Artificial intelligence and energy intensity nexus in European Union economies: the moderating role of digital transformation

Andrzej Geise[a]

Abstract. Reduction of energy intensity is the central challenge to the European Union's green and digital transition. The role of artificial intelligence innovation in this process has still not been fully analyzed. In particular, there is limited empirical evidence on whether digital maturity conditions the relationship between AI innovation and energy intensity across EU economies. Our study examines the impact of the AI innovation capacity on energy intensity in the EU, with digitalization moderating the effect. Using static panel data models for EU countries over the period of 2017-2022, the analysis employs fixed-effects models and proxies AI innovation capacity by AI-related patents. The main results show that AI innovation capacity is negatively associated with energy intensity, suggesting that knowledge-based AI innovation may contribute to more energy-efficient economic performance. However, this relationship is heterogeneous and depends on the level of digital development. EU economies with the level of digitalization above the median (more digitally advanced) can better translate AI-related innovation into energy-efficiency outcomes, whereas in economies with the level of digitalization index below the median (less digitally advanced), the effect is weaker and less robust. These findings highlight the need to integrate AI policy, digitalization strategies and energy-efficiency measures into the EU's twin transition agenda.

Keywords: artificial intelligence, energy intensity, digitalization, innovation, panel models

JEL: Q43, Q48, C23

1. Introduction

Rapid advancement of artificial intelligence (AI) is actively reshaping the challenges of socio-economic development across economies. The use of AI continues to expand across sectors, including industry, transport, energy, services, trade, healthcare, education (Ghahramani et al., 2020; Zhai et al., 2021) and markets – mostly financial, capital, commodity and derivatives (Abe & Nakayama, 2018; Cao, 2022). In the above-mentioned sectors, AI is primarily used to optimize a broad range of decisions. From the point of view of AI adaptability and its potential benefits, increased energy consumption represents a crucial challenge, where AI solutions can deliver the greatest improvements in energy efficiency and the sustainability of the economy.

[a] Nicolaus Copernicus University in Toruń, Institute of Economics and Finance, Department of Econometrics and Statistics, ul. Gagarina 13A, 87-100 Toruń, Poland, e-mail: a.geise@umk.pl, ORCID: https://orcid.org/0000-0003-4581-5484.

Within the framework of production theory, energy, together with capital and labor, constitutes the fundamental input in the production function (Stern, 2011). At the same time, energy consumption based primarily on fossil fuels (coal and crude oil) generates substantial CO2 emissions, which drive global warming, accelerate climate change, and contribute to the degradation of ecosystems and biodiversity (Bölük & Mert, 2014; Intergovernmental Panel of Climate Change [IPCC], 2023; Jie & Rabnawaz, 2024; Le, 2022; Shayanmehr et al., 2020; Zakari et al., 2022). As energy demand continues to rise, so do greenhouse gas emissions. Therefore, coordinated activity to limit emissions is necessary. In the EU, energy production and use account for more than 75% of the greenhouse gas emissions (European Commission, 2022). Reducing CO2 emissions is essential to prevent further environmental degradation and climate change, and this reduction can be achieved by improving energy efficiency, lowering the economy's energy intensity, shifting to low-carbon energy sources, and promoting sustainable consumption patterns (Altın, 2024; Lei et al., 2022).

To achieve energy efficiency and advance Sustainable Development Goals (SDGs), politicians need to address key issues related to energy sources and environmental constraints. A low-carbon economic transformation requires a transition from the conventional, energy-intensive growth model into one that prioritizes green energy, technological innovation and digitalization as the core of sustainable development (Rame et al., 2024). In the European Union, shifting the economy's energy-intensive model and reducing energy intensity are directly linked to climate policy objectives that aim to decouple economic growth from energy consumption and reduce greenhouse gas emissions (European Commission, 2022). By lowering energy intensity, member states can progress towards their binding targets for emission reductions and renewable energy shares while maintaining economic competitiveness.

This article focuses on the main question: how does the AI innovation capacity affect the energy intensity of the economy in EU countries, and whether the digital transition is accelerating these effects. To answer this question, we designed an empirical study and a set several specific goals:

- Goal 1: To review and present the existing definitions of artificial intelligence and to discuss the indicators that can be used to proxy AI development, adoption, and innovation capacity in empirical research;
- Goal 2: To assess the impact of AI innovation capacity on energy intensity in EU countries with regard to digital maturity (low vs high digitalization level across EU members);
- Goal 3: To assess the significance of accelerating AI innovation capacity through digitalization for energy intensity in EU member states during and after the pandemic.

This study examines the effect of AI innovation capacity (measured by the number of AI-related patents) on energy intensity in EU member states taking into account the moderating role of the level of digitalization. We built panel-data models for 27 EU countries from 2017 to 2022.

Our article contributes to the existing literature in several ways. First, in terms of theory, we systematize the concepts of artificial intelligence applied to empirical research, offering clear guidelines which variables can capture the development and implementation of AI innovation at the national level. This approach helps to fill a gap in the existing literature, where AI has often been narrowly addressed only as a part of digitalization. Second, in the methodological section, we analyze AI in a wider context of digital transformation, incorporating a comprehensive set of control variables. These include fundamental factors of production (capital and labor), indicators reflecting the structure of energy consumption, and the factors of an innovative economy, providing a fuller picture of the determinants of energy intensity. Third, the empirical contribution of the study lies in examining a dataset covering 27 EU Member States over the period of 2017–2022. While most existing research has focused on the role of digitalization, this article treats AI as the primary factor in the analysis, highlighting its distinct and independent impact on energy intensity. Finally, we emphasize AI's dual role both as a technological tool that improves energy efficiency and a catalyst of broader structural transformation. We further provide evidence for policymakers that AI requires dedicated strategies rather than being addressed solely within general digitalization policies.

2. Literature review – energy intensity, AI and digitalization

2.1. Artificial intelligence and proxy variables

The first references to artificial intelligence appeared in the literature in the 1950s, in which AI was defined as the science of creating intelligent machines, with a focus on programmability and the simulation of human-like capabilities (McCarthy et al., 2006). Since the 1950s, the definition of AI has evolved from intuitive descriptions to more precise and system-oriented formulations.

In empirical research on the economic and environmental impact of AI, the challenge is to use valid proxy variables that capture the essence of AI, which is defined in both functional and capability-oriented terms. The term artificial intelligence refers to "a machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations, or decisions influencing real or virtual environments", thereby highlighting task-oriented applications (Organisation for Economic Co-operation and Development [OECD], 2019). This definition has been widely adopted in policy frameworks, such as the European Union AI Act. In contrast, we define AI as "the capability of an engineered system to acquire, process, and apply knowledge and skills", reflecting a broader technological potential applicable across systems and industries (ISO/IEC 22989:2022). In both cases, these abstract definitions are not directly measurable and thus must be operationalized through observable indicators.

