Politická ekonomie

Volume 75
Forthcoming articles
https://doi.org/10.18267/j.polek.1531
Open Access

VŠE / PRAGUE UNIVERSITY OF ECONOMICS AND BUSINESS

Labor in the Age of AI: Productivity Trends Across the EU

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Abstract

This study investigates the impact of Artificial Intelligence (AI) readiness on labour productivity across 27 European Union (EU) countries between 2019 and 2024. Using a dynamic panel approach, we apply Pooled OLS, Fixed Effects, Difference GMM, and System GMM estimators to account for endogeneity and persistence in productivity. The System GMM model is preferred for its robustness and reliability. Results show that AI readiness positively influences labour productivity, though the effect remains modest, reflecting disparities in adoption across regions. Other significant drivers include foreign direct investment and R&D expenditure, while government consumption and labour costs have a negative impact. Unexpectedly, trade openness shows a negative association, likely due to structural differences in value chain integration. Education and institutional quality were statistically insignificant in the short term. The findings suggest that EU policymakers should prioritize AI implementation, digital infrastructure, skill development, and innovation to close regional gaps and promote inclusive productivity growth.

Keywords: Artificial Intelligence, labor productivity, EU, System GMM, digital transformation.

JEL Classification: O31, O33, J24

Citation: Kjosevski, J., Petkovski, M., Stojkov, A.: Labor in the Age of AI: Productivity Trends Across the EU. *Politická ekonomie*, 2027, 75, Forthcoming articles, https://doi.org/10.18267/j.polek.1531

Introduction

The rapid integration of Artificial Intelligence (AI) across sectors is reshaping labor productivity and economic performance. In the European Union (EU), AI adoption is recognized as a strategic priority, with member states actively developing frameworks to harness its economic potential. As a general-purpose technology (GPT), AI can significantly enhance productivity by automating routine tasks, improving decision-making, and enabling innovation in business processes (Brynjolfsson & McAfee, 2014; Agrawal, Gans & Goldfarb, 2018). The EU's diverse composition of 27 member states offers a unique context for investigating AI's productivity impact, given substantial differences in technological readiness, infrastructure, regulatory environments, and labor market dynamics (European Commission, 2021a).

Labor productivity – commonly defined as output per hour worked – is a key driver of long-term economic growth and living standards (Solow, 1957). AI complements human labor by enhancing efficiency, enabling predictive analytics, and supporting more complex tasks (Autor, 2015; Acemoglu & Restrepo, 2018). However, the extent of AI's impact varies across EU countries due to differences in economic development, digital infrastructure, workforce skills, and complementary investments (Graetz & Michaels, 2018; European Commission, 2021a).

From a theoretical perspective, the role of AI in productivity gains can be understood through both neoclassical and endogenous growth models. While the neoclassical framework emphasizes capital accumulation and labor input alongside technological progress (Solow, 1957), endogenous growth theory underscores the importance of innovation – particularly in information and communication technologies (ICT) – for sustained productivity growth (Romer, 1990). As an advanced ICT, AI has the potential to transform production processes, enable new data-driven business models, and generate innovation spillovers (Brynjolfsson, Rock & Syverson, 2019). Its versatility allows for productivity improvements across industries ranging from manufacturing to finance and healthcare (Agrawal, Gans & Goldfarb, 2018).

Despite AI's transformative potential, empirical evidence on its macroeconomic productivity effects in the EU remains limited. Most existing studies focus on firm-level outcomes or individual countries, often using static models that overlook dynamic feedback effects. Recent findings suggest that while AI adoption is associated with productivity and employment gains in innovation-leading EU states, aggregate effects remain uneven and dependent on enabling conditions such as digital infrastructure, skills, and supportive policies (Guarascio & Reljic, 2025; Van Roy, Vértesy & Vivarelli, 2022; OECD, 2024). Without targeted investments in skills, data governance, and R&D, the EU may fail to fully capture AI's macroeconomic benefits (OECD, 2024).

This study aims to fill this gap by empirically assessing the relationship between AI adoption and labor productivity across all EU-27 countries from 2019 to 2024. We employ the System Generalized Method of Moments (System GMM) estimator, which accounts for endogeneity, reverse causality, and the dynamic nature of productivity growth (Blundell & Bond, 1998; Roodman, 2009). This approach is well-suited for the unbalanced nature of our panel data and improves upon earlier studies that rely on static or OLS-based methods.

The main contributions of this paper are fourfold:

1. **Scope** – We provide one of the first EU-wide dynamic panel data analyses linking AI adoption to labor productivity, explicitly incorporating structural differences in regulatory environments, digital readiness, and labor market characteristics.
2. **Theory** – We integrate insights from both the Neoclassical Growth Model and Endogenous Growth Theory, offering a framework that captures both short-term capital deepening effects and long-term innovation spillovers from AI adoption.
3. **Methodology** – By applying System GMM, we address econometric challenges and offer more robust estimates than static models.
4. **Policy relevance** – We identify enabling conditions under which AI adoption yields the greatest productivity gains, providing evidence-based recommendations for investments in digital infrastructure, workforce upskilling, and regulatory adaptation.

The findings have important policy implications for ensuring that AI-driven productivity gains are both substantial and inclusive. For the EU to sustain global competitiveness and foster economic resilience, policymakers must combine digital infrastructure investment with targeted workforce development and adaptive regulation. This is essential for mitigating regional disparities and managing labor market transitions while maximizing the economic benefits of AI adoption (European Commission, 2021).

The remainder of the paper is structured as follows. Section 2 reviews relevant literature on AI and productivity. Section 3 outlines the data sources and variables, while Section 4 details the methodology. Section 5 presents the empirical results and discusses their policy implications, and Section 6 concludes with key insights and directions for future research.

2. Literature review

2.1. Theoretical Perspective

The economic impact of Artificial Intelligence (AI) on productivity and employment can be understood through both historical insights and two complementary growth paradigms: the Neoclassical Growth Model and the Endogenous Growth Model. These perspectives, along with the historical debate on technological disruption, provide a robust theoretical foundation for the empirical specification used in this study and directly address the reviewers' recommendation to connect theory to the model, variable selection, and interpretation.

