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AI adoption, productivity and employment: Evidence from European firms

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Abstract

This paper provides new evidence on how the adoption of artificial intelligence (AI) affects productivity and employment in Europe. Using matched EIBIS-ORBIS data on more than 12,000 non-financial firms in the European Union (EU) and United States (US), we instrument the adoption of AI by EU firms by assigning the adoption rates of US peers to isolate exogenous technological exposure. Our results show that AI adoption increases the level of labor productivity by 4%. Productivity gains are due to capital deepening, as we find no adverse effects on firm-level employment. This suggests that AI increases worker output rather than replacing labor in the short run, though longer-term effects remain uncertain. However, productivity benefits of AI adoption are unevenly distributed and concentrate in medium and large firms. Moreover, AI-adopting firms are more innovative and their workers earn higher wages. Our analysis also highlights the critical role of complementary investments in software and data or workforce training to fully unlock the productivity gains of AI adoption.

JEL Codes: D22, J24, L25, O33, O47
Keywords: Artificial intelligence, firm productivity, Europe, digital transformation.

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1 Introduction

Artificial intelligence (AI) is poised to transform the global economy by simultaneously affecting aggregate demand and productivity on the supply side. Yet robust evidence on its firm-level effects outside the United States (US) remains scarce. While optimistic projections predict that AI could drive productivity booms (Baily, Brynjolfsson, and Korinek, 2023), others caution that adoption barriers and productivity constraints from unbalanced growth may significantly limit the gains from AI adoption (Acemoglu, 2024; Filippucci, Gal, and Schief, 2024). Europe's position is both central and paradoxical: it boasts world-leading researchers and strong industrial capacity but suffers from a persistent and growing gap in the development of new AI technologies compared to the US and China (EIB, 2025). Understanding how AI affects European firms is therefore essential for policymakers seeking to harness its benefits while managing the associated risks.

This paper provides the first causal evidence on how AI adoption affects productivity and employment in European firms, leveraging a unique survey on EU and US non-financial firms matched to administrative financial data. We address two core questions. First, we explore the firm characteristics that predict AI adoption in Europe, which is key to characterize the selection process into using AI tools. We then investigate how AI adoption influences firm productivity and employment. The first question thus provides the empirical groundwork for a credible identification of the second.

The analysis reveals four key insights. First, AI adoption increases labor productivity by 4% on average after addressing endogeneity. Second, the gains stem from capital deepening rather than job displacement. Third, benefits are concentrated in medium and large firms – posing risks of widening inequality in the benefits from AI adoption. Fourth, the productivity gains are larger if firms carry out complementary investments in software and data or employee training. Our findings cast some doubts on claims of dramatic AI-driven job destruction, while underscoring pressing concerns about its uneven economic impact.

We leverage data of the European Investment Bank Investment Survey (EIBIS), an annual survey covering approximately 12,000 non-financial firms across the EU and 800 US non-financial firms, matched with ORBIS data on corporate financial statements. Our final sample used in the analysis is a pooled cross-section that runs from 2019 to 2024. The survey's stratified design ensures representative coverage across firm size, sector and country (Brutscher et al., 2020), while its detailed questions identify AI adoption based on whether firms use big data analytics and AI technologies in their operations. Crucially, EIBIS also captures granular firm characteristics on investment behavior, investment finance and innovation activity, enabling a rigorous analysis of both the drivers and consequences of AI adoption.

Three stylized facts emerge from the data, informing our approach for causal identification of the effects of AI. First, adoption is highly stratified: 45% of large firms (more than 250 employees) deploy AI, compared to only 24% of small firms (10 to 49 employees).[1] This echoes technology diffusion theories (Comin and Hobijn, 2010). Second, emerging EU economies (e.g., Romania, 22%) exhibit adoption rates substantially below more financially developed EU countries (e.g., Sweden, 52%) and the US (34%). Third, AI-adopting firms are more innovative in general, invest more intensively, and face tighter skilled-labor constraints – suggesting endogenous adoption patterns that require robust identification.

To establish causality, we develop a novel instrumental variable (IV) strategy inspired by the work on financial dependence and growth following Rajan and Zingales (1998). We match each EU firm with comparable US firms (same sector and size) that exhibit similar levels of innovation intensity, investment, managerial practices and external finance. We then assign the US firms' AI adoption rate as an exogenous proxy for EU firms' adoption rate. This approach leverages cross-continental variation in AI exposure, while holding firm characteristics constant, effectively isolating the effects of AI adoption. Propensity-score balancing tests confirm the validity of the identification strategy, with matched US and EU firms exhibiting near-identical distributions across key firm characteristics.

Our results show a robust causal link between AI adoption and productivity. Controlling for a wide set of country, sector and year fixed effects and observable financial variables, we find that firms adopting AI have 4% higher labor productivity. This effect is economically significant and aligns with mid-range macroeconomic projections recently reported in the literature (Acemoglu, 2024; Bergeaud, 2024), rather than with optimistic "productivity boom" scenarios (Baily, Brynjolfsson, and Korinek, 2023). Crucially, the gains reflect capital deepening: AI augments worker output without reducing employment, consistent with micro-level evidence of AI-aided efficiency gains in cognitive tasks (Noy and Zhang, 2023; Gambacorta et al., 2024). Moreover, we find that workers in

[1] The shares are calculated using value added (VA) weights.

AI-adopting firms have so far benefited from higher wages. The productivity benefits are unevenly distributed, with medium and larger firms experiencing significantly higher productivity gains than their smaller peers. The stratification highlights concerns that AI could exacerbate income gaps (Cazzaniga et al., 2024; Cornelli, Frost, and Mishra, 2023), particularly given Europe's SME-dominated industrial structure.

The findings carry significant implications for European policy makers seeking to harness the productivity-enhancing potential of AI while ensuring inclusive and balanced growth. Given the disruptive nature of AI and the higher returns associated with AI adoption for larger companies, a balanced policy approach should focus on creating an environment suitable for small and innovative firms' growth, accompanied by targeted incentives to fully exploit the benefits of AI adoption. In this context, developed financial markets play a crucial role.

Our results also highlight the importance of complementary investments in intangible assets – particularly software and data or workforce training – in realizing AI's productivity dividends. To maximize the returns from AI deployment, public policy must go beyond hardware subsidies and incentivize firm-level investment in integration, workflow redesign, and continuous learning. Workforce re-skilling programs should prioritize "fusion skills", such as prompt engineering, data stewardship and human-in-the-loop decision-making that enhance human-AI complementarity.

The structure of the paper is as follows. Section 2 reviews the related literature on AI adoption, productivity and labor market effects. Section 3 describes the data and presents stylized facts that motivate the empirical strategy. Section 4 outlines our identification approach and empirical methodology. Section 5 reports the main results on productivity and employment, along with several robustness checks. Section 6 concludes by discussing policy implications and avenues for future research.

2 Related literature

Our study engages with three interconnected strands of research on AI and its economic implications. First, the literature on firm-level technology adoption provides critical frameworks for understanding AI diffusion patterns. Seminal studies by Comin and Hobijn (2010) and Comin and Mestieri (2018) establish that technological innovations diffuse unevenly across countries, with adoption lags determined by human capital and predecessor technologies – a pattern we observe in Europe's AI uptake. Recent studies by Babina et al. (2024) and Bonney et al. (2024) document robust AI adoption among US firms, particularly large innovators in knowledge-intensive sectors. Yet evidence for non-US firms remains sparse, with Rückert, Weiss, and Revoltella (2020) being a notable exception that documents Europe's adoption gap with the US.