To distinguish between the two concepts, empirical studies typically differentiate between narrow AI, which involves domain-specific applications (e.g., robotics, predictive algorithms), and general AI, which denotes human-level flexibility and reasoning. It should be observed that general AI is currently beyond real-world implementation. Given this distinction and the lack of standardized AI metrics, researchers often resort to proxy variables. Artificial intelligence is commonly proxied in empirical research through indicators such as the number or stock of installed industrial robots (Acemoglu & Restrepo, 2022; Gao & Wang, 2025; Graetz & Michaels, 2018; Huang et al., 2022; Lee et al., 2024; J. Liu et al., 2022; L. Liu et al., 2021; Xie & Wang, 2024; Zhang et al., 2022). In this context, AI refers to automated, intelligent executive systems deployed in industry, often associated with robotization driven by algorithmic decision-making. Such robot-based measures tend to reflect the extent of intelligent manufacturing rather than offering a comprehensive view of AI development.

A more holistic perspective is provided by AI patent data, which captures AI as a knowledge-based technology and represents innovation capacity, a field of innovative activity marked by the generation of novel technological solutions. This conceptualization is widely applied in the economics of innovation and knowledge, particularly in regional studies assessing technological capabilities and the diffusion of general-purpose technologies (GPTs) (Biggi et al., 2025; Chun & Hwang, 2025; Kopka & Grashof, 2022; Podrecca et al., 2024; Xie & Wang, 2024). Still, some limitations remain, as many studies rely on narrow keyword sets in identifying AI-related patents.

More systemic approaches employ AI concept indices that capture technological, institutional, and market dimensions of AI development, reflecting its multifaceted nature (Lyu et al., 2025). Given this heterogeneity, the choice of AI proxy is critical, as it directly affects the interpretation of AI's role in energy intensity and the robustness of policy-relevant conclusions. An overview of proxy variables used in previous empirical studies is provided in the Appendix, Table A2.

Proxy variables for AI differ substantially in scope and interpretation, ranging from measures of technological adoption (e.g., industrial robots) to indicators of knowledge creation or policy commitment, such as AI-related patents or national AI strategies. In this study, AI is proxied by the number of AI-related patents, reflecting its role as knowledge-based innovation activity.

2.2. AI and energy improvements in the economy

The pathway to fostering a sustainable energy policy requires integrating digital technologies and artificial intelligence, reducing energy intensity across sectors, and enhancing collaboration among stakeholders. Recent literature has confirmed that energy intensity is driven by technological change, which mostly has been ICT (information and communication technology) and AI in recent years. So, the increased use of AI contributing to technological change may have impact on energy intensity (Liu et al., 2021). Also, given the close interrelationships among energy intensity, energy efficiency, energy consumption and the energy transition, the literature review takes into consideration all aspects relevant to the empirical study (see Table A1).

The positive impact of AI use in various sectors has been confirmed by several researchers (Gao & Wang, 2025; Kopka & Grashof, 2022; Kwilinski et al., 2023; Lee et al., 2024; X. Liu et al., 2021; Lyu et al., 2025; Melnychenko, 2019; Nishant et al., 2020; Xie & Wang, 2024; Zhang et al., 2022). AI can enhance energy efficiency and reduce energy intensity by optimizing energy consumption patterns (Nishant et al., 2020), improving performance within energy-intensive industries (Kopka & Grashof, 2022), and monitoring equipment performance in real-time (Morand et al., 2024). It can also foresee failures before they occur (Ucar et al., 2024; Yadav et al., 2024), predict the volume of energy generated from renewable resources (Şerban & Lytras, 2020), and reduce reliance on fossil fuels for energy backup (International Energy Agency [IEA], 2025), all of which contribute to decreasing overall energy intensity.

The relationship between AI and energy intensity is further delineated in the literature. Liu et al. (2021) provided empirical evidence showing that AI adoption significantly reduced energy intensity in China's industrial sector. Their study shows that AI not only enhances output but also cuts down energy consumption, particularly in industries with high initial energy intensity. Also, AI mitigates energy vulnerability by accelerating structural changes in industry to improve energy efficiency and reduce energy intensity, catalyzing green innovation and optimizing governance capabilities (Gao & Wang, 2025; L. Liu et al., 2021). Similarly, Zhang et al. (2022) found that the deployment of industrial intelligence reduces energy intensity by improving processes and optimizing resource use, thereby corroborating previous findings (Zhang et al., 2022). Such a reduction in energy intensity is vital for advancing industrial sustainability and alleviating environmental concerns.

AI systems have also demonstrated a strong ability to improve energy efficiency across the economy and various sectors. For instance, Luan et al. (2022) highlighted the critical role of industrial robots in enhancing energy efficiency and observed their positive influence on air pollution, showing that improved manufacturing processes can lead to lower energy consumption and better environmental outcomes (Luan et al., 2022). Kwiliński et al. (2023) emphasized the transformative impact of digitalization on energy efficiency in the European Union, asserting that technologies such as smart grids and data analytics can significantly optimize energy use and minimize waste (Kwiliński et al., 2023). These advancements underscore the potential of AI-driven solutions to facilitate energy-efficient practices key to sustainable development.

AI plays a crucial role in optimizing energy consumption patterns. Dzwigoł et al. (2024) explore how digitalization shifts energy consumption frameworks across EU countries, demonstrating that technological innovations lead to substantial reductions in overall energy use while allowing a more efficient distribution. Ghahramani et al. (2020) emphasize that AI-driven smart manufacturing processes can lead to reductions in energy consumption by optimizing operational workflows and allowing real-time adjustments based on data analytics. These adjustments ensure resources are used more wisely, thus contributing to greater sustainability. Furthermore, AI is instrumental in facilitating broader energy transition towards sustainable and renewable energy systems. Researchers also underline the potential of AI to support carbon-neutrality efforts by optimizing industrial emissions-reduction strategies through advanced predictive analytics and operational enhancements. AI is actively promoting reductions in carbon intensity, and this effect is further strengthened by green total factor productivity and energy efficiency (Li et al., 2022; Nishant et al., 2020). This capacity for data-driven decision-making is pivotal as global energy systems increasingly move towards incorporating renewables, needing AI to manage the intricacies of this transition effectively.

3. Research Design and Methodology

3.1. Study Design

The main variables used in the study include: energy intensity, AI innovation capacity, and the level of digitalization of economies.

