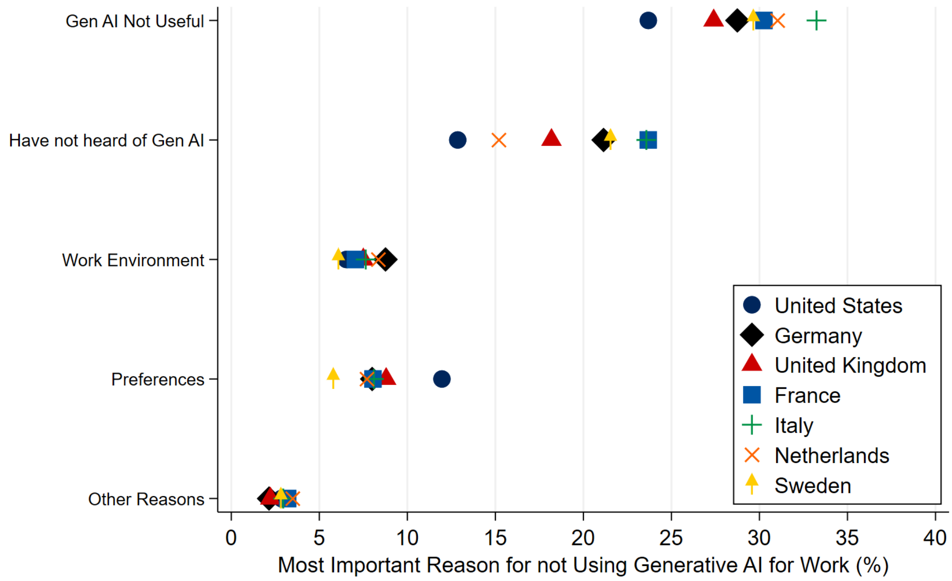
(b) With employer encouragement



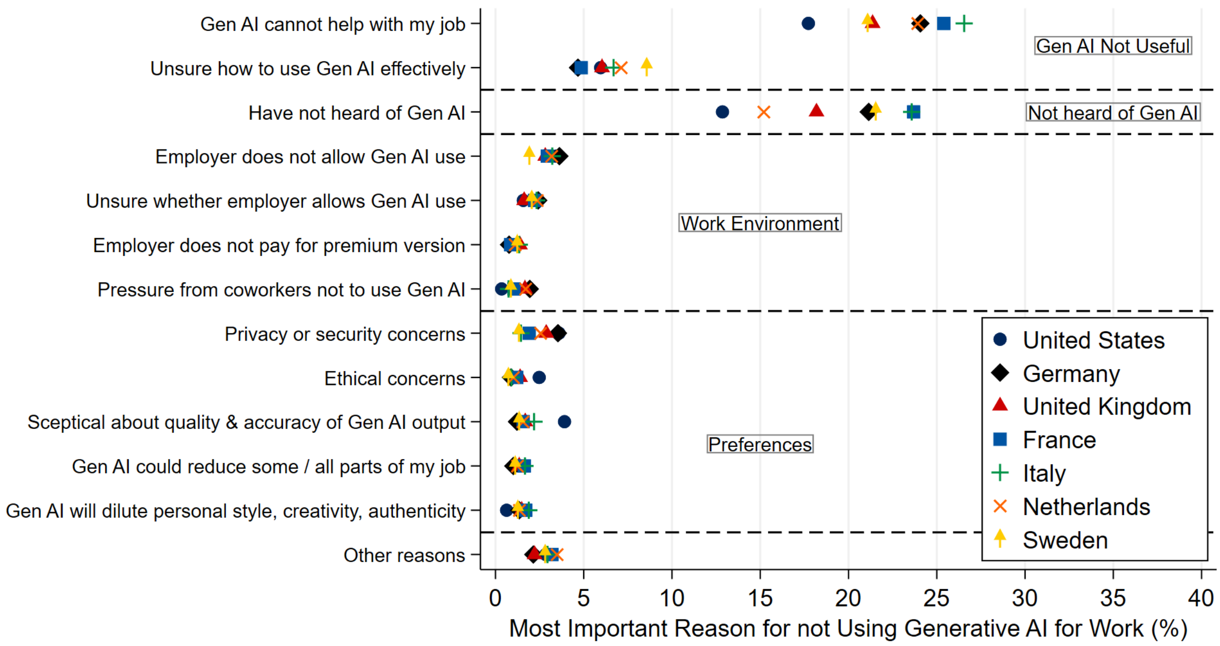
Notes: Figure shows an Oaxaca-Blinder decomposition of Generative AI adoption rates of workers in the Netherlands relative to other European countries. Dark gray represents the residual difference not accounted for by demographics, industry, occupation, firm size and employer encouragement (in the case of panel (b). The sample is restricted to workers in dependent employment (private or public sector). Figures 10 and 15 show the same decompositions with the US as the baseline country. Data source: Authors' own survey on Generative AI adoption of workers in in May-June 2025 and January-February 2026.