Technological change has long raised questions about its dual impact: creating new industries and jobs, while displacing existing workers. As early as 1767, Sir James Steuart warned that abrupt technological adoption could trigger short-term unemployment, though gradual implementation might enhance productivity and lead to long-run benefits. Economic writer Thomas Mortimer (1772) expressed concern about machinery like sawmills displacing workers – a phenomenon later called the *displacement effect*.

David Ricardo, in *Principles of Political Economy* (1821 [1971]), revised his earlier optimism about machinery, acknowledging potential harm to the laboring classes when human labor was substituted. Still, he argued that productivity gains and cost savings would eventually stimulate labor demand, an early articulation of what later became the *productivity effect*. Similar views emerged from John Stuart Mill, who eventually concluded that production improvements seldom harmed workers in aggregate, and Karl Marx, who recognized short-term disruption but highlighted technology's role as a long-term driver of prosperity.

Evidence from the First Industrial Revolution illustrates the complexity of these dynamics. Productivity gains in sectors like textile weaving reduced labor per unit of output, lowering prices and raising demand, which eventually created more jobs (Economist, 2014). However, total factor productivity (TFP) growth was initially modest (Feinstein, 1998; Mokyr, 2004), with significant acceleration only in the mid-19th century. Complementary innovations – such as high-pressure steam – were often necessary before transformative effects materialized (Crafts, 2004). Meanwhile, higher wages were often accompanied by longer working hours and harsh conditions (Voth, 2001).

The 20th century saw renewed concerns. Wassily Leontief predicted in 1952 that machines might increasingly replace human labor (Dorfman, 1973), and Robert F. Kennedy later emphasized the social challenges of automation (Culey, 2018). Modern economic theories remain divided: while classical growth models see technological progress as the engine of long-run growth (Solow, 1957; Romer, 1990), contemporary studies note risks such as wage polarization and skill-biased technological change (Autor *et al*., 2003; Barbieri *et al*., 2020). Automation may displace workers in the short term (Vivarelli, 1995, 2013; Autor & Dorn, 2013), but efficiency gains and productivity effects can ultimately expand employment if properly managed (Acemoglu & Restrepo, 2018a). In the age of AI, the central question is whether productivity gains will outweigh displacement effects.

The Neoclassical Growth Model, formalized by Solow (1956), views long-run per capita income growth as driven by exogenous technological progress, with capital deepening subject to diminishing returns. In this framework, AI represents a technology shock that shifts the production function upward by enabling more efficient combinations of labor and capital. Short- to medium-term productivity gains stem from capital deepening – investments in AI systems, digital infrastructure, and skilled labor to operate these tools (Acemoglu & Restrepo, 2018).

However, once AI is fully embedded in the capital stock, diminishing marginal returns may slow growth unless further innovations arise. Cross-country variation in AI's impact can be explained by differences in capital allocation efficiency, infrastructure quality, and absorptive capacity (Hall & Jones, 1999). In the EU, disparities in capital intensity, digital readiness, and workforce skills help explain the heterogeneity in observed productivity effects.

The Endogenous Growth Model (Romer, 1990; Aghion & Howitt, 1992) endogenizes technological progress, emphasizing innovation, human capital accumulation, and knowledge spillovers as drivers of sustained growth. In this view, AI is more than a capital input – it is a *general-purpose technology* (GPT) (Bresnahan & Trajtenberg, 1995) that enables ongoing productivity improvements through complementary innovations in products, processes, and organizational structures.

AI sustains long-term growth if it accelerates knowledge creation, supports idea recombination, and augments human capabilities, freeing labor for higher-value activities (Brynjolfsson & McAfee, 2017; Acemoglu *et al*., 2022). Unlike the diminishing returns predicted by the neoclassical model, the endogenous framework allows for increasing returns through strong knowledge spillovers and network effects. In the EU, these effects are amplified by cross-border R&D programs, a harmonized digital market, and integrated supply chains (Griffith *et al*., 2004).

Synthesizing these perspectives, AI influences productivity through four interconnected channels:

1. Capital Deepening (Neoclassical) – AI investments in tangible and intangible assets raise the capital–labor ratio and efficiency.
2. Total Factor Productivity Gains (Both Models) – AI optimizes processes, reduces inefficiencies, and facilitates innovation.
3. Human Capital Augmentation (Endogenous) – AI complements skilled labor, enhancing analytical and creative capacity (Acemoglu *et al*., 2022).
4. Knowledge Spillovers & Network Effects (Endogenous) – Adoption in one firm or country benefits others, particularly in an integrated EU market (Van Roy *et al*., 2022).

The relative importance of these channels varies by country. Innovation-driven economies at the technological frontier (e.g., Finland, the Netherlands) are more likely to benefit from sustained, innovation-led growth, while others may first experience gains through capital deepening before transitioning to innovation-based dynamics (Aghion & Howitt, 2006). EU integration facilitates diffusion via policy coordination, but uneven skill distribution, regulatory fragmentation, and infrastructure gaps may slow convergence (European Commission, 2023).

Our empirical model reflects these theoretical insights by:

- Capturing capital effects through measures of AI-related investment and ICT infrastructure.
- Proxifying innovation and knowledge accumulation via R&D intensity, human capital indicators, and ICT skills measures.
- Controlling for institutional and structural differences with country fixed effects, representing regulatory frameworks and absorptive capacity.

By grounding the analysis in both neoclassical and endogenous growth traditions – and informed by historical evidence on technological change – we recognize that AI-driven productivity growth in the EU is not a single-stage process, but an evolving interplay of short-run capital deepening and long-run innovation dynamics, with complex employment implications.

2.2. Review of Empirical studies

The relationship between AI and labor productivity has been widely examined using both qualitative and quantitative approaches, yielding mixed findings due to differences in analytical level (firm, sector, macro), data sources, geographic scope, and time periods. At the micro level, highly innovative firms often generate jobs through R&D-driven technological change (Dosi *et al.*, 2021). However, sectoral-level results are less consistent (Aldieri & Vinci, 2018; Falk & Hagsten, 2018; Dosi & Mohnen, 2019). Macro-level analyses provide a broader perspective, as process innovations can boost productivity while potentially reducing employment unless offset by product innovations and inter-sectoral job creation (Dosi *et al*., 2019).