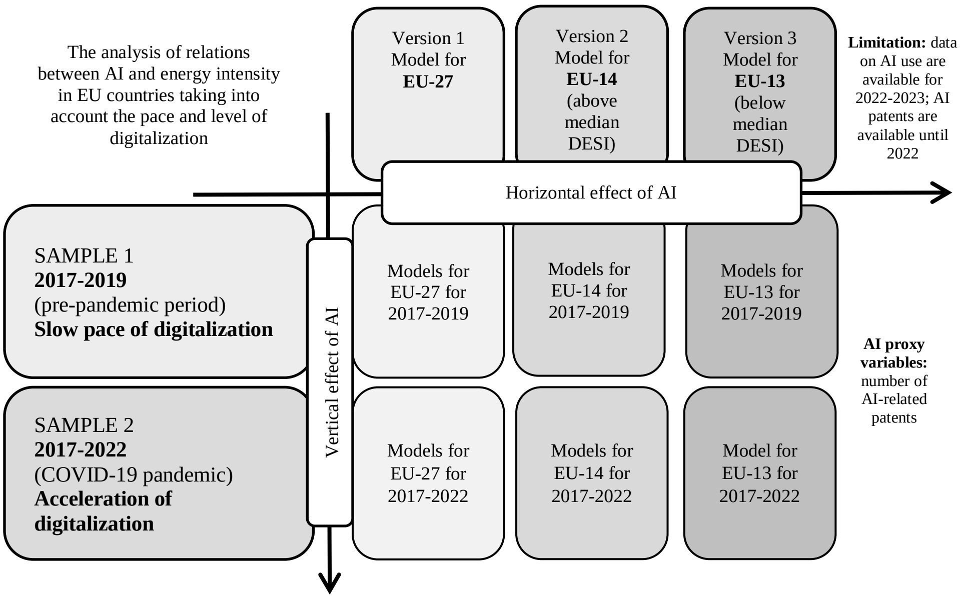
Energy intensity is the dependent variable, measured as primary energy use per unit of GDP, expressed in 2015 purchasing power parity. This indicator captures the amount of primary energy required to produce one unit of economic output and therefore reflects the energy efficiency of an economy.

The AI innovation capacity is proxied by the number of AI-related patent applications filed with the European Patent Office (EPO). In the EPO statistics, artificial intelligence is treated as a technological area within computer technologies and includes AI-related subfields such as neural networks, machine learning, pattern recognition and image and video recognition (OECD, 2025). The variable used in our study measures AI-related patenting activity and thus serves as a proxy for AI innovation capacity, rather than as a direct measure of AI implementation. The list of Cooperative Patent Classification (CPC) subclasses and keywords used to identify AI-related patents is provided in the report referenced above, titled *Identifying emerging AI technologies using patent data: A semi-automated approach* by OECD (2025).

The digital transformation is measured using the DESI index, which provides a synthetic measure of digital maturity across EU economies. The index captures several dimensions of digital development, including human capital, connectivity, digital technology integration, and digital public services (European Commission, n.d.). In this study, the aggregate DESI index is used to capture the overall level of digital transformation and to assess its moderating role in the relationship between AI innovation capacity and energy intensity.

The empirical analysis covers the 27 member states of the European Union and is based on annual data from the period from 2017 to 2022. A visual overview of the study's design is presented in Figure 1.

Figure 1. Research diagram



Source: author's work.

The empirical design of this study integrates two dimensions related to the level and dynamics of digitization across EU Member States in order to examine the impact of knowledge-based AI proxy on energy intensity (Figure 1). The horizontal dimension captures cross-country variation by distinguishing two clusters of countries based on their DESI scores – those above and below the median level of digital development. The classification of economies into the EU-14 and EU-13 groups is time-invariant. Countries were assigned to these groups on the basis of their average DESI over the analyzed period, meaning they do not move between groups from year to year. This allows the assessment of whether the AI–energy intensity relationship differs across levels of digital infrastructure and technological readiness.

The vertical dimension addresses temporal dynamics by segmenting the study period into two samples (sample 1: 2017–2019; sample 2: 2017–2022), with a structural break in 2020, coinciding with the COVID-19 pandemic and the associated acceleration in digital adoption (e.g., remote work, digital services). This division allows an assessment of whether the pace of digital transformation influences the strength and direction of the AI–energy intensity nexus over time.

Three research hypotheses were formulated on the basis of the planned study:

- *H1*: AI innovation capacity contributes to reducing energy intensity across the EU economies;
- *H2*: The relationship between AI innovation capacity and energy intensity is moderated by the level of digital development, which means that the marginal effect of AI innovation capacity on energy intensity changes along the varying level of DESI;

- *H3*: The pandemic-induced structural shift amplifies the moderating effect of digital development on the relationship between AI innovation capacity and energy intensity due to the accelerated digital transformation.

3.2. Theoretical framework

The theoretical framework used in the analysis is based on Schumpeterian endogenous growth theory. This theory provides the basics for explaining energy intensity as a function of innovation-driven technological and structural changes. Endogenous growth theories posit that technological advancement stems from innovative activities undertaken by firms and entrepreneurs, driven by profit incentives. The Schumpeterian perspective highlights that innovation enhances productivity and fosters long-term economic growth, while the process of "creative destruction" enables the replacement of obsolete technologies with new ones, thereby facilitating sectoral transformation and sustained development (Aghion et al., 2013, 2015a, 2015b).

The Schumpeterian framework emphasizes that innovation fosters knowledge spillovers, which drive technological progress and productivity growth. These spillovers are beneficial only when firms and countries have sufficient absorptive capacity to assimilate and utilize external knowledge (Aghion & Jaravel, 2015).

In the context of digital economy, AI can be interpreted as a frontier technology that expands the economy's knowledge and shifts the technological frontier outward. AI-based innovations improve predictive capabilities, process automation, resource optimization and decision-making efficiency. In energy-intensive sectors, these mechanisms may substantially improve the efficiency of transforming energy inputs into economic output. Therefore, AI innovation might be viewed as a modern "Schumpeterian" engine of technological advancement that has a direct impact on energy efficiency.

Following the endogenous growth framework, aggregate output in country *i* at time *t* is represented by an augmented Cobb-Douglas production function:

$$Y_{it} = A_{it} K_{it}^{\alpha} L_{it}^{\beta} \vartheta_{it}^{\delta}, \tag{1}$$

where Y denotes total output, K represents physical capital, L stands for labor input, A denotes the economy's technological stock, and ϑ represents other production determinants.

According to Aghion and Jaravel (2015), technological progress is assumed to depend on both innovation intensity and absorptive capacity. Consequently, the evolution of technological knowledge (growth rate of technology) may be expressed as:

$$\frac{\dot{A}_{it}}{A_{it}} = g = \psi AI_{it}\phi_{it}, \tag{2}$$

where AI denotes the innovation capacity of artificial intelligence proxied by AI-related patents, ψ stands for the productivity of innovation activities, and ϕ represents the absorptive capacity of an economy.