Our paper extends this work by demonstrating how capital intensity, the financial dependence theory of Rajan and Zingales (1998) and firm size mediate AI adoption in Europe – findings that align with the analysis of technology-job complementarities of Acemoglu et al. (2022). This seems particularly relevant in the context of the growing importance of AI adoption for EU labor markets. Using occupation-level data for 16 European countries over 2011-2019, Albanesi et al. (2024) document that employment shares increase in occupations more exposed to AI, with the strongest gains in occupations employing younger and higher-skilled workers.

Second, research on the productivity effects of AI highlights stark contrasts between macroeconomic projections and microeconomic evidence. Most macro studies suggest relatively modest aggregate effects: for example, Acemoglu (2024) estimates only 0.07% US annual growth in total factor productivity over a decade, while the general equilibrium model of Filippucci, Gal, and Schief (2024) shows how Baumol's disease effects could limit gains to 0.2–0.6 percentage points annually. In contrast, micro-level field experiments report large efficiency improvements in the short run: Noy and Zhang (2023) and Brynjolfsson, Li, and Raymond (2025) find 14–40% productivity gains in writing and customer service tasks, with Gambacorta et al. (2024) showing similar effects for coding. Our results reconcile this divergence: we identify a causal 4% labor productivity gain at the firm level, echoing the mid-range estimates of Bergeaud (2024), while confirming that micro efficiency improvements are not fully reflected in aggregate growth due to adoption frictions.

Third, the literature on distributional effects underscores the unequal impact of AI across workers, firms, and regions. Cazzaniga et al. (2024) predicts widening income inequality due to AI-skilled labor complementarity, while Hennig and Khan (2025) warns of cross-country divergence as AI benefits concentrate in advanced economies. The concerns resonate with evidence that technology diffusion gaps explain at least 25% of global income differences (Comin and Mestieri, 2018). Our heterogeneity analysis validates these predictions, showing larger productivity gains in medium and large firms compared to micro and small enterprises.

Our contribution bridges these strands by: (i) providing the first causal evidence on the effects of AI adoption on firm productivity and employment effects in Europe, addressing gaps noted by Aldasoro et al. 2024, (ii) developing a novel IV strategy that extends Rajan and Zingales (1998)'s financial dependence approach to technology diffusion, (iii) presenting evidence of capital-deepening, rather than labor-replacing, effects that can contribute to refining Aghion and Bunel (2024)'s growth theories, and (iv) discussing which investment strategies enable the productivity dividends of AI.

3 Data

We use data from the European Investment Bank Investment Survey (EIBIS), an annual survey initiated in 2016 encompassing approximately 12,000 non-financial corporations across the EU. This survey employs a stratified random sampling method, targeting firms in all 27 EU countries.[2] Since 2019, EIBIS also covers a sample of 800 firms in the US, allowing for a comparison of investment dynamics between the EU and the US. The respondents to the interviews are senior managers or financial directors with responsibility for investment decisions and how investments are financed – for example, the owner, chief financial officer or chief executive officer. Brutscher et al. (2020) provide evidence that EIBIS is representative of the business population in the EU, as described by Eurostat's Structural Business Statistics.

Since 2019, firms participating in EIBIS are asked about the use of big data analytics and AI. In the EIBIS questionnaire, big data analytics and AI are defined as technologies that intelligently automate tasks and provide insights that augment human decision making, like machine learning, robotic process automation, natural language processing (NLP), algorithms, neural networks. Firms are asked the following question: "To what extent, if at all, are big data analytics and artificial intelligence used within your busi-

[2]The EIBIS sample is stratified disproportionally by country, sector and firm size class, and proportionally by region within each country. The firms have at least five employees, with both full-time and part-time employees being counted as one employee, and employees working less than 12 hours per week being excluded. An enterprise is defined as a company trading as its own legal entity. As such, branches are excluded from the target population. However, the definition is broader than in a typical enterprise survey because some company subsidiaries are their own legal entities.

ness? A. Not used in the business. B. Used in parts of the business. C. Entire business is organized around this technology." We define AI adopters as firms that use big data analytics and AI in parts of the business or if the entire business is organized around AI.

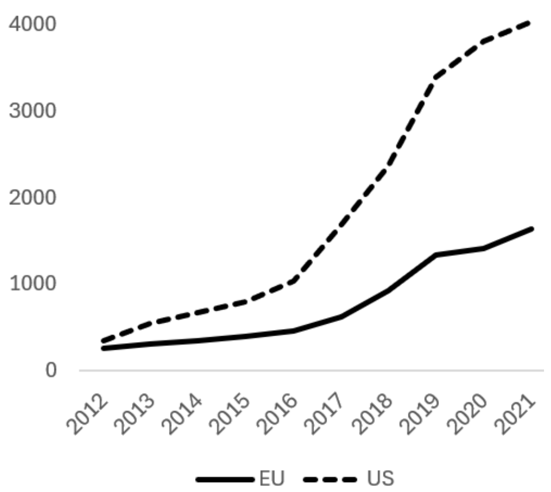
EIBIS provides a comprehensive dataset that captures a wide spectrum of firm-level characteristics and investment-related information across surveyed firms. It includes quantitative data – such as annual turnover, number of employees, value of fixed assets, total wages, investment in different categories of tangible and intangible assets – as well as demographic data, for instance on firm age and sector, offering a deep understanding of the structural profile of businesses. Beyond these metrics, EIBIS also gathers qualitative insights through survey responses, shedding light on firms' internal perceptions and strategic outlooks. This includes assessments of managerial competencies, financing strategies, perceived barriers to invest and investment focus.

To enrich and validate the self-reported survey data, EIBIS is complemented by administrative financial information sourced from Moody's ORBIS database. This integration allows for a more robust analysis by incorporating detailed financial statements on balance sheets and profit and loss accounts. The combination of subjective perceptions and objective financial data enables a better understanding of investment dynamics and firm performance in different sectors, countries and market segments.

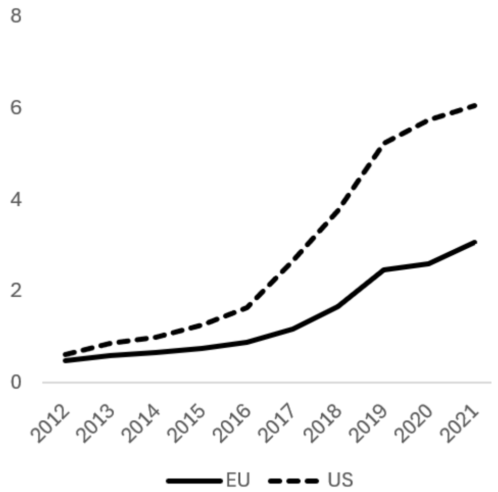
3.1 Descriptive statistics and stylized facts

AI innovation in Europe continues to lag behind the United States. In particular, the EU trails the US in the number of AI-related patents, with the gap widening further after the pandemic (EIB, 2025). While the absolute number of AI patents is higher in the US than in the EU (Figure 1a), the higher share of AI patents relative to total patents also underscores the stronger specialization in AI innovation in the US (Figure 1b).

Figure 1: AI patents



(a) AI patents in domestic portfolio (count).



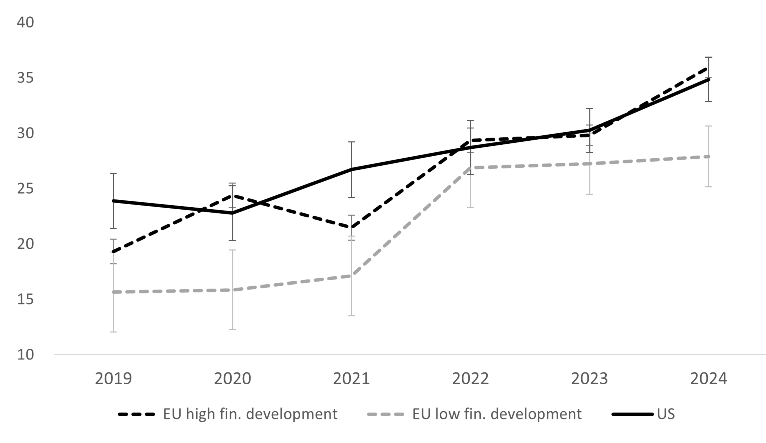
(b) Share AI patents in total domestic portfolio (%).