Baily, Brynjolfsson, & Korinek (2023) note that official statistics may understate productivity gains because knowledge work output is difficult to measure. Frey & Osborne (2017) estimate that 47% of U.S. jobs face high computerization risk, particularly affecting Afro-American and Hispanic workers, while Brynjolfsson & McAfee (2014) argue that cognitive automation may substitute rather than complement human labor. In contrast, Alexopoulos & Cohen (2016) find that past technological waves ultimately increased employment.

Automation's effects extend beyond directly affected industries. Autor & Salomons (2017) show that while automation reduces employment within automated sectors, spillover effects can generate gains elsewhere. Bessen (2017) finds that productivity-enhancing technologies can boost employment in markets with unmet demand but reduce jobs in saturated industries like manufacturing. Using German data, Dauth *et al*. (2017) estimate that each industrial robot displaces two manufacturing jobs, but service-sector growth offsets these losses.

Frey & Osborne's (2017) framework – based on a Gaussian process classifier applied to O*NET data – has been extended internationally: Brzeski & Burk (2015) estimate 59% of German jobs at risk. Autor *et al*. (2003) distinguish between routine tasks, which are easily automated, and non-routine activities, which are more resilient. Goos & Manning (2007) highlight job polarization – growth in high-skill cognitive and low-skill manual roles alongside decline in mid-skill routine work – a pattern confirmed by Acemoglu & Autor (2018b) and Darvas & Wolff (2016) in the U.S. and Europe. In Europe, managerial and engineering roles are growing, machine-operator roles are declining, and non-routine service jobs are expanding, underscoring the need for digital skill development.

The rapid rise of AI is mirrored in patent trends (De Prato *et al*., 2018; Fujii & Managi, 2018; Cockburn *et al*., 2019; Van Roy *et al*., 2022), with China, Japan, South Korea, and the U.S. leading in telecom, software, and electronics, alongside adoption in other industries. Saam (2024) notes the absence of evidence for massive job losses from AI, while Kassa & Worku (2025) find heterogeneous productivity impacts, suggesting the need for sector-specific analysis.

Despite limited aggregate-level evidence, multiple studies confirm productivity gains. Graetz & Michaels (2018) show robots raised productivity by over 15% in 17 countries (1993–2007). A European Commission (2016) survey of 3,000 manufacturers reports similar productivity benefits.

Recent Europe-focused empirical research highlights context-dependent effects. Marioni, Rincon-Aznar, & Venturini (2024) find AI-oriented firms across 15 European countries (2011–2019) achieve statistically significant productivity gains using a difference-in-differences approach. Calvino & Fontanelli (2023) show that AI adopters enjoy productivity premia over non-adopters, but these disappear when controlling for complementary digital transformation assets. Fernandez de Arroyabe *et al*. (2024) demonstrate that internal digital and innovation capabilities, more than external environment factors, drive AI adoption in SMEs. Guarascio & Reljic (2025) show that AI exposure correlates with employment growth in innovation-strong countries, pointing to the role of national innovation systems. Licht & Wohlrabe (2024) report sharp increases in AI adoption in Germany's manufacturing sector, with managerial risk tolerance influencing decisions. Finally, ECB (2025) emphasizes that AI's productivity potential materializes only with active use, sufficient investment, and supportive regulation.

3. Model and Data

Our study dataset consists of a sample of 27 EU members states and uses annual data from 2019 to 2024. The panel is unbalanced given that the study features many “new” EU member states, not all of the indicators were available for each country over the entire period. The selection of countries was mainly based on similarities in terms of historical and socio-economic developments as well as geographical, institutional, and cultural proximity. On the other hand, there are also substantial differences among these countries that made them a heterogenous group. These differences were mostly reflected in the high disparities observed with respect to the level of public debt, GDP growth, unemployment, etc.

The internationally comparable and reliable data were obtained from Eurostat, International Labor Organization (ILOSTAT), UNESCO, International monetary Fond- IMF and The World Justice Project.

The dependent variable, expressed as the annual growth rate of output per worker (GDP at constant 2017 international dollars, purchasing power parity (PPP)) in percent, provides a comprehensive indicator of economic efficiency and workforce performance. This measure reflects the ability of an economy to generate output with its available labor resources and is widely used in growth accounting frameworks (Solow, 1956). Theoretically, labor productivity is influenced by factors such as capital accumulation, technological progress, and human capital development, which together drive economic growth (Romer, 1990). Empirical studies have demonstrated that higher labor productivity is associated with improvements in technology, infrastructure, and education. For example, Bosworth and Collins (2003) find that advancements in technology significantly explain productivity differences across countries. This measure is particularly relevant in cross-country analyses, as it accounts for differences in PPP terms, enabling a more accurate comparison of productivity levels and growth rates. This variable we used with logarithm.

The main explanatory variable in our study is AI adoption, measured using the Government AI Readiness Index, developed by Oxford Insights. Launched in 2019, this index evaluates national governments’ preparedness to implement AI in public services, using 39 indicators across three pillars: Government, Technology Sector, and Data and Infrastructure. Initially covering 160 countries, the index has expanded to 193 by 2023, reflecting a growing global focus on AI governance. Countries such as Singapore, the UK, and Germany consistently rank highly due to strong digital governance and robust institutions (Oxford Insights, 2019; Government of Vietnam, 2024).

The index serves multiple functions: benchmarking readiness, informing evidence-based

AI policy, and encouraging equity and collaboration, especially for low-income nations (IDRC, 2023). As AI's role expands globally, the index provides critical insight into how governments can responsibly manage this technology.

To isolate the effects of AI readiness, we include control variables: trade openness, total investments, energy intensity, gross tertiary enrollment, FDI, R&D expenditure, average wages, and the Rule of Law Index.

Trade openness (as % of GDP) boosts productivity by exposing firms to global competition, knowledge, and technologies. Frankel and Romer (1999) show openness correlates with technology diffusion and productivity growth.