Consistent with the theory of knowledge spillovers, the absorptive capacity determines the extent to which economies can internalize external technological knowledge. In the digital era, absorptive capacity increasingly depends on the advancement of digital infrastructure, digital skills, data accessibility and institutional readiness (Aghion & Jaravel, 2015). Therefore, this study assumes that absorptive capacity is a function of digital transformation:

$$\phi_{it} = f(D_{it}), \tag{3}$$

where D represents the level of digital transformation.

Energy intensity is defined as:

$$EI_{it} = \frac{E_{it}}{Y_{it}} = \frac{E_{it}}{A_{it}K_{it}^{\alpha}L_{it}^{\beta}\vartheta_{it}^{\delta}}, \tag{4}$$

$$\ln(EI_{it}) = \ln(E_{it}) - \ln(Y_{it}) == \ln(E_{it}) - \ln(A_{it}) - \alpha\ln(K_{it}) - \beta\ln(L_{it}) - \delta\ln\vartheta_{it}. \tag{5}$$

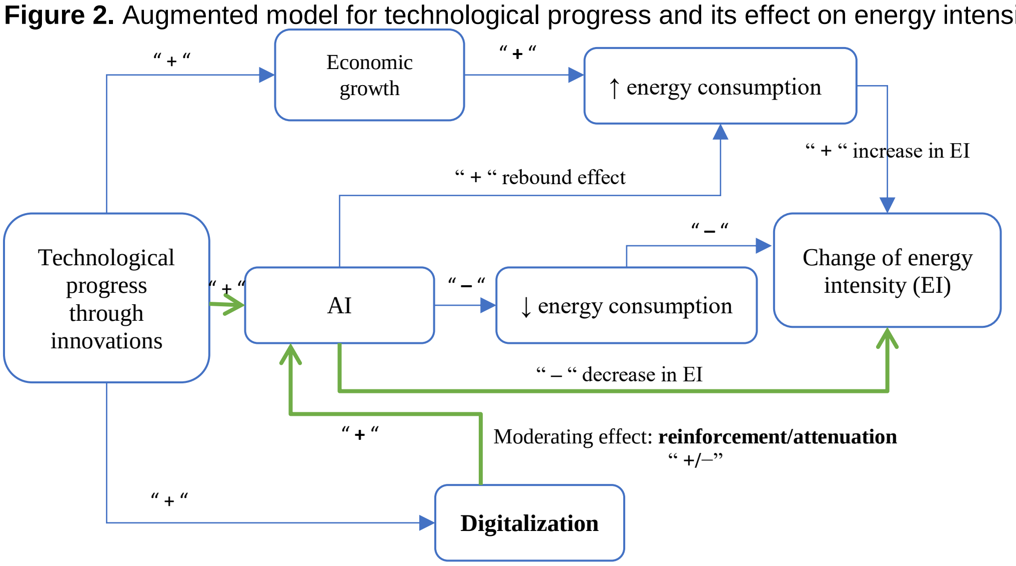
Equation (4) demonstrates that technological progress reduces energy intensity by increasing the productivity of conventional production factors. Since AI accelerates technological upgrading through automation, predictive maintenance, real-time optimization and improved allocation of productive resources, greater AI innovation capacity should reduce the energy required to generate one unit of economic output.

Moreover, the Schumpeterian literature suggests that the economic benefits of innovation are heterogeneous across countries, depending on their proximity to the technological frontier and their absorptive capacity. Accordingly, the energy-efficiency effects of AI are expected to be stronger in digitally advanced economies, where complementary digital assets facilitate the diffusion and implementation of AI-based technologies (Yuan et al., 2009).

3.3. Conceptual model

Improvements in energy intensity may indirectly result from the adoption of energy-saving innovations, such as artificial intelligence, digital process optimization, and cleaner industrial technologies (Yuan et al., 2009). In this context, AI can be conceptualized as a general-purpose technology capable of reshaping production processes, resource allocation and energy use across sectors, thereby contributing to more energy-efficient economic growth (Acemoglu et al., 2018). Figure 2 reflects this logic by showing that technological progress may increase energy demand through growth, but can also reduce energy intensity when embodied in AI-based efficiency-enhancing solutions.

Figure 2. Augmented model for technological progress and its effect on energy intensity



Source: author's work based on Yuan et al. (2009).

Although the Schumpeterian perspective usefully links innovation, technological progress and economic growth, it does not fully capture the multidimensional nature of energy intensity. It is shaped not only by technological change, but also by structural, market, regulatory, and behavioural factors, and may decline as a result of both efficiency improvements and broader structural transformations in the economy (Croner & Frankovic, 2018; Deichmann et al., 2018).

Moreover, declines in energy intensity do not necessarily reflect deliberate innovation-driven improvements in energy efficiency. They may also result from passive structural adjustments, such as the relocation or outsourcing of energy-intensive production, changes in the final demand, or a shift towards less energy-intensive sectors (Amadei et al., 2024; Levinson, 2021; Mulder & de Groot, 2012). In such cases, a decline in energy intensity may indicate a shift in the structure of domestic production rather than genuine technological progress or improved energy performance.

Finally, the relationship between innovation and energy efficiency is mediated by institutional and policy frameworks. Because the latter condition energy efficiency obtained through innovation, the Schumpeterian framework alone is insufficient to explain variations in energy intensity, and should be complemented by insights from environmental economics and regulatory studies.

3.4. Analytical framework

Given the limited availability of data, the initial strategy for modeling relationships focused on static models. Consequently, the pooled OLS estimator for panel data assumes that the units are homogeneous and that the errors are identically distributed across individuals (*i*) and time (*t*). However, in practice, these assumptions often prove to be unrealistic. To account for heterogeneity in panel data analysis, the fixed-effects (FE) estimator is commonly used. In that model, the individual-specific effects are treated as fixed parameters. In this approach, cross-sectional differences are reflected in varying intercept values. The estimation is performed using a within transformation, which eliminates individual effects by subtracting time-varying variables. This allows consistent parameter estimation on the transformed panel data.

Subtracting time averages $\bar{y}_i = 1/T \sum_t y_{it}$ from the initial model

$$y_{it} = \alpha + x'_{it}\beta + z'_i\gamma + c_i + u_{it} \tag{6}$$

yields the *within model*

$$\ddot{y}_{it} = \ddot{x}'_{it}\beta + \ddot{u}_{it}, \tag{7}$$

while $\ddot{y}_{it} = y_{it} - \bar{y}_i$, $\ddot{x}_{itk} = x_{itk} - \bar{x}_{ik}$ and $\ddot{u}_{it} = u_{it} - \bar{u}_i$. Please note the individual-specific effect c_i, the intercept α, and the time-invariant regressors z_i.