Note: AI patents are a subdomain of the digital patent classification based on EPO (2017). *Source:* PATSTAT.

The picture is somewhat more nuanced when looking at AI deployment and adoption. On average, AI adoption levels are similar in the EU and the US. Nevertheless, as shown in Figure 2, the share of firms using big data and AI technology is structurally lower in EU countries with low financial development.[3] There was a relatively strong catch-up in less financially developed countries in 2022 (from 17% in 2021 to 27% of firms in 2022), but a gap has opened up again in 2023-24 as adoption has remained flat. EU countries with high financial development have a similar share of firms adopting AI as in the US for the period 2019-24.

[3]The classification is based on the index of financial development proposed by Betz et al. (2025). The index uses financial market data from 2015 to 2023 and consists of two composite indicators: (i) financial market size and integration, and (ii) financial market depth. The group of EU countries with high financial development includes: Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Luxembourg, Netherlands, Poland, Spain, and Sweden. The group of EU countries with low financial development includes: Bulgaria, Croatia, Cyprus, Czechia, Estonia, Greece, Hungary, Malta, Latvia, Lithuania, Portugal, Romania, Slovakia, and Slovenia.

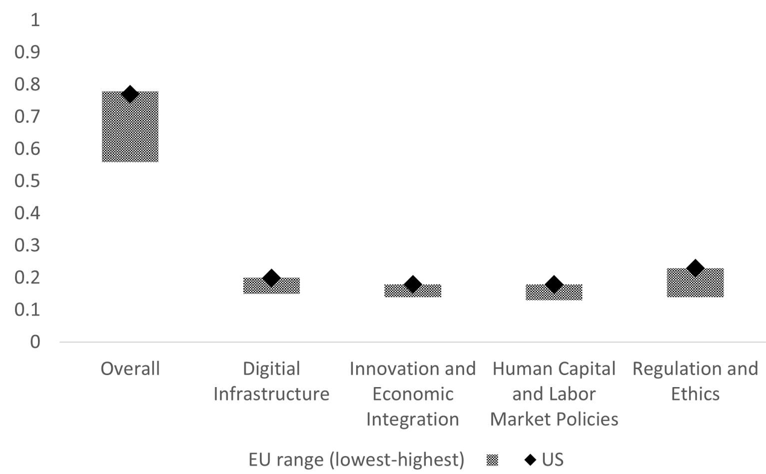
Figure 2: Use of big Data Analytics and AI (% of firms)



Note: Average share of firms reporting to use AI by country groups, controlling for firms' sector. The error bars represent 95% confidence intervals. *Source:* EIBIS 2019-2024.

Beyond EIBIS data, a benchmark indicator of AI preparedness points to the US being more conducive to AI adoption and better suited to make the most of it. Figure 3 shows the IMF's AI preparedness index, which measures how ready countries are to adopt AI based on factors like digital infrastructure, human capital, innovation, and regulation (Cazzaniga et al., 2024). Across the key categories of the index, the US scores lie in the upper range of scores for the European countries in our sample.

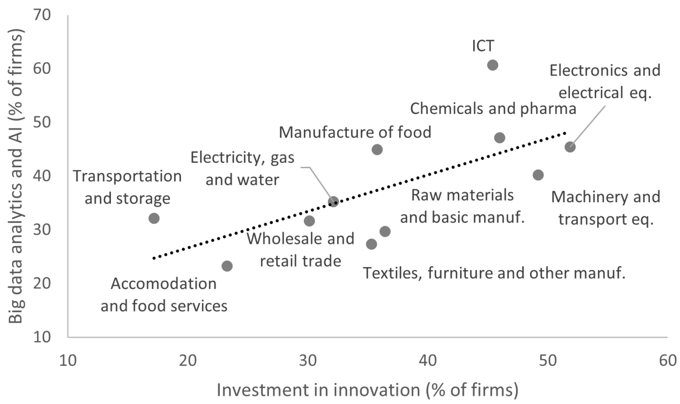
Figure 3: AI Preparedness Index



Note: The AI Preparedness Index for the EU ranges from the minimum to the maximum across EU countries. *Source:* Cazzaniga et al. (2024).

Beyond cross-country differences, AI adoption also varies significantly across sectors. This variation is driven by several structural and operational factors that influence both the applicability and the perceived benefits of AI technologies. Sectors such as Information and Communications Technology (ICT) and manufacturing tend to be early adopters due to their high data intensity, well-established digital infrastructure, and clear use cases for automation and predictive analytics. These industries often possess the technical capabilities and investment capacity required to integrate AI into core business processes, unlike a sector like accommodation and food services, where firms are significantly smaller on average. Some sectors may thus face greater barriers to adoption, including lower levels of digital maturity, limited availability of structured data, and fewer standardized AI applications. Additionally, the regulatory environment, workforce skill levels and cultural openness to technological change play a critical role in shaping sectoral adoption patterns. For example, stringent data privacy regulations can slow down implementation. The cross-sector differences are illustrated by the strong correlation between investment in innovation and AI adoption. Figure 4 shows AI uptake across EU firms, broken down by 12 sectors and corresponding innovation levels. While high-tech sectors – such as ICT and pharmaceuticals – are unsurprisingly among the highest adopters, some traditional sectors, like food manufacturing, also show above-average levels of AI uptake.

Figure 4: AI and investment in innovation by industrial sector (% of firms, 2024)



Note: Firms are weighted by value added. *Source:* EIBIS 2024.

On a more granular level, there are several firm-level factors which correlate with AI adoption. To keep the list transparent and manageable, we group EIBIS and ORBIS variables into stylised groups in terms of financial and non-financial metrics, which help to distinguish between AI adopters and non-adopters. Table 1 reports that firms adopting AI are larger on average, invest more per employee, are more innovative and are more likely use strategic business monitoring systems. They also tend to have less problems with access to finance, since they are more likely to rely on alternative sources of financing, such as equity or bonds, they are more likely to be publicly listed, and they are less likely to be finance constrained.