Total investment reflects resource allocation to capital formation, enhancing labor efficiency. Ahamed (2021) finds public and private investments drive growth in developing economies. The OECD (2016) links weak investment to sluggish productivity, while Singh (2023) highlights the importance of efficient labor investment.

Energy intensity (Euro per KGOE) measures efficiency; lower intensity implies better productivity. Mulder and de Groot (2007), and Jorgenson and Fraumeni (1981) show improvements in energy use lead to cost savings and higher output.

Gross tertiary enrollment boosts human capital and labor productivity. Barro and Lee (1994), and Hanushek and Woessmann (2007) find strong links between education, innovation, and economic competitiveness. However, Wolff (2001) and Duflo (2001) argue that in some contexts, higher enrollment doesn't guarantee productivity growth due to underemployment or misalignment with labor market needs.

FDI (net inflows as % of GDP) contributes to productivity via technology transfer and skill development. Borensztein *et al*. (1998) stress the importance of human capital in maximizing FDI benefits. Alfaro *et al*. (2004) and Carkovic and Levine (2005) emphasize that FDI improves capital efficiency and resource allocation.

R&D expenditure (as % of GDP) drives innovation. Griffith *et al*. (2004) show a positive correlation between R&D and productivity. Cohen and Levinthal (1989) highlight absorptive capacity, while Hall *et al*. (2010) note significant spillover benefits.

Higher wages can increase productivity by incentivizing performance. Krueger and Summers (1988), Card and Krueger (1995), and Akerlof and Yellen (1986) argue that better pay attracts skilled labor and boosts morale. Fedderke and Mariotti (2002) find that wage growth unaccompanied by productivity gains may hurt employment. Baker (2017) points out that rising wages can eliminate unproductive jobs, indirectly increasing average productivity. This variable we used with logarithm.

The World Justice Project (WJP) Rule of Law Index is another vital control variable. Since 2009, it has assessed 142 countries on constraints on government power, corruption, open government, rights, security, regulatory enforcement, civil, and criminal justice. Based on over 214,000 household and 3,500 expert surveys, it is one of the most comprehensive legal system indicators globally (World Justice Project, 2024a; 2024b).

The rule of law underpins labor productivity by ensuring contract enforcement, reducing corruption, and supporting transparent governance. North (1990) and Kaufmann *et al*. (2005) highlight the institutional foundations necessary for efficient economic activity. Strong legal systems promote investment in skills, reduce transaction costs, and foster human capital development, all of which are crucial for sustainable productivity growth.

Table 1 presents the descriptive statistics for all the variables used in the regressions.

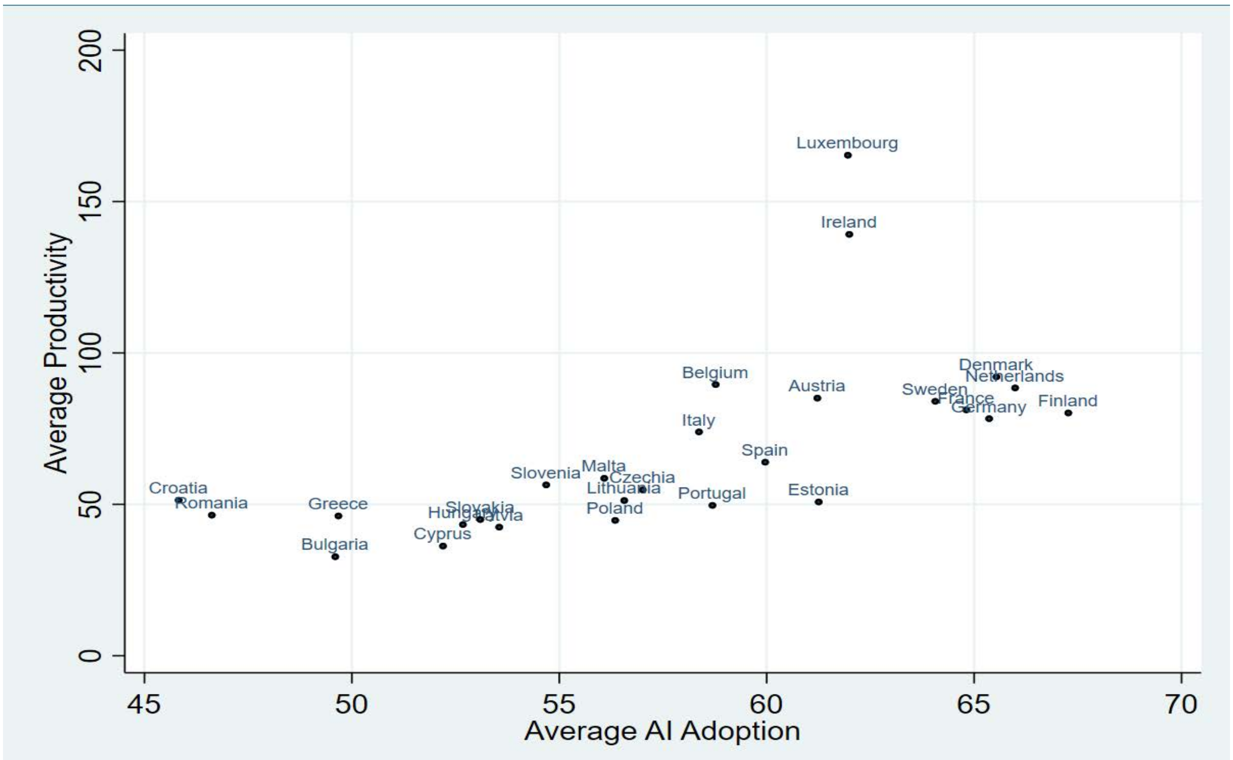
Table 1: Definition of variables

Variables	Symbol	Units	Source
Labour Productivity	*LP*	Output per worker (GDP constant 2017 international $ at PPP) (%)	International Labor Organization (ILOSTAT)
The Government AI Readiness Index	*AIRI*	Index spans from 0 to 100	Oxford Insights
Trade openness	*TRADE*	(% of GDP)	IMF
Energy intensity	*ENER*	Euro per kilogram of oil equivalent	EUROSTAT
School enrollment, tertiary	*EDU*	(% of the relevant age group)	UNESCO
Foreign direct investment, net inflows	*FDI*	(% of GDP)	EUROSTAT
Research and development expenditure	*RDE*	(% of GDP)	EUROSTAT
Average annual wages	*WAGE*	In euros	EUROSTAT
Rule of Law	*RL*	Index ranges from 0.00 to 1.00	World Justice Project Rule of Law Index