The fixed effects estimator or the within estimator of the slope coefficient β estimates the within model by OLS:

$$\hat{\beta}_{fe} = \left(\ddot{X}'\ddot{X}\right)^{-1}\ddot{X}'\ddot{y}. \quad (8)$$

Please note that parameters α and γ are not estimated by the within estimator.

4. Empirical Research

4.1. Data description and model specification

To explain energy intensity across European Union countries, we incorporate the fundamental production factors, i.e., capital and labor, into control variables that capture the energy sector's characteristics and the economy's structural composition. These controls include fossil fuel, renewable energy consumption and research and development expenditure (Table 1).

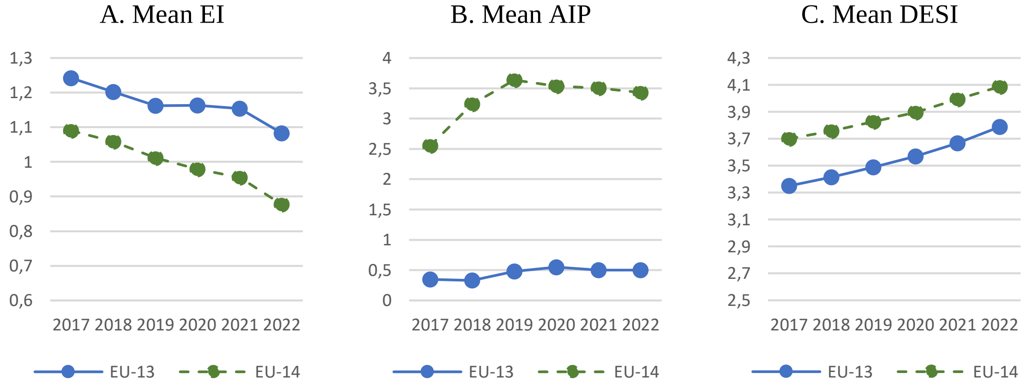
Table 1. Variables and data sources used in empirical research

Variable	Name	Description	Source
		Dependent variable	
EI_{it}	Energy intensity	Log of energy intensity level of primary energy (MJ/2015 PPP GDP)	World Bank
		Explanatory variables: AI, digitalization and technology development	
AIP_{it}	AI-related patents	Log of number of applicants	EPO (European Patent Office)
$DESI_{it}$	Digital economy and society index	Log of index	Eurostat
ACC_{it}	Acceleration of AI through digitalization	$logAIP_{it} \times logDESI_{it}$	Author's calculations
		Control variables	
		Production factors, energy variables	
K_{it}	Capital	Log of gross fixed capital formation (constant 2015 million US$)	World Bank
UR_{it}	Labor	Log of unemployment rate, total (% of working-age population, 15-64yo)	World Bank
RD_{it}	Research and development expenditure	Log of % of GDP	World Bank
$FUEL_{it}$	Fossil fuel	Log of fossil fuel energy consumption (% of total)	World Bank
$RENEW_{it}$	Renewable energy consumption	Log of % of total final energy consumption	World Bank

Note. All interaction and nonlinear terms were constructed after logarithmic transformation.
Source: author's work.

Figure 3 (A-C) shows clear differences between the EU-13 and EU-14 groups regarding the changes in average energy intensity, AI innovation capacity and digital maturity. From 2017 to 2022, energy intensity decreased in both groups, but in the EU-13 consistently more so than in the EU-14. At the same time, the mean AI innovation capacity was significantly higher in the EU-14, indicating a much greater concentration of AI-related patent activity in more digitally advanced economies. By the same token, the DESI index continued to increase in both groups, but in the EU-14 group significantly more so. Overall, Figure 3 suggests that digitally mature economies combine lower energy intensity with higher innovation capacity and digital transformation, whereas the EU-13 economies are characterized by higher energy intensity and weaker AI innovation capacity.

Figure 3. Evolution of key variables in EU-13 and EU-14 economies in 2017–2022



Source: author's work.

This study uses the following model, in which all variables are expressed in logarithms:

1) model without control variables:

$$EI_{it} = \beta_1 AIP_{it} + \varphi_1 DESI_{it} + \varphi_2 DESI_{it}^2 + \gamma_1 ACC_{it} + FE_i + \varepsilon_{it}, \quad (9)$$

2) model with control variables:

$$EI_{it} = \beta_1 AIP_{it} + \varphi_1 DESI_{it} + \varphi_2 DESI_{it}^2 + \gamma_1 ACC_{it} + FE_i + \alpha X_{it} + \varepsilon_{it}, \quad (10)$$

while EI_{it} is the annual average energy intensity of primary energy in country *i* over a specific period *t* from 2017 to 2022. $ACC_{it} = AIP_{it} \times DESI_{it}$ is the interaction between AI-related patents (AIP_{it}), and $DESI_{it}$ index, which captures the acceleration of the AI effect on the energy intensity (EI) through the digitalization level, and X_{it} is the set of control variables (see Table 1).

Given the presence of the acceleration factor (ACC_{it}), it is necessary to interpret the relationship between AI and EI in terms of marginal effects. As emphasized by Brambor et al. (2006), multiplicative interaction models imply that the intensity of the effect of one variable depends on the level of another.

Following this approach, the marginal effect of AI innovation capacity is calculated as the partial derivative of energy intensity with respect to the digitalization level. In the baseline specification, the effect is given by Brambor et al. (2006):

$$\frac{\partial EI_{it}}{\partial AIP_{it}} = \beta_1 + \gamma_1 DESI_{it}, \tag{11}$$

where $\beta_1$denotes the coefficient of AI innovation capacity, and $\gamma_1$represents the coefficient of the interaction term.

The use of marginal effects also improves the substantive interpretation of the estimated models. Williams (2012) argues that marginal effects and adjusted predictions help translate regression coefficients into quantities that are easier to interpret in substantive and practical terms. Moreover, graphical presentation of marginal effects with confidence intervals provides a clearer way to assess how the estimated relationship changes across different values of the moderating variable (Williams, 2012).