Table 1: Descriptive statistics

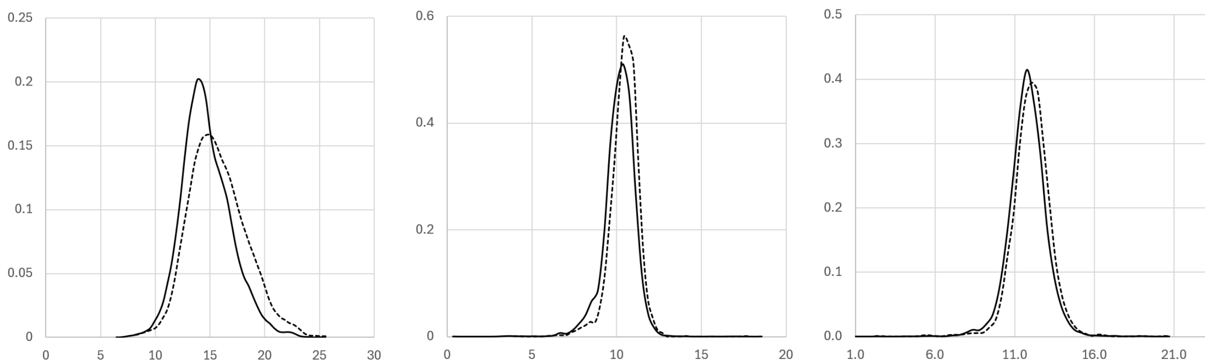
		AI	**Non-AI**	**All firms**			
		Mean	**Mean**	**Obs**	**St. Dev.**	**p10**	**p90**
Productivity	Labor productivity (log)	12.1	11.9	59,208	1.10	10.6	13.2
Age	Young (less than 10 years)	0.06	0.08	60,868	0.26		
Size	SMEs	0.29	0.52	60,868	0.50		
	Size (log of total assets)	17.6	16.4	47,414	2.10	13.8	19.3
Investment	Investment/employee (log)	8.80	8.30	53,058	1.70	6.20	10.5
	Fixed assets growth	0.13	0.13	46,033	0.75	-0.18	0.38
Access to finance	Newly issued bonds/equity	0.04	0.01	60,868	0.14		
	Publicly listed	0.04	0.01	60,567	0.14		
	Financial leverage (debt/total assets)	0.23	0.20	37,886	0.24	0	0.51
	Financial constraints	0.05	0.06	58,013	0.23		
Innovation	Innovator	0.49	0.37	59,448	0.49		
	Innovation new to the country	0.06	0.03	59,448	0.20		
	Innovation new to the global market	0.11	0.06	59,448	0.26		
Management	Business monitoring system	0.71	0.46	59,453	0.50		
	Profitability (EBITA/total assets)	0.13	0.11	41,863	0.15	0	0.26
	Profitability (Net income/total assets)	0.07	0.06	41,678	0.14	-0.04	0.20

Note: Labor productivity is calculated as turnover per employee. Innovators are companies which developed or introduced new products, processes or services that can be new to the company, the country or the global market. Business monitoring systems describe firms using a formal strategic business monitoring system that compares the firm's current performance against a series of strategic key performance indicators (KPIs). *Source:* EIBIS 2019-2024.

The heterogeneity in AI development and adoption between the US and EU is at the core of our empirical approach. By leveraging detailed survey and financial data, our analysis aims to capture the exogenous component of AI adoption for EU firms, using data on similar firms in the US. This approach helps mitigate endogeneity bias in the subsequent regression analysis, which may arise if AI adoption is correlated with unobserved firm-specific factors, such as managerial quality, innovation culture or strategic priorities. By using AI adoption patterns in the US – where firms operate under different institutional and policy environments – as a benchmark, we isolate variation in AI uptake that is plausibly exogenous to the EU context. This cross-country comparison allows us to construct an instrumental variable or control function that reflects external drivers of AI adoption, thereby improving the causal interpretation of our estimates.

Last but not least, we explore the link between AI adoption and productivity in a stylized distributional exercise. Figure 5 compares the distribution of firm size, average wage per employee and labor productivity for firms that adopted AI and those that did not. The distributions for firms using AI are shifted to the right. Firms that have adopted big data and AI technologies are, on average, larger (in line with descriptive evidence discussed above), pay higher wages and have slightly higher productivity. This provides preliminary evidence that firms that use AI tend to perform better than other companies.

Figure 5: Distributions of firm characteristics for firms using AI (dashed) and firms not using AI (solid line)



(a) Firm size. (b) Average wage. (c) labor productivity.

Note: The graphs show the distributions net of country and sector fixed effects. Firm size is measured using the logarithm of total assets. EU firms only. *Source:* EIBIS 2019-2024.

4 Empirical methodology

We estimate the causal impact of AI adoption on firm-level productivity with a two-stage empirical strategy using EIBIS data. Our primary specification is a linear probability model, which allows for a straightforward interpretation of the marginal effects of AI adoption on the likelihood of observing productivity improvements. The identification challenge is that AI adoption is potentially endogenous, i.e. firms that are more productive or better managed may be more likely to adopt AI technologies, leading to biased estimates if not properly addressed.

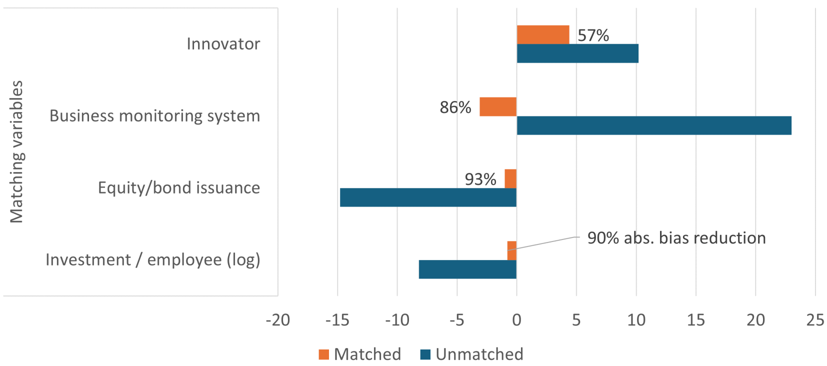
To mitigate endogeneity concerns, we develop an identification strategy inspired by Rajan and Zingales (1998). Their seminal insight is that characteristics measured in a benchmark economy can serve as an exogenous source of variation when applied to other countries. Whereas Rajan and Zingales (1998) assign US sectoral rankings of financial dependence to all countries, we extend this logic using a more granular, firm-level design. Specifically, we construct an external proxy for AI exposure by matching each EU firm to a set of comparable US firms – similar in sector, size class, investment intensity, innovation activity, financing structure and management practices – and transferring the US firms' AI adoption scores to the EU firm. Because US firms operate in a technological and institutional environment that is arguably exogenous to the EU, the matched US adoption measure captures the component of AI exposure that is unrelated to EU-specific policies, economic conditions or unobserved firm characteristics. This firm-level matching approach, which exploits cross-continental variation while tightly conditioning on underlying fundamentals, refines earlier sector-level strategies, such as the use of US sectoral AI adoption rates as in Gambacorta et al. (2025).

The matching between EU and US firms is implemented using a stratified propensity score matching (PSM) approach, which ensures comparability across firms based on observable characteristics. Building on the firm characteristics reported in Section 3.1, our strategy is the following. We stratify firms by two main categorical dimensions that seem to be crucial for AI adoption: sector and size class. Within each stratum, we match firms on variables for which the observed difference is the highest between AI and non-AI firms, as reported in Table 1. The chosen four key covariates are: (i) investment intensity per employee (in log), (ii) a binary indicator for whether a company issued bonds or equity, (iii) a binary indicator for innovation activity, and (iv) a binary indicator for the use of a strategic business monitoring system. The variables are not only motivated by our initial investigation of the main drivers of AI adoption in the previous Section but are also closely linked to the literature on firm productivity and technology adoption, highlights the importance of financial capacity, innovation orientation and managerial quality as determinants of both AI adoption and productivity outcomes (Bloom, Sadun, and Van Reenen, 2016; Hall, 2010).[4]

[4] We confirm that the selected variables have high predictive power over AI adoption decisions in the EU and US, using a stylized linear regression model. The results are presented in Table B.1 in the Appendix.

The use of stratified PSM helps us to address selection bias by ensuring that matched firms are similar in terms of observable characteristics that jointly influence both AI adoption and productivity. Moreover, by using US firms as a benchmark, we exploit variation in AI adoption that is plausibly exogenous to EU-specific institutional or policy environments. This strategy enhances the credibility of our identification and allows us to interpret the estimated effects as causal under the assumption of conditional independence (Rosenbaum and Rubin, 1983; Dehejia and Wahba, 2002).[5]

Figure 6: Balancing properties before and after matching



Note: The bars present the standardized percentage biases before and after matching for the selected variables, with the numbers highlighting the absolute bias reduction after matching (positive values mean that EU firms score higher). For each EU firm, the matched sample includes the five nearest-neighbour US firms based on propensity scores calculated using the specified matching variables. *Source:* EIBIS 2019-2024.