Source: Authors' own calculations

To better understand the relationship between AI adoption and labor productivity across the EU, it is important to examine the spatial distribution and clustering of countries based on these indicators. This variation reflects not only technological capabilities but also differences in institutional frameworks, economic structures, and policy environments. Visualizing these patterns helps highlight how AI readiness interacts with productivity outcomes in diverse national contexts. As presented in Figure 1, Luxembourg and Ireland stand out as outliers, combining relatively high AI adoption scores with exceptionally high productivity compared to other EU member states. Central and Eastern European countries (e.g., Bulgaria, Romania, and Croatia) are characterized by both below-average AI adoption and labour productivity. In contrast, Northern and Western European economies (e.g., Denmark, Netherlands, Finland, and Germany) exhibit high AI adoption paired with moderate to high productivity. Southern European countries such as Italy, Spain, and Portugal occupy mid-range positions. The cross-country variation underlines the importance of accounting for structural and institutional when interpreting the AI–productivity relationship in the EU context.

Figure 1: AI Readiness Index and Average Labour Productivity in EU-27 (2019–2024)



Source: Authors' own elaboration

4. Methodology

This section outlines the econometric method chosen to investigate the relationship between AI and labor productivity. Empirical studies have shown that productivity levels often exhibit inertia, where past performance significantly influences current outcomes (Klette 1996). This framework is particularly relevant for analyzing the gradual adjustment of firms' productivity over time, which static models fail to capture. By incorporating lagged productivity as a determinant, the dynamic model allows us to reflect the process of gradual convergence in efficiency levels between firms. This approach recognizes that firms lagging in productivity may improve more rapidly due to factors such as learning-by-doing, technology diffusion, or policy interventions (Blundell and Bond 2000). Moreover, the dynamic specification addresses key econometric challenges, such as endogeneity and unobserved heterogeneity, which are common in productivity analysis (Lokshin *et al*. 2008; Hall *et al*. 2010). In the context of AI adoption, where the effects on productivity may evolve over time and vary across firms, the dynamic framework ensures that our analysis captures both the short-term adjustments and the long-term trends. This choice enhances the robustness of the results and aligns with established practices in the productivity literature.

Bond (2002) emphasizes that dynamic relations in analyzing the base process can be decisive for proper and consistent estimations of parameters of the observed independent variables. Specific characteristics of the sample covering 27 countries over the period of 6 years, or the situation when $T < N$, is an important argument for choosing a dynamic panel model (Greene, 2008). The dynamic panel model is also a good method of estimation when potential endogeneity is considered, which is the case in our model (Greene, 2008). The dynamic panel model offers the possibility of generating internal instruments (external are typically difficult to find), so the treatment of potential endogeneity is comprehensive, and the estimations are more consistent (Baum, 2006).

Various econometric methods are available for estimating dynamic panel data models. The dynamic panel data approach is advantageous as it accounts for the endogeneity of explanatory variables and considers unobservable, time-invariant country effects (Baek, 2016; Yerdelen Tatoglu, 2018). To address the issue of endogeneity, Arellano and Bond (1991) introduced the difference generalized method of moments (difference GMM), which uses instrumental variables to derive GMM estimates of the relevant moment conditions. This method involves taking the first difference of the regression equation to eliminate individual fixed effects, using lagged variables as instruments for endogenous variables in the differenced equation. While this approach effectively mitigates endogeneity concerns, it may suffer from "weak instruments" in finite samples, leading to reduced precision (Bond *et al*., 2001). To overcome this limitation, Arellano and Bover (1995) and Blundell and Bond (1998) proposed the system GMM estimator, which enhances the difference GMM by using lagged variables as instruments in both the differenced and level equations.

$$y_{it} = \sum_{j=1}^{p} \alpha_j y_{i,t-j} + x_{it}\beta_1 + w_{it}\beta_2 + v_i + \varepsilon_{it}\; i = 1,\ldots,N \; = 1,\ldots,T \tag{1}$$

where the αj are p parameters to be estimated, $x_{i,t}$ is a $1 \times k_1$ vector of strictly exogenous covariates, β_1 is a $k_1 \times 1$ vector of parameters to be estimated, $w_{i,t}$ is a $1 \times k_2$ vector of predetermined or endogenous covariates, β_2 is a $k_2 \times 1$ vector of parameters to be estimated, v_i are the panel-level effects (which may be correlated with the covariates), and $\varepsilon_{i,t}$ are independently and identically distributed across the whole sample with variance σ^2. The v_i and the $\varepsilon_{i,t}$ are assumed to be independent for each i overall t.

There are several compelling reasons for favoring system GMM over difference GMM in empirical analysis. First, when dealing with variables close to a random walk, lagged levels of the regressors, as utilized in difference GMM, tend to be poor instrumental variables (IVs) for the first-differenced regressors (Arellano and Bover, 1995). Second, unbalanced panels can exacerbate data gaps when employing first differences, a characteristic of difference GMM. Third, the standard errors associated with difference GMM are often biased downwards (Blundell and Bond, 1998). Fourth, difference GMM tends to perform inadequately with small sample sizes, whereas system GMM exhibits better properties in such scenarios (Blundell and Bond, 2000). Fifth, system GMM provides additional IVs by incorporating a second equation, wherein variables in levels are instrumented with their own first differences (Arellano and Bover, 1995). Sixth, the use of more IVs in system GMM enhances estimation efficiency compared to difference GMM. Seventh, system GMM is better suited for modeling non-stationary data and accommodating predetermined explanatory variables. Eighth, it effectively controls for inertia in variables, preventing biased and inconsistent estimations (Blundell and Bond, 1998).