4.2. Empirical models for energy intensity in EU countries: AI and digitalization in energy intensity models for the pre-2020 period and the whole sample

The models are estimated using an FE framework, which accounts for the unobserved, time-invariant heterogeneity across countries. This approach enables us to identify within-country changes in the AI-energy intensity relationship and to examine the moderating role of digitalization across the EU-27 sample and the EU-14 and EU-13 subsamples. Based on the Wald, Breusch-Pagan and Hausman tests, the fixed-effects estimator was selected over pooled OLS and random-effects specifications. The corresponding *p*-values were below the 0.05 significance level, justifying the use of the FE framework. Given the short panel and the strong common time variation in key variables, year fixed effects (two-way FE) could absorb a substantial share of the variation relevant to the research question. Therefore, country fixed effects are used to control for time-invariant heterogeneity, while common shocks, such as the COVID-19 pandemic, are acknowledged as a limitation.

The results of panel regression models are presented in Table 2 (for the pre-2020 sample) and Table 3 (for the whole sample). In the EU-27, EU-14 and EU-13 models, the DESI index shows generally negative and statistically significant coefficients (φ_1 or φ_2) in both the pre-2020 and the whole sample. In the pre-2020 sample, the effect of digitalization on energy intensity is linear across all (1)-(6) models. In the whole sample, however, this linear relationship is true for the EU-14 and EU-13 clusters only – the EU-27 model results indicate a non-linear pattern. The EU-27 model for the whole sample exhibits an inverted-U relationship, as indicated by the negative and significant coefficient of φ_2. Based on the whole sample, we observed that digitalization has a stronger impact on energy intensity in the EU-14 group (−0.808% without controls and −0.614% with controls) than in the EU-13 group (−0.329% without controls and −0.235% with controls). The energy-efficiency benefits of digital transformation may be more visible in digitally mature economies. That might imply that digital technologies, such as smart grids, IoT devices or predictive maintenance can substantially improve energy optimization, thereby reducing energy consumption and emissions (Khan et al., 2025).

In the pre-2020 sample, the elasticity coefficients of AI innovation capacity (β_1) are negative across all the estimated specifications, i.e. in all the (1)–(6) models. The negative coefficients may serve as initial evidence that increased AI innovation capacity is associated with reduced energy intensity. However, this relationship is statistically significant only in one specification – EU-27 without controls (model 1). This limitation is particularly relevant because the pre-2020 sample covers only three annual observations (2017–2019), which may reduce the precision of the estimates and inflate standard errors. For this reason, the pre-2020 results should be interpreted with considerable caution and treated mainly as a pre-pandemic benchmark and a starting point for subsequent analyses. The main interpretation of the study is based on the whole-sample estimates and the marginal effects (2017–2022).

Table 2. Regression results of energy intensity models for EU-27, EU-14 and EU-13 for the pre-2020 sample (2017-2019)

Variable	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
	EU-27	EU-27	EU-14	EU-14	EU-13	EU-13
AIP_{it}	−0.1394 (0.048) ***	−0.1564 (0.1135)	−0.2752 (0.3043)	−0.2586 (0.1937)	−0.3248 (0.1994)	−0.4309 (0.1681)
$DESI_{it}$	−0.5701 (0.0603) ***	−0.2343 (0.1507)	−0.6886 (0.2882) **	−0.4214 (0.2016) *	−0.6301 (0.138) ***	−0.4505 (0.1541) *
ACC_{it}	0.0328 (0.0129) **	0.0382 (0.0306)	0.0677 (0.0785)	0.0689 (0.0502)	0.0889 (0.0572)	0.1210 (0.0474)
RD_{it}	−	−0.0690	−	−0.1866	−	0.2426

		(0.1073)		(0.146)		(0.1569)
K_{it}	–	−0.0733 (0.045)	–	−0.0337 (0.0477)	–	−0.0899 (0.1240)
UR_{it}	–	0.0831 (0.0812)	–	0.0828 (0.0929)	–	0.2604 (0.1375)
$FOSIL_{it}$	–	0.6628 (0.1660) ***	–	0.691 (0.1991) ***	–	−0.3109 (0.2376)
$RENEW_{it}$	–	−0.0055 (0.1007)	–	−0.1148 (0.1350)	–	−0.0240 (0.0987)
$Constant$	3.216 (0.1959) ***	−0.1023 (1.0724)	3.7082 (1.0619) ***	0.4562 (1.2246)	3.3509 (0.4703) ***	4.5750 (1.567) ***
N	27	27	14	14	13	13
T	3	3	3	3	3	3
Estimator	*Fixed effect*	*Fixed effect*	*Fixed effect*	*Fixed effect*	*Fixed effect*	*Fixed effect*

Note. *, **, *** − significance at 10%, 5% and 1%, respectively.
Source: author’s work based on calculations.

The elasticity coefficients in the whole sample suggest that AIP_{it} in EU member states is negatively and significantly associated with energy intensity. Considering the EU-27, a 1% rise in AI-related patents is associated with an average decline of 0.12–0.16% in energy intensity (models 7 and 8). This effect is substantially stronger in EU-14, where a 1% increase in AI-related patents is associated with an average decrease of −0.31% (without controls) and −0.28% (with controls) in EI (models 9–10). This result suggests that EU-14 economies may have greater absorptive capacity and more advanced complementary digital infrastructure. In the EU-13, the elasticity coefficients are smaller than those in the EU-14 models (about −0.13% without controls and −0.15% with controls), and the coefficients (β_1) are only marginally significant after adding controls (α=10%). This might indicate that in economies with weaker digital infrastructure the relationship between AI innovation capacity and energy-efficiency improvements is weaker (Table 3).

At the same time, it should be emphasized that the direct interpretation of these coefficients is limited, as they do not show how the effect of AI innovation capacity changes as the level of digital transformation does. For this reason, further interpretation should focus on marginal effects calculated for different values of DESI, which may indicate that the actual impact of AI innovation capacity is weaker than suggested by the baseline coefficients.

Table 3. Regression results of energy intensity models for EU-27, EU-14 and EU-13 for the whole sample (2017–2022)

Variable	Model (7)	Model (8)	Model (9)	Model (10)	Model (11)	Model (12)
	EU-27	EU-27	EU-14	EU-14	EU-13	EU-13
AIP_{it}	−0.1607 (0.07) **	−0.1194 (0.07) *	−0.3056 (0.126) **	−0.2808 (0.119) **	−0.1262 (0.081)	−0.1516 (0.08) *
$DESI_{it}$	1.7367 (0.51)***	0.8625 (0.59)	−0.808 (0.128)***	−0.614 (0.125)***	−0.329 (0.039)***	−0.235 (0.06)***