Overall, our matching procedure is effective, as evidenced by the substantial reduction in covariate imbalances between EU and US firms. Prior to matching, US firms exhibit a significantly higher investment intensity – by approximately 8.2 percent – compared to their EU counterparts. After matching, this difference narrows to just 0.8 percent, representing a 90% reduction in the initial gap (Figure 6). Similar improvements are observed across all other matching variables, indicating that the matched US firms closely

[5]We use the k-nearest neighbour approach to find the best possible match between US and EU firms. We choose $k = 5$ to balance the trade-off between having enough variation for a reasonable match while reducing potential overlap across matches. Lower values of k risk putting too much weight on any given US company. In turn, since our sample of US firms is considerably smaller than that of EU firms, expanding the set of nearest neighbours used for matching risks a high degree of overlap in the matching for any given pair of EU firms. Nonetheless, our main results remain robust to matching procedures with $k = 3$ and $k = 7$.

resemble EU firms in terms of observable characteristics.[6]

We run pooled cross-section regressions to investigate the effects of AI adoption on labor productivity and employment :

$$y_{it} = \beta_1 Adopter_{it} + \beta_{\mathbf{2}} \mathbf{X_{it-1}} + \nu_{age} + \phi_{size} + \mu_{cst} + \epsilon_{it}, \tag{1}$$

where i denotes the firm and t the year. The dependent variable y_{it} is either labor productivity or employment at the firm level. The explanatory variable $Adopter_{it}$ takes value 1 for AI-adopting firms and 0 otherwise (either the actual series or the AI adoption instrumented after matching with US firms, as discussed above)[7] and $\mathbf{X_{it-1}}$ is a vector of controls which includes investment, profitability, financial leverage and the logarithm of total assets (all lagged by one period to moderate simultaneity effects). We add a full set of fixed effects, including (i) size groups $\phi_{size} \in \{micro, small, medium, large\}$ to control for the possibility that AI adoption differs for different size categories, (ii) age groups $\nu_{age} \in \{< 5y, 5 - 10y, 10 - 20y, > 20y\}$ to account for potentially confounding variation that may be a function of firm age, and (iii) country-sector-wave fixed effects to absorb possible idiosyncratic shocks in AI adoption rates across firms in the same country-sector-time group. We control for the three sets of fixed effects in all specifications.[8]

To investigate potential heterogeneity in the effects of AI adoption on labor productivity, we augment Equation (1) by introducing interaction terms between AI adoption and two key dimensions: (i) firm size group and (ii) the share of investment allocated to different categories of tangible and intangible assets. For the latter, we use EIBIS reported data on investment in the last financial year (divided by total assets) attributed to any of the six categories: (i) land and buildings, (ii) machinery and equipment, (iii) research and development, (iv) data, software and IT, (v) training and (vi) business processes and organization.

When estimating regressions, it is important to account for the fact that we use

[6]The effectiveness of the matching procedure is further supported by the strong explanatory power of matching covariates in accounting for differences in AI adoption rates between US-matched and non-matched firms, as documented in the Appendix.

[7]Since the matching algorithm uses k-nearest neighbors, a US-matched value is set to 1 if the majority of the nearest neighbors are AI adopters, and 0 otherwise.

[8]Even in the presence of an exogenous instrument, there may still be unobserved global shocks or sectoral trends affecting both US and EU firms. We account for this by running the baseline model with different set of fixed effects in Table B.2 in the Appendix. In particular, we separate country-wave from sector-wave fixed effects.

predicted values of AI adoption, which must be reflected in the standard errors of the OLS estimator. In our setting, AI adoption is constructed through a nonparametric matching procedure, which complicates the derivation of a closed-form or plug-in correction for standard errors. To address this issue of inference, for the main regressions with US-matched adoption rates, we report bootstrap standard errors, which is a valid procedure in this context. Specifically, we generate 500 bootstrap replications by resampling US firms with replacement within each size and sector stratum, while keeping the EU sample fixed. For each bootstrap replica, the matching is re-performed for every EU firm, and the same OLS specification as presented in Equation (1) is re-estimated. Standard errors are then computed from the bootstrap replications.[9] In other specifications, we report standard errors clustered at the country-sector-wave level.

5 Results

Table 2 presents our main results. The first two columns use labor productivity (LP) as the dependent variable and the actual AI adoption rates of EU firms as the key explanatory variable of interest, without and with controls respectively. The results from column (1) suggest that, conditional on size, age and country-sector-wave fixed effects, adoption by EU firms raises labor productivity by about 16%, a very large number even when considering it is a one-off increase estimated from a pooled cross-section of firms over a period of five years. When controlling for time-varying firm-specific characteristics such as investment, profitability, leverage and size, the effect of adoption is significantly reduced in size but remains statistically significant. The estimates from column (2) suggest that more profitable and larger firms tend to have higher labor productivity, whereas more leveraged firms exhibit lower productivity.

The third and fourth columns present our key results, when using predicted AI adoption through the matching procedure using US firms described in Section 4. The estimates in column (3) do not include firm controls and suggest that the effect of instrumented AI adoption on labor productivity remains high, as in column (1). When controlling for firm characteristics, the effect of AI adoption on firm-level labor productivity is reduced but remains statistically significant. The estimate shows that AI adoption leads to an

[9]Table 2 reports statistical significance based on the normal approximation, although the results remain robust when using empirical p-values.

increase in labor productivity by 4% when instrumenting for AI adoption – a plausible figure that aligns with the more moderate effects found in the literature and discussed in Section 2. For the firm-specific controls, the results remain consistent with those in column (2). An exception is investment, which is now also statistically significant and positive (i.e. firms that invest more are also more productive).

Table 2: Effects of AI adoption on labor productivity

	(1) LP (log) No controls	(2) LP (log) With controls	(3) LP (log) No controls	(4) LP (log) With controls
AI adoption (actual)	0.162***	0.028***		
	(0.011)	(0.011)		
AI adoption (US-based)			0.156***	0.041***
			(0.03)	(0.019)
Investment (lagged)		0.009*		0.009***
		(0.005)		(0.003)
Profitability (lagged)		0.590***		0.618***
		(0.038)		(0.019)
Financial leverage (lagged)		-0.178***		-0.151***
		(0.025)		(0.012)
Total assets (log, lagged)		0.386***		0.386***
		(0.006)		(0.002)
Size FE	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes
Country-sector-wave FE	Yes	Yes	Yes	Yes
Observations	53730	35648	44844	30228
R-squared	0.373	0.541	0.380	0.551
Adjusted R-squared	0.352	0.519	0.355	0.526

Note: The dependent variable is labor productivity, calculated as the log of turnover per employee, and is derived from EIBIS. AI adoption (actual) is the EIBIS-reported AI implementation status. AI adoption (US-matched) is the AI implementation status derived from similar firms in the US. Investment is expressed as the annual change in total fixed assets. Profitability is the ratio of EBIT to total assets. Financial leverage is the ratio of loans and long-term debt to total assets. All control variables come from ORBIS and are lagged by 1 year. Standard errors clustered at the country-sector-wave level in columns (1) and (2), and bootstrapped in columns (3) and (4) are reported in parentheses. *, **, *** correspond to 0.1, 0.05 and 0.01 significance levels, respectively.