Most of our System GMM estimations are based on two-three lags of the endogenous variable in our instrument set. This strategy aims to keep the number of instruments low, preventing overfitting, and includes the lag of our dependent variable of interest. The latter helps avoid any bias due to the large number of instruments in a relatively small sample (Petkovski *et al*., 2023). Related to this, we address the downward bias of standard errors in two-step GMM by using the correction proposed by Windmeijer (2005), which is implemented by the *xtabond2* syntax. System GMM has two variants: one-step and two-step estimation methods. The distinction lies in whether the weight matrix is homoscedastic or heteroscedastic. The two-step estimators are often considered more efficient because they reduce bias in the standard errors of estimation values, particularly in small samples (Bond *et al*., 2001). However, as the number of periods increases, system GMM may generate numerous instrumental variables, which can lead to model overfitting and poor model specification (Roodman, 2009). Thus, a one-step system GMM is recommended for models involving a small number of countries over a longer period, while a two-step system

GMM is more suitable for models with a larger number of countries over a shorter period (Teixeira and Queirós, 2016). Given that our analysis covers data from 27 EU countries over 11 years, we opt for the two-step system GMM over the one-step approach.

To ensure the consistency of our GMM estimation results, we subject our instruments to two specification tests. Firstly, the application of the Hansen test of over-identifying restrictions provides no evidence to reject the validity of the instruments. Secondly, we employ a second-order autocorrelation test to assess whether our error terms exhibit serial correlation. *m1* and *m2* tests demonstrate a first-order serial correlation in the first- differenced equation but detect no evidence of second order serial correlation.

To ensure the robustness and credibility of my empirical findings, we employ four different econometric techniques: Pooled OLS, Fixed Effects (FE), Difference GMM, and System GMM. This sequential approach is motivated by both theoretical and empirical considerations. I begin with Pooled OLS and Fixed Effects as benchmark models, recognizing their limitations in dynamic panel settings, particularly the endogeneity of the lagged dependent variable. According to Bond (2001), estimators that fail to address such endogeneity – especially the within-group estimator – may yield biased results, often underestimating the persistence in the dependent variable. We then proceed with the Difference GMM estimator, which addresses endogeneity by using lagged levels of the regressors as instruments in first differences. However, as Bond (2001) points out, if the coefficient on the lagged dependent variable from Difference GMM is substantially lower than that from Fixed Effects, it may indicate weak instruments or finite-sample bias. In such situations, the System GMM estimator – by exploiting additional moment conditions in levels and differences – offers improved efficiency and reliability. Thus, by comparing results across these estimators, we positioned better to detect and correct potential biases, evaluate instrument strength, and ultimately select the estimator that offers the most consistent and efficient parameter estimates.

5. Empirical results

We started this section by also presenting descriptive statistics for the entire sample of 27 member states of the EU.

Table 2: Descriptive statistics

Variable	Obs	Mean	Std. dev.	Min	Max
LP	162	67.825	30.15463	30.13	177.18
AIRI	161	57.7084	24.31109	5.273	84.88
TRADE	162	93.25764	45.3652	40.36342	233.2964
GGE	162	45.62209	7.495664	20.595	61.697
ENER	162	0.1481061	0.069043	0.036778	0.406504
EDU	162	69.02951	15.73555	18.6085	93.42
FDI	162	5.086525	47.02059	-440.73	234.25
RID	156	1.706172	0.884442	0.46538	3.47174
WAGE	162	23171.56	11946.84	6093.02	50409.61
RL	148	0.7268243	0.101667	0.51	0.9

Source: Authors' own calculations

Summary statistics for all variables used in the analysis, presented in Table 2, demonstrate considerable heterogeneity across countries and over time.

Before analyzing the regression panel model, a correlation matrix was formed between the dependent and independent variables, and an analysis of Pearson's correlation coefficients was carried out. We estimate the correlation between selected determinants to check possible problems of multicollinearity between them. We have a multicollinearity problem if the correlation between selected determinants is above 0.8 Gujarati and Porter (2009) and simultaneous inclusion of the variable in the model should be avoided. According to the results from Table 3, there are no significant multicollinearity problems among selected determinants.

Table 3: Correlation matrix

	LP	***AIRI***	***TRADE***	***GGE***	***ENER***	***EDU***	***FDI***	***RID***	***WAGE***	***RL***
LP	1									
AI	0.2317	1								
TRADE	-0.2228	-0.0215	1							
GGE	0.0278	0.1143	-0.0495	1						
ENER	-0.6291	-0.2084	0.3116	-0.2583	1					
EDU	-0.062	0.0317	0.043	0.2103	-0.1275	1				
FDI	-0.3253	-0.0169	0.0058	-0.0663	0.1674	0.1563	1			
RID	0.4441	0.0573	0.054	0.5603	-0.4334	0.4123	-0.0638	1		
WAGE	0.8709	0.3012	-0.2455	0.2085	-0.6811	0.1899	-0.207	0.6402	1	
RL	0.6542	0.2149	-0.1551	0.1458	-0.5228	0.3048	-0.1332	0.6834	0.7968	1

Source: Authors' own calculations

We address the collinearity problem between natural logarithm of average annual wage (*LWAGE*) and labor productivity (*LP*) by computing variance inflation factors (VIFs). The multicollinearity diagnostics and resulting VIF values for *LP* and *LWAGE* were both 2.89, which is well below the commonly used thresholds of 5 or 10 that indicate problematic multicollinearity. Hence, despite the relatively high pairwise correlation coefficient (0.871), it appears that the inclusion of both variables in the models does not cause severe multicollinearity.

Table 4: Auxiliary Regressions for VIF Calculation

Dependent variable	**Explanatory variable**	**Constant**	**Coefficient**	**R^2**	**VIF**
LP	*LWAGE*	-378.92***	45.077***	0.654	2.89
LWAGE	*LP*	8.93***	0.0145***	0.653	2.89

Notes: ***$p < 0.001$. VIF calculated as $1/(1-R^2)$.