Figure D.12: Most Important Reason for Not Using Gen AI Among Employees

(a) Grouped Reasons

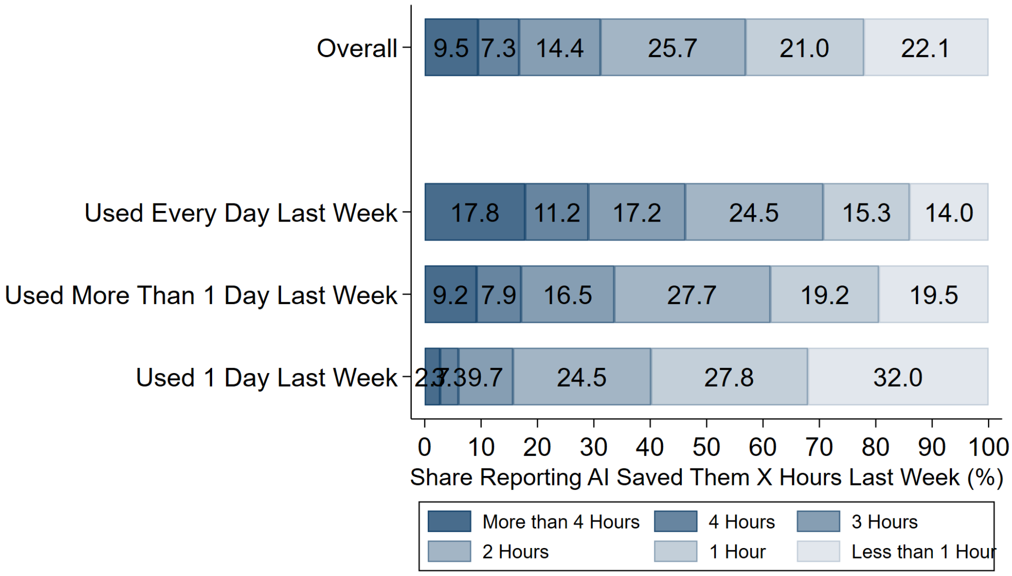


(b) All Reasons



Notes: Respondents indicating not using AI at work were asked to select among the displayed reasons why they are not using AI. If multiple reasons were selected, they were asked to indicate the most important reason. The sample is restricted to workers in dependent employment (private or public sector). Data source: Authors' own survey on Generative AI adoption of workers in in May-June 2025 and January-February 2026

Figure D.13: Reported Time Savings Due to Generative AI



Notes: Time savings from using AI are estimated by asking survey participants using AI how many more working hours they would have needed in the past week to complete the same tasks. Respondents could indicate i) less than 1 hour, ii) 1 hour, iii) 2 hours, iv) 3 hours, v) 4 hours, vi) more than 4 hours. We conservatively assumed 0 hours saved for option i) and 5 hours for option vi). Time savings are then divided by weekly working hours. Upper bar shows time savings for all AI users, bottom three bars differentiate by how many days in the previous week AI was used. The sample is restricted to last week's users. Data source: Authors' own survey on Generative AI adoption of workers in in May-June 2025 and January-February 2026