Table 3: Effects of AI adoption on employment

	(1) Empl. (log) No controls	(2) Empl. (log) With controls	(3) Empl. (log) No controls	(4) Empl. (log) With controls
AI adoption (actual)	0.125***	0.079***		
	(0.006)	(0.006)		
AI adoption (US-based)			0.053***	-0.012
			(0.010)	(0.010)
Investment (lag)		-0.003		-0.003
		(0.003)		(0.003)
Profitability (lag)		0.153***		0.167***
		(0.019)		(0.022)
Financial leverage (lag)		0.034**		0.045***
		(0.014)		(0.015)
Total assets (log, lag)		0.178***		0.189***
		(0.003)		(0.003)
Size FE	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes
Country-sector-wave FE	Yes	Yes	Yes	Yes
Observations	55020	36259	45340	30446
R-squared	0.915	0.926	0.912	0.924
Adjusted R-squared	0.912	0.922	0.908	0.920

Note: The dependent variable is the log of number of employees and is derived from EIBIS. AI adoption (actual) is the EIBIS-reported AI implementation status. AI adoption (US-matched) is the AI implementation status derived from similar firms in the US. Investment is expressed as the annual change in total fixed assets. Profitability is the ratio of EBIT to total assets. Financial leverage is the ratio of loans and long-term debt to total assets. All control variables come from ORBIS and are lagged by 1 year. Standard errors clustered at the country-sector-wave level are reported in parentheses. *, **, *** correspond to 0.1, 0.05 and 0.01 significance levels, respectively.

We next examine whether the improvement in labor productivity stems from a reduction in employment. The results indicate that this is not the case. Table 3 reports the results, following a structure similar to Table 2, but with the logarithm of employment as the dependent variable. When using the actual series of AI adoption, the estimates suggest a positive effect on employment of 8% without controls (column (2)). In contrast, when instrumenting AI adoption using our PSM strategy and controlling for firm characteristics, we find no significant effect on employment (column (4)).

Taking the results from Tables 2 and 3 together begs the question whether the increase in labor productivity translates into benefits for workers. Table 4 addresses this issue by replicating our main regression with controls and all fixed effects, but using either the total wage bill or the average wage per employee, both at the firm level. The results show that AI-adopting firms display higher wages (overall and per employee) than non-adopting firms, after controlling for age, size and country-sector-wave fixed effects. The results suggest that productivity gains have so far benefited employees. It remains to be seen whether the patterns will hold in the medium to long term.

Our empirical analysis yields three key insights regarding AI adoption by non-financial firms in Europe. First, the instrumental variable estimates confirm a positive causal effect of AI adoption on labor productivity. AI adoption raises productivity by 4%, an effect that remains statistically significant even after controlling for firm-specific characteristics such as investment intensity, profitability, leverage and size.[10]

While direct comparisons with the macroeconomic literature are not straightforward – given that our results focus on labor productivity and reflect a one-off effect, whereas macro studies typically estimate long-run impacts on total factor productivity (TFP) – our findings appear more consistent with mid-range projections (e.g., Bergeaud (2024)'s 0.3 percentage points annual TFP gains or Aghion and Bunel (2024)'s 0.7 percentage points). The magnitude suggests that AI acts as a complementary input that enhances efficiency, though its aggregate impact is moderated by implementation frictions and skill gaps, contrasting with more optimistic projections of transformative productivity booms (e.g., Baily, Brynjolfsson, and Korinek (2023)'s 1.7 percentage points scenario). The increase in the coefficient from 2.8% (before matching) to 4.1% (after matching) indicates that endogenous adoption – whereby not all productive firms self-select into AI – understates perceived benefits. After isolating exogenous variation by benchmarking with the US adoption rates, the net effect remains positive, significant and economically plausible, reflecting incremental gains from task automation and cognitive augmentation.

[10] In the baseline specification, labor productivity is expressed as turnover per employee. However, the effect remains significant at 3.4% when use instead value added per employee (see Table B.3 in the Appendix).

Table 4: Effects of AI adoption on wages

	(1) Wage (log) With controls	(2) Wage (log) With controls	(3) Wage/Empl.(log) With controls	(4) Wage/Empl.(log) With controls
AI adoption (actual)	0.135***		0.069***	
	(0.010)		(0.008)	
AI adoption (US-based)		0.024*		0.033***
		(0.014)		(0.011)
Investment (lag)	0.002	-0.000	0.005	0.002
	(0.004)	(0.005)	(0.004)	(0.004)
Profitability (lag)	0.226***	0.269***	0.160***	0.193***
	(0.033)	(0.033)	(0.028)	(0.028)
Financial leverage (lag)	-0.129***	-0.107***	-0.120***	-0.108***
	(0.022)	(0.023)	(0.017)	(0.019)
Total assets (log, lag)	0.342***	0.354***	0.170***	0.171***
	(0.005)	(0.005)	(0.004)	(0.004)
Size FE	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes
Country-sector-wave FE	Yes	Yes	Yes	Yes
Observations	34249	29304	34249	29304
R-squared	0.865	0.868	0.569	0.580
Adjusted R-squared	0.859	0.860	0.548	0.556

Note: The dependent variables are the log of the total wage bill (Columns 1-2) and the log of the average wage per employee (Column 3-4), and they are derived from EIBIS. AI adoption (US-matched) is the AI implementation status derived from similar firms in the US. Investment is expressed as the annual change in total fixed assets. Profitability is the ratio of EBIT to total assets. Financial leverage is the ratio of loans and long-term debt to total assets. All control variables come from ORBIS and are lagged by 1 year. Standard errors clustered at the country-sector-wave level are reported in parentheses. *, **, *** correspond to 0.1, 0.05 and 0.01 significance levels, respectively.

Second, we find no evidence that AI adoption reduces employment in the short run, though longer-term effects remain uncertain. While our naïve specifications associate AI with 8% higher employment, the relationship vanishes after using predicted AI adoption. Moreover, our results suggest that on average the employees of AI-adopting firms benefit in terms of higher wages. This pattern alleviates near-term concerns about job destruction but raises questions about wage inequality. Indeed, benefits may accrue disproportionately to skilled workers coordinating AI-augmented workflows.[11]

The divergence between significant productivity gains and null employment effects suggests that AI primarily enables capital deepening. This implies that firms increase worker output without reducing headcount, consistent with micro-level evidence that AI tools accelerate task completion without displacing labor (e.g., Noy and Zhang (2023)'s 40% time reduction in writing tasks; Baily, Brynjolfsson, and Korinek (2023)'s 14% productivity lift in customer support). To further support the capital deepening mechanism, we also test whether AI-adopting firms are more innovative. Table B.4 in the Appendix presents the results, based on both actual adoption and our instrumented version, including firm-level controls and the same fixed effects as before. AI-adopting firms are more likely to develop products, services, or processes that are new for the firm (columns 1-2), country (columns 3-4) or global frontier (columns 5-6).

Third, in Table 5 we break down the effects of AI adoption by firm size groups. This heterogeneity analysis reveals that AI's productivity benefits are concentrated. Medium and large firms exhibit stronger gains, highlighting the role of scale in absorbing integration costs and accessing complementary assets (e.g., data infrastructure, technical talent). This is also consistent with the important role that midcaps play in Europe (EIB, 2024). The disparities point to risks of widening productivity gaps between firms and regions. This echoes the warnings in Cazzaniga et al. (2024) about AI exacerbating inequality.

[11] We also test whether the impact on employment varies by country using various indicators from the OECD employment protection database. We find no heterogeneous effects for the EU. The results are available upon request.