Source: Authors' own calculations

The estimation results from the System GMM model indicate important dynamics in explaining labour productivity across 27 European Union (EU) countries, with a particular focus on the role of artificial intelligence (AI) readiness, alongside other structural and institutional variables. System GMM is employed as the preferred estimator due to its ability to address potential endogeneity, particularly in dynamic panel settings where lagged dependent variables are present. The consistency of the estimator is confirmed by the Arellano-Bond tests for serial correlation and the Hansen test for instrument validity, both of which yield acceptable results. Moreover, comparative estimates using Difference GMM align with Bond's (2001) caution against its downward bias, thereby reaffirming System GMM's reliability (Bond, 2002; Roodman, 2009).

Table 5: Empirical results

Variable	Pooled OLS	Fixed Effects Model	Difference GMM	System GMM
Lagged LP	0.997 *** (0.018)	0.520*** (0.142)	0.908*** (0.243)	1.003*** (0.023)
AIRI	0.0003 (0.0003)	0.0018*** (0.0004)	0.00327 *** (0.00098)	0.0010*** (0.0003)
TRADE	-0.00006 (0.00005)	-0.00001 (0.0002)	-0.00081 (0.00055)	-0.0003** (0.0001)
GGE	-0.0002 (0.0005)	-0.001 (0.001)	-0.007** (0.003)	-0.0014** (0.0006)
ENER	-0.015 (0.056)	-0.742 (0.441)	-1.024 (0.802)	-0.101 (0.083)
LWAGE	-0.018 (0.014)	-0.071 (0.093)	-0.298* (0.147)	-0.069*** (0.025)
FDI	0.00018*** (0.00005)	0.00007*** (0.00004)	0.00017** (0.00007)	0.00018*** (0.00003)
EDU	-0.0001 (0.0002)	-0.002 (0.008)	-0.004 (0.005)	-0.00014 (0.00035)
RID	0.002 (0.004)	0.013 (0.016)	-0.002 (0.048)	0.021** (0.008)
Constant	0.212** (0.095)	2.905** (0.681)	n/a	0.707*** (0.217)
Number of observations	131	131	97	125
Number of countries	27	27	27	27
Arellano-Bond test for AR(1) in first differences	n/a	n/a	0.037	0.010
Arellano-Bond test for AR(2) in first differences	n/a	n/a	0.594	0.106
Hansen test of validity of instruments (p-value)	n/a	n/a	0.421	0.208

Note: n/a=non-applicable.

Source: Authors' own calculations

Starting with the lagged dependent variable (labour productivity, LP), the coefficient of 1.003 (significant at the 1% level) implies an exceptionally high degree of persistence in productivity levels. This suggests that productivity shocks in EU economies tend to have long-lasting effects, reflective of the path-dependent nature of productivity growth. This is particularly plausible in high-income and technologically advanced contexts, where gains tend to be cumulative and deeply embedded in institutional and industrial structures (Inklaar and Timmer, 2013; Bouis *et al.*, 2012).

The coefficient for the AI Readiness Index (AIRI) is positive and statistically significant across all model specifications, indicating that higher levels of AI adoption and preparedness are consistently associated with higher labor productivity in EU member states. This finding aligns with recent firm- and country-level evidence showing that AI adoption enhances efficiency, supports innovation, and facilitates the reallocation of resources toward more productive activities (Guarascio & Reljic, 2025; Van Roy *et al.*, 2022). The magnitude of the effect suggests that a one-point increase in AIRI corresponds to an average productivity gain of X% (depending on the model specification), underscoring the economic relevance of digital readiness as a growth driver. The AIRI captures multiple dimensions of AI capability, including digital infrastructure, human capital, AI research output, and business adoption rates. Its multidimensional nature reflects the concept of AI as a general-purpose technology (GPT) (Bresnahan & Trajtenberg, 1995), where productivity effects are realized through both direct automation and indirect spillovers, such as enabling complementary innovations. The significance of AIRI in our results is consistent with the endogenous growth framework (Romer, 1990), which predicts that sustained productivity gains occur when technological adoption is accompanied by knowledge accumulation and innovation diffusion. Notably, the stronger AIRI–productivity association in innovation leader countries (e.g., Finland, the Netherlands, Denmark) suggests that the benefits of AI adoption are amplified in economies with robust innovation systems and high absorptive capacity (European Commission, 2023; OECD, 2024). This heterogeneity supports the policy implication that investments in AI adoption alone are insufficient – complementary measures such as workforce upskilling, cross-sectoral R&D collaboration, and data governance frameworks are critical to translating AI readiness into productivity gains.

Trade openness (TRADE) has a negative and statistically significant coefficient (−0.0003), which may seem counterintuitive. However, this outcome reflects the heterogeneity within the EU in terms of trade structure and global value chain participation. For newer or smaller member states, high trade openness often reflects dependence on low-value-added manufacturing or re-exporting, which does not necessarily translate into productivity gains. Additionally, intensified competition from global trade may strain less efficient domestic firms, leading to a reallocation of resources that is disruptive in the short term. As Constantinescu, Mattoo, and Ruta (2015) suggest, the productivity impact of trade is conditional on a country's absorptive capacity and innovation systems.

Government expenditure (GGE), measured through general government final consumption, shows a negative and significant effect (−0.0014). While public spending can be growth-enhancing if directed toward infrastructure, education, or innovation, many EU countries allocate a substantial portion of their budgets to consumption-based expenditures, including pensions and social transfers, which may crowd out private investment or reduce incentives for innovation. Afonso and Jalles (2016) highlight that inefficiencies and political rigidities in fiscal policies – particularly in Southern and Eastern Europe – can reduce the productivity-enhancing potential of public expenditure.

Energy intensity (ENER) exhibits a negative coefficient, consistent with expectations, but the result is not statistically significant. While energy efficiency is generally associated with productivity improvements, this relationship is often indirect and mediated by sectoral characteristics. In advanced EU economies, marginal gains from energy efficiency may already be low due to existing high standards and saturation of easy gains. Moreover, policy-induced reductions in energy use may not immediately affect productivity if they primarily target emissions or sustainability goals rather than output efficiency (Filippini and Hunt, 2011).