${DESI^2}_{it}$	−0.2995 (0.07)***	−0.1625 (0.08)**	–	–	–	–
ACC_{it}	0.0417 (0.02)**	0.0323 (0.019)*	0.0825 (0.033)**	0.0783 (0.03)**	0.0325 (0.022)	0.0419 (0.022)*
RD_{it}	–	0.1699 (0.069)**	–	0.1948 (0.106)*	–	0.0604 (0.0796)
K_{it}	–	0.0205 (0.05)	–	0.0359 (0.0653)	–	-0.0271 (0.0887)
UR_{it}	–	0.0983 (0.038)**	–	0.1117 (0.058)*	–	0.1273 (0.047)**
$FOSIL_{it}$	–	0.6301 (0.14)***	–	0.6045 (0.1619)***	–	0.4051 (0.2426)*
$RENEW_{it}$	–	−0.0871 (0.061)	–	−0.1485 (0.0864) *	–	−0.034 (0.0797)
$Constant$	−1.231 (0.896)	−2.772 (1.155)**	4.076 (0.478)***	0.5378 (1.205)	2.3217 (0.138)***	0.3757 (1.529)
N	27	27	14	14	13	13
T	6	6	6	6	6	6
Estimator	*Fixed effect*	*Fixed effect*	*Fixed effect*	*Fixed effect*	*Fixed effect*	*Fixed effect*

Note. *, **, *** – significance at 10%, 5% and 1%, respectively.
Source: author's work based on calculations.

The interaction term ACC_{it} in the pre-2020 sample is insignificant. However, in the whole sample, the interaction coefficient (γ_1) becomes statistically significant in specifications for EU-27 and EU-14, while remaining weaker and less robust for EU-13 (Table 3). The positive coefficient of the interaction term suggests that, as AI innovation capacity increases and economies become more digitally mature, the initially negative effect of AI innovation capacity on energy intensity weakens and may eventually become positive. This might mean that, at higher levels of digital transformation, the potential efficiency gains from AI-related innovation can be partly offset by the energy requirements of digital and computational infrastructure. Therefore, a full interpretation requires examining marginal effects at different levels of DESI.

Among the control variables, fossil fuel energy consumption is the most consistently significant and positively associated with energy intensity, indicating that economies more reliant on fossil fuels tend to be characterized by higher energy intensity. The remaining controls are generally not statistically significant, especially in the pre-2020 sample, and therefore should not be overinterpreted.

The findings indicate that AI innovation capacity has the potential to reduce energy intensity. However, this potential is not automatic and seems to be conditional on a sufficient level of development and effective sectoral integration of digital transformation.

Marginal effects of AI innovation capacity on energy intensity across levels of digital transformation

Recognizing that the coefficients in Tables 2 and 3 can only shed limited light on the analyzed relationship, we also present a figure (Figure 4A-C) that graphically illustrates how the marginal effect of AI innovation capacity in EU economies changes across the range of digital transformation. The marginal effects were calculated for the EU-27, EU-14 and EU-13 samples. To facilitate their interpretation, the detailed marginal effects calculated at the 25th (P25), median (P50), and 75th (P75) percentiles of DESI are presented in Table A4 in the Appendix. A 95% confidence interval around the marginal effect enables us to determine the conditions under which AI innovation capacity has a statistically significant effect on energy intensity in the EU economies. If the upper and lower bounds of the confidence interval are both above (or below) the zero line, the marginal effect is statistically significant (Brambor et al., 2006).

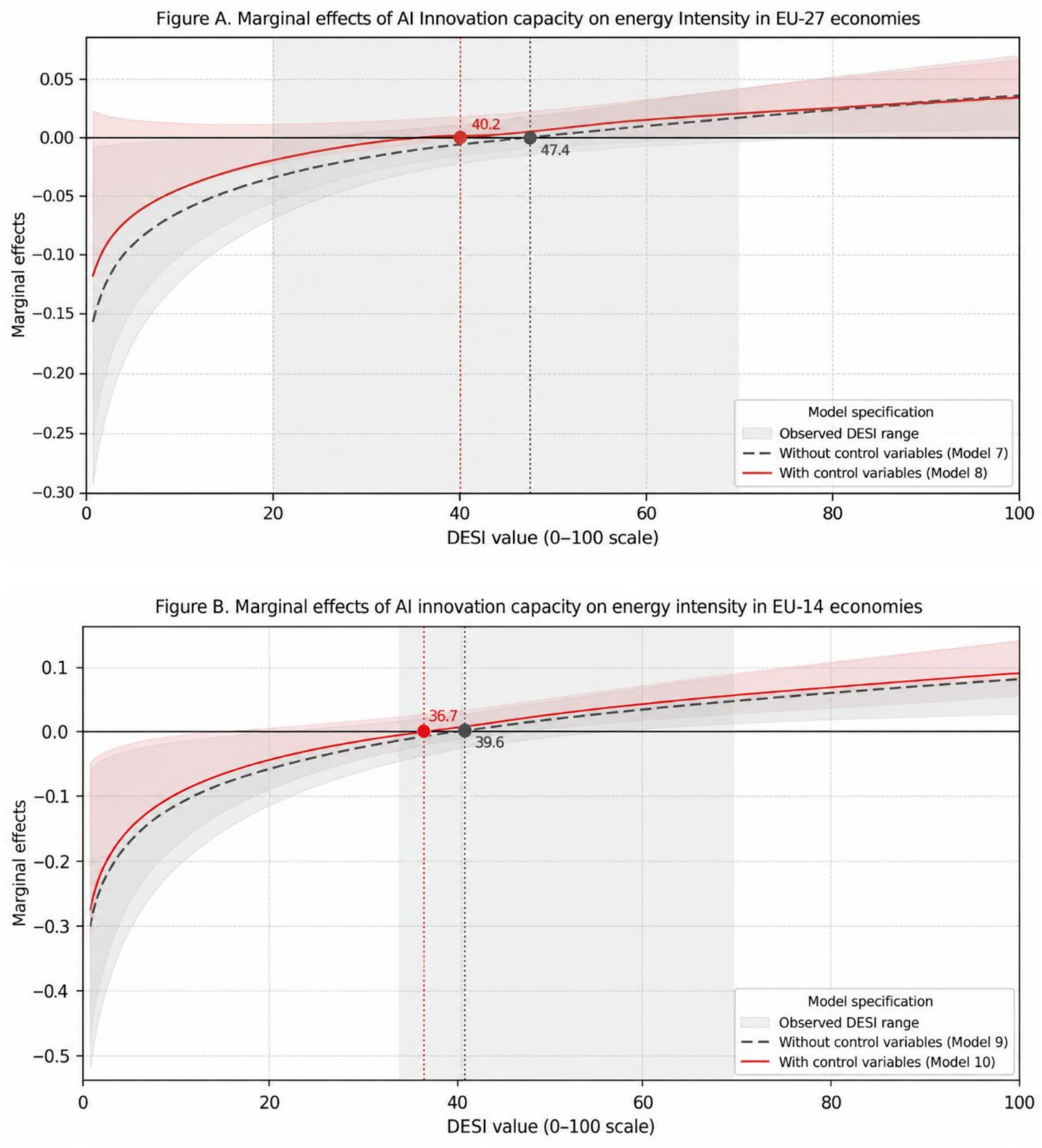
Generally, at low levels of DESI, the marginal effects of AI innovation capacity are negative, suggesting that AI-related innovation may contribute to reductions in energy intensity. However, this effect weakens as digital transformation progresses and, once DESI exceeds a certain threshold, becomes positive, suggesting that at higher levels of digitalization, AI innovation capacity may be associated with higher energy intensity (Figure 4, Table A4).