Table 5: Effects of AI adoption on labor productivity by company size

	(1) LP (log) Micro (5-9)	(2) LP (log) Small (10-49)	(3) LP (log) Medium (50-249)	(4) LP (log) Large (250+)
AI adoption (US-based)	-0.059	-0.041	0.040*	0.079***
	(0.068)	(0.046)	(0.024)	(0.024)
Investment (lag)	0.010	0.009	0.004	0.025
	(0.012)	(0.008)	(0.014)	(0.020)
Profitability (lag)	0.326***	0.658***	0.735***	0.608***
	(0.089)	(0.080)	(0.080)	(0.092)
Financial leverage (lag)	-0.256***	-0.162***	-0.072	-0.190***
	(0.080)	(0.050)	(0.046)	(0.049)
Total assets (log, lag)	0.468***	0.414***	0.383***	0.325***
	(0.020)	(0.012)	(0.010)	(0.011)
Age FE	Yes	Yes	Yes	Yes
Country-sector-wave FE	Yes	Yes	Yes	Yes
Observations	3761	7859	11256	6340
R-squared	0.597	0.615	0.590	0.583
Adjusted R-squared	0.522	0.560	0.535	0.500

Note: The dependent variable is labor productivity, calculated as the log of turnover per employee, and is derived from EIBIS. AI adoption (US-matched) is the AI implementation status derived from similar firms in the US. Investment is expressed as the annual change in total fixed assets. Profitability is the ratio of EBIT to total assets. Financial leverage is the ratio of loans and long-term debt to total assets. All control variables come from ORBIS and are lagged by 1 year. Standard errors clustered at the country-sector-wave level are reported in parentheses. *, **, *** correspond to 0.1, 0.05 and 0.01 significance levels, respectively.

Last but not least, we shed more light on firm-specific enablers that spur productivity gains from AI adoption. Table 6 reports the size of marginal benefits from AI adoption, conditional on the level of complementary investments in different tangible and intangible assets. Investment in buildings and infrastructure seem to multiply the benefits of AI adoption (column (1)). However, those gains are small in magnitude compared to firms that invest in software and data (column (4)) or training (column (5)). An extra percentage point spent on software and data increases the effect of AI adoption on labor productivity by around 2.4%, and an extra percentage point spent on training by 5.9%.

Table 6: Effects of AI adoption on productivity with complementary investment in tangible and intangible assets

	(1) LP (log) Buildings	(2) LP (log) Machinery	(3) LP (log) R&D	(4) LP (log) Software	(5) LP (log) Training	(6) LP (log) Org.
AI adoption x Inv. share	0.007***	0.000	-0.005	0.024**	0.059**	0.012
	(0.003)	(0.002)	(0.005)	(0.010)	(0.025)	(0.012)
Inv. share	0.000	0.003***	0.001	0.010***	0.019**	0.005
	(0.001)	(0.001)	(0.002)	(0.004)	(0.008)	(0.004)
AI adoption (US-based)	0.032	0.045*	0.066***	0.030	0.035	0.050**
	(0.025)	(0.026)	(0.025)	(0.025)	(0.025)	(0.024)
Investment (lag)	0.011**	0.010*	0.012**	0.011**	0.011**	0.012**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Profitability (lag)	0.629***	0.612***	0.634***	0.627***	0.632***	0.635***
	(0.043)	(0.042)	(0.043)	(0.043)	(0.042)	(0.043)
Financial leverage (lag)	-0.149***	-0.159***	-0.146***	-0.149***	-0.147***	-0.147***
	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
Total assets (log, lag)	0.391***	0.397***	0.390***	0.395***	0.395***	0.391***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Size FE	Yes	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-sector-wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27593	27593	27593	27593	27593	27593
R-squared	0.566	0.567	0.566	0.567	0.567	0.566
Adjusted R-squared	0.540	0.541	0.540	0.541	0.541	0.540

Note: The dependent variable is labor productivity, calculated as the log of turnover per employee, and is derived from EIBIS. AI adoption is the AI implementation status derived from similar firms in the US. Investment shares are EIBIS-reported investment in (1) Land, business buildings and infrastructure, (2) Machinery and equipment, (3) Research and development (including the acquisition of intellectual property), (4) Software, data, IT networks and website activities, (5) Training of employees and (6) Organisation and business process improvements, scaled by total assets. Investment is expressed as the annual change in total fixed assets. Profitability is the ratio of EBIT to total assets. Financial leverage is the ratio of loans and long-term debt to total assets. All control variables come from ORBIS and are lagged by 1 year. Standard errors clustered at the country-sector-wave level are reported in parentheses. *, **, *** correspond to 0.1, 0.05 and 0.01 significance levels, respectively.

6 Conclusion

This paper provides causal evidence that the adoption of artificial intelligence significantly enhances productivity in European firms, while simultaneously reshaping our understanding of its labor market implications. The results show that the adoption of AI increases labor productivity by 4% on average – a substantial yet measured gain that aligns with mid-range macroeconomic projections rather than more transformative estimates. Crucially, the productivity improvements stem from capital deepening rather than workforce reduction: AI augments worker output without diminishing employment levels in the short term, countering prevalent concerns about immediate job displacement. Moreover, the evidence suggests that, so far, workers in AI-adopting firms have benefited in terms of higher wages. The productivity benefits are, however, disproportionately concentrated among larger firms, financially advanced regions and technology-intensive sectors, risking heightened economic polarization.

The findings yield two key policy directions. First, targeted financial support mechanisms can help companies grow and reach the critical mass to benefit from AI transformation. Our analysis shows that firms in an environment with more sophisticated financial market options are better equipped to invest in AI. Therefore, developing more effective and sophisticated financial markets is a priority. This underscores the importance of focusing on the EU Savings and Investment Union, which is crucial for fast-growing, innovative companies. Second, workforce development can prioritize human-AI complementarity through retraining and upskilling programs that upgrade worker skills towards prompt engineering, data stewardship and AI-augmented decision-making. This requires coordinated investments in vocational training, tertiary education and lifelong learning programs that will equip workers with the technical and cognitive capabilities needed to collaborate effectively with AI systems.

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A Are US-matched firms different from non-matched firms?

While the EIBIS results indicate virtually no aggregate difference in AI adoption between US and EU firms, particularly in financially developed countries (see Section 3.1), it is important exercise to examine which US firms are selected by the matching algorithm and how they differ from their non-matched counterparts, for at least three reasons.

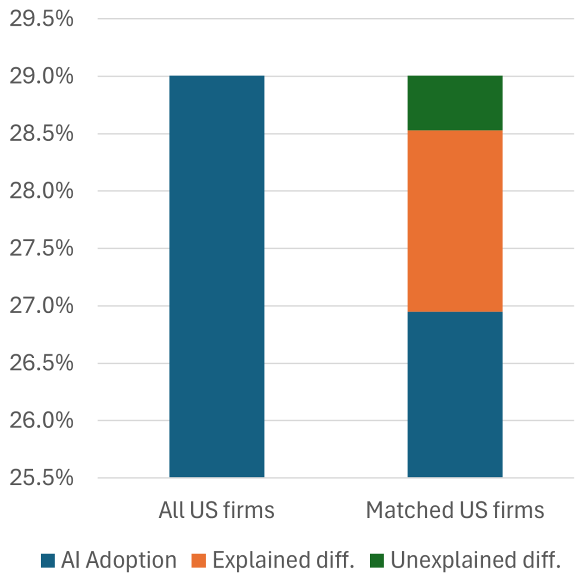
First, the comparison can provide a robustness check on the matching methodology itself, shedding light on whether the algorithm systematically favors certain types of firms (e.g. larger, more innovative or less financially constrained). Second, even if average adoption rates are similar across the US and EU, the characteristics of firms driving adoption may diverge, with potential implications for productivity dynamics. Finally, contrasting matched and non-matched US firms can reveal whether transatlantic comparisons are shaped by differences in firm composition rather than adoption per se, thus helping to interpret the aggregate similarities more carefully.