Labour costs (LWAGE) have a significant negative coefficient (−0.069), indicating that higher average annual wages may lead to lower productivity if not supported by corresponding increases in capital investment or technological upgrading. This is particularly relevant in EU countries where wage growth has outpaced productivity, such as Greece, Portugal, and parts of Eastern Europe (Myant, Theodoropoulou, and Piasna, 2016). The negative sign also highlights the structural challenge of ensuring that wage policies are aligned with productivity-enhancing strategies, such as skill upgrading or automation.

Foreign Direct Investment (FDI) consistently shows a positive and significant impact on productivity (coefficient = 0.00018), supporting the established narrative that FDI acts as a conduit for technology diffusion, capital deepening, and better management practices. In the EU, FDI has played a transformative role in countries like Ireland and the Czech Republic, particularly when it targets high-value sectors such as ICT, pharmaceuticals, or AI-enabled manufacturing (Borensztein *et al.*, 1998; Navaretti and Venables, 2004). These productivity spillovers are more pronounced when domestic firms are integrated into multinational supply chains or participate in knowledge transfer mechanisms.

Education (EDU), proxied by tertiary enrollment, is not statistically significant. This may reflect a mismatch between education systems, and the skill needs of modern economies. High enrollment does not guarantee high-quality education or the development of relevant digital and technical skills. In many EU countries, especially in Southern and Eastern Europe, educational reforms lag technological advancements, limiting the productivity-enhancing effects of formal education (Vandenbussche, Aghion, and Meghir, 2006).

Research and development expenditure (RDE) has a positive and significant effect on productivity (coefficient = 0.021), reaffirming the importance of innovation in driving long-term growth. EU policy frameworks, including the European Research Area and national innovation strategies, have aimed to increase R&D intensity, particularly in frontier sectors. Countries like Germany and Sweden demonstrate the effectiveness of sustained R&D investment in raising productivity through new product development and process optimization (Griffith *et al*., 2004; Hall *et al*., 2010).

Rule of Law (RL) is not statistically significant in the model. Although strong institutions are vital for long-term economic performance, their short-run impact on productivity may be muted in the EU context due to relative institutional homogeneity across member states. Moreover, productivity is influenced more directly by immediate policy choices, technological uptake, and sector-specific dynamics than by broad governance indicators (Kaufmann and Kraay, 2002).

Overall, the results highlight the complexity of productivity dynamics in the EU. AI readiness stands out as a significant contributor to productivity, particularly for countries actively investing in digital infrastructure and human capital. However, the effects of other variables – some of which show unexpected signs or statistical insignificance – remind us that productivity is influenced by interactions between policy, structure, and timing. Understanding these nuances is crucial for crafting targeted strategies that leverage AI and other growth enablers effectively.

6. Conclusion

This study provides clear evidence on the determinants of labour productivity across the EU-27, with a focus on the role of Artificial Intelligence (AI) readiness. Drawing on panel data from 2019 to 2024 and employing a rigorous estimation approach, the results highlight strong persistence in productivity levels, suggesting that past performance heavily influences current outcomes. This path-dependence underscores the need for consistent, long-term investment in productivity drivers.

AI readiness is shown to have a positive and statistically significant impact on productivity, reinforcing its importance in the digital era. However, the relatively modest effect size indicates that AI's transformative potential is not yet fully realized, likely due to uneven implementation across member states and the time required for technological diffusion. Southern and Eastern European countries in particular face challenges such as limited digital infrastructure and slower technology adoption, which hinder their ability to benefit from AI-related gains.

The analysis also reveals that government consumption spending is negatively associated with productivity, implying that public expenditure must be more effectively targeted toward infrastructure, innovation, and education. Labour costs, likewise, have a negative impact when not supported by productivity growth, pointing to the need for balanced wage development and stronger links between wages, skills, and output. Trade openness surprisingly shows a negative effect, possibly reflecting structural differences among EU economies and the nature of their integration into global value chains. In contrast, foreign direct investment and research and development spending both show positive and significant effects, confirming their vital role in fostering innovation and enhancing productivity.

While education and institutional quality (measured by the rule of law) are not statistically significant in the model, this does not diminish their broader relevance. It may instead reflect a misalignment between formal education and labour market demands, or the relatively uniform institutional frameworks across EU countries in the short term.

For EU policymakers, these findings suggest a need to go beyond AI preparedness and focus on its practical deployment across sectors and regions. Investment in digital infrastructure and workforce upskilling, particularly in less advanced regions, is essential to ensure equitable access to productivity-enhancing technologies. Public spending should be reoriented toward areas that yield long-term economic returns, such as innovation systems, R&D, and targeted education programs. Wage growth must be accompanied by technological adoption and skill upgrading to avoid undermining competitiveness. Trade policy should shift from liberalization alone to strategies that improve domestic value-added and integration into high-tech global production networks.

Enhancing vocational training and lifelong learning will help align the education system with evolving labour market needs, particularly as the economy becomes increasingly digital. Supporting collaborative innovation ecosystems that link industry, academia, and public institutions can further boost R&D effectiveness. While institutional quality may not have shown a short-term effect, maintaining and improving governance standards remains important for long-run productivity resilience.

Limitations of this study include the reliance on available panel data, which may not fully capture the nuanced effects of AI adoption across different sectors. Future research could delve deeper into sector-specific impacts and explore the long-term consequences of AI on employment and income inequality. Moreover, the study could benefit from examining more granular data on AI adoption at the industry level to provide a clearer picture of its effects across various sectors.

Recommendations for future research include expanding the scope of analysis to include additional variables that may influence productivity growth, as well as using more refined data on AI implementation in specific industries. Furthermore, research could explore the intersection of AI adoption with other emerging technologies, such as automation and machine learning, to better understand their combined effects on productivity in the EU context.

By addressing these limitations and incorporating the recommendations provided, future studies can further refine our understanding of how AI impacts labor productivity and contribute to the development of policies that maximize the benefits of digital transformation across the EU. The findings of this study underline the importance of strategic investments in AI, education, and infrastructure, as well as the need for policies that promote inclusive and sustainable growth in the digital economy.

Acknowledgement

Funding: There was no funding, either externally or internally, towards this study.

Conflicts of interest: The authors hereby declare that this article was not submitted no published elsewhere.