To this end, we apply the Oaxaca–Blinder decomposition to a synthetic dataset that compares all US firms with the subset of US firms identified as nearest neighbours in the matching procedure. In the exercise, we include only firms that disclose the full set of matching variables such that the average AI adoption rate in the sample deviates slightly from the unconditional US average. We therefore treat this as an approximation.

The decomposition, originally developed by Blinder (1973) and Oaxaca (1973), partitions the mean difference in AI adoption into components explained by observable firm characteristics and a residual unexplained part. Consistent with the matching strategy described in Section 4, we compute the decomposition relative to sector- and size-normalised means of value added, which controls for compositional shifts in the fixed effects.

Figure A.1 shows that US-matched firms exhibit, on average, a 2 percentage points lower AI adoption rate than the full set of US firms. Close to 80% of this gap is explained by differences in matching variables and sector- and size-class composition. This supports the robustness of the matching design.

Figure A.1: AI adoption among US-matched and all US firms



Note: Average AI adoption rates across all US firms and US firms matched with EU counterparts. Propensity score matching is based on the 5 nearest neighbors in terms of investment intensity, innovator binary indicator, bond issuance binary indicator and business monitoring system binary indicator in the same sector and company size category. The difference between the unconditional and conditional US means is decomposed into the component that can be explained by the matching variables, normalization fixed effects and the residual, based on the Oaxaca-Blinder decomposition. Values are weighted by value added.

B Additional results

Table B.1: Explanatory power of matching variables for AI adoption

	(1) AI Adoption EU	(2) AI Adoption US
Investment/employee (log)	0.017***	0.014***
	(0.001)	(0.004)
Business monitoring system	0.111***	0.124***
	(0.004)	(0.014)
Equity/bond issuance	0.092***	0.059
	(0.018)	(0.048)
Innovator	0.058***	0.050***
	(0.004)	(0.013)
Size FE	Yes	Yes
Age FE	Yes	Yes
Country-sector-wave FE	Yes	Yes
Observations	45785	2966
R-squared	0.200	0.124
Adjusted R-squared	0.168	0.102

Note: The dependent variable is AI adoption and is derived from EIBIS. Standard errors clustered at the country-sector-wave level are reported in parentheses. *, **, *** correspond to 0.1, 0.05 and 0.01 significance levels, respectively.

Table B.2: Effects of AI adoption on labor productivity with different fixed effects

	(1) LP (log) With controls	(2) LP (log) With controls	(3) LP (log) With controls	(4) LP (log) With controls	(5) LP (log) With controls
AI adoption (US-based)	0.076***	0.033**	0.040***	0.042***	0.041***
	(0.015)	(0.015)	(0.011)	(0.013)	(0.011)
Investment (lag)	0.008	0.009	0.012**	0.010*	0.011*
	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)
Profitability (lag)	0.694***	0.591***	0.657***	0.661***	0.661***
	(0.058)	(0.047)	(0.050)	(0.045)	(0.049)
Financial leverage (lag)	-0.128***	-0.188***	-0.131***	-0.132***	-0.131***
	(0.046)	(0.031)	(0.036)	(0.026)	(0.036)
Total assets (log, lag)	0.471***	0.408***	0.389***	0.387***	0.388***
	(0.012)	(0.007)	(0.012)	(0.006)	(0.012)
Size FE	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes
Sector FE	No	No	No	Yes	No
Country FE	No	No	Yes	No	No
Sector-wave FE	Yes	No	Yes	No	Yes
Country-wave FE	No	Yes	No	Yes	Yes
Observations	30327	30657	30327	30327	30327
R-squared	0.432	0.441	0.513	0.516	0.517
Adjusted R-squared	0.430	0.437	0.511	0.513	0.514

Note: The dependent variable is labor productivity, calculated as the log of turnover per employee, and is derived from EIBIS. AI adoption (US-matched) is the AI implementation status derived from similar firms in the US. Investment is expressed as the annual change in total fixed assets. Profitability is the ratio of EBIT to total assets. Financial leverage is the ratio of loans and long-term debt to total assets. All control variables come from ORBIS and are lagged by 1 year. Standard errors clustered at the country-sector-wave level are reported in parentheses. *, **, *** correspond to 0.1, 0.05 and 0.01 significance levels, respectively.

Table B.3: Effects of AI adoption on labor productivity (turnover and value added approach)

	(1)	(2)
	LP Turnover (log) With controls	LP Value Added (log) With controls
AI adoption (US-based)	0.041***	0.034*
	(0.015)	(0.018)
Investment (lag)	0.009*	0.009
	(0.006)	(0.006)
Profitability (lag)	0.618***	1.374***
	(0.041)	(0.066)
Financial leverage (lag)	-0.151***	-0.182***
	(0.026)	(0.041)
Total assets (log, lag)	0.386***	0.375***
	(0.006)	(0.006)
Size FE	Yes	Yes
Age FE	Yes	Yes
Country-sector-wave FE	Yes	Yes
Observations	30228	23575
R-squared	0.551	0.861
Adjusted R-squared	0.526	0.852

Note: The dependent variable is labor productivity, calculated as the log of turnover per employee or log of value added per employee, and is derived from EIBIS. AI adoption (US-matched) is the AI implementation status derived from similar firms in the US. Investment is expressed as the annual change in total fixed assets. Profitability is the ratio of EBIT to total assets. Financial leverage is the ratio of loans and long-term debt to total assets. All control variables come from ORBIS and are lagged by 1 year. Standard errors clustered at the country-sector-wave level are reported in parentheses. *, **, *** correspond to 0.1, 0.05 and 0.01 significance levels, respectively.

Table B.4: Effects of AI adoption on innovation activity

	(1) Firm	(2) Firm	(3) Country	(4) Country	(5) World	(6) World
AI adoption (actual)	0.035***		0.025***		0.055***	
	-0.007		-0.004		-0.004	
AI adoption (US-based)		0.078***		0.015***		0.033***
		-0.01		-0.005		-0.006
Investment (lag)	0.001	0	0.002	0.001	0.004**	0.004**
	-0.002	-0.003	-0.001	-0.002	-0.002	-0.002
Profitability (lag)	0.049***	0.036*	0.008	0.008	-0.004	-0.008
	-0.016	-0.02	-0.01	-0.012	-0.011	-0.013
Financial leverage (lag)	0.015	0.017	-0.001	0.001	0.007	0.012
	-0.011	-0.013	-0.006	-0.007	-0.007	-0.008
Total assets (log, lag)	-0.001	-0.004*	0.001	0.001	0.006***	0.008***
	-0.002	-0.002	-0.001	-0.001	-0.001	-0.001
Size FE	Yes	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-sector-wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	35427	30446	35427	30446	35427	30446
R-squared	0.081	0.082	0.082	0.089	0.123	0.126
Adjusted R-squared	0.038	0.032	0.038	0.039	0.081	0.078

Note: The dependent variable is a binary indicator for innovation activity for firms that report to develop products, services or processes that are new at the level of the firm (Columns 1-2), the country (Columns 3-4) or the global frontier (Columns 5-6). AI adoption (US-matched) is the AI implementation status derived from similar firms in the US. Investment is expressed as the annual change in total fixed assets. Profitability is the ratio of EBIT to total assets. Financial leverage is the ratio of loans and long-term debt to total assets. All control variables come from ORBIS and are lagged by 1 year. Standard errors clustered at the country-sector-wave level are reported in parentheses. *, **, *** correspond to 0.1, 0.05 and 0.01 significance levels, respectively.

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