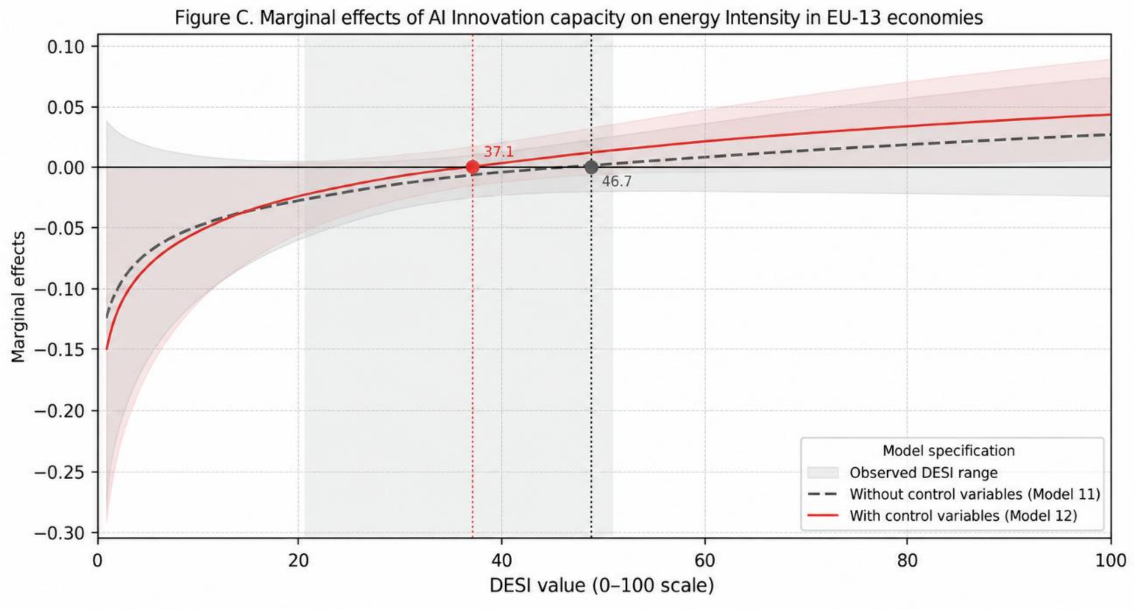
In the EU-27 model with control variables, the marginal effect of AI innovation capacity on EI equals zero at DESI approximately equal to 40.2, whereas in the model without control variables, this point is reached at around 47.4 (Figure 4A). Above these values, the marginal effect turns positive, indicating that at higher levels of digital transformation, AI innovation capacity is associated with higher energy intensity. However, for the EU-27, marginal effects remain statistically insignificant across the 25th and 75th percentiles of DESI. This may partly reflect the heterogeneity of the group, with the average effect masking differences between more and less digitally advanced economies. Consequently, by dividing EU economies into those with higher (EU-14) and lower (EU-13) levels of digital development, we can obtain more detailed and consistent results and relationships.

For the EU-13, the marginal effects between the 25th and 75th percentiles are generally negative or near zero and remain insignificant. This may suggest that economies with lower levels of digital development do not experience a conditional effect of AI innovation capacity on energy intensity, while at the same time moving toward a point where the marginal effect becomes positive.

For the EU-14, the marginal effect becomes positive and statistically significant at high levels of DESI (Figure 4, Table A4). In the specification with control variables (model 10), the marginal effect rises from 0.0151 at the 25th percentile of DESI to 0.0325 at the 75th percentile. At that level, a 1% increase in AI innovation capacity is associated with an approximately 0.0325% increase in energy intensity, ceteris paribus. This indicates that in economies with more advanced digital infrastructure, greater capacity for artificial intelligence innovation is associated with increased energy consumption when digital transformation is already substantial.

Figure 4. Marginal effects of AI innovation capacity on energy intensity, conditional on digital transformation





Note: Dots and dotted vertical lines mark the DESI value where the marginal effect equals zero. Grey area indicates the observed DESI range in the estimation sample.
Source: author's work.

The development and diffusion of AI require digital and computational infrastructure, including data centers, cloud services and increasing computing power, all of which generate additional energy demand. As a result, the energy-saving potential of AI innovation capacity may be partly offset by the energy requirements of this infrastructure, especially if AI technologies are not yet sufficiently mature or widely integrated into energy-efficient production and service processes (Masanet et al., 2020). Such an interpretation is also consistent with the literature, which suggests that digitalization does not necessarily reduce energy demand in a direct or automatic way. Digital technologies may foster energy savings, but they also require ICT infrastructure, data processing capacity and computing power, which may increase energy use, especially in more digitally advanced economies (Lange et al., 2020; Masanet et al., 2020). Similar concerns are raised in the AI literature, where the environmental cost of training and deploying AI systems is increasingly emphasized (Dhar, 2020; Schwartz et al., 2020). Therefore, the positive marginal effects observed at higher DESI levels may be interpreted as the potential efficiency gains from AI being partly offset by the energy requirements of digital infrastructure and the possible rebound effects (Brockway et al., 2021; Gillingham et al., 2016).

4.3. Robustness check

The robustness of the results is tested by constructing additional model specifications to assess the sensitivity of the findings to the assumed linear functional form.

The first alternative form of the model includes a squared term for AI innovation capacity to test for nonlinear effects, while the model takes the following form:

$$EI_{it} = \beta_1 AIP_{it} + \beta_2 AIP_{it}^2 + \varphi_1 DESI_{it} + \gamma_1 ACC_{it} + FE_i + \alpha X_{it} + \varepsilon_{it}. \tag{12}$$

The second alternative model specification examines the lagged influence of AIP and DESI on EI, thereby enabling us to assess the robustness of the results to alternative timing assumptions and to partially address potential endogeneity concerns. The model has the following form:

$$EI_{it} = \beta_1 AIP_{i,t-1} + \varphi_1 DESI_{i,t-1} + \gamma_1 ACC_{i,t-1} + FE_i + \alpha X_{it} + \varepsilon_{it}. \tag{13}$$

The results of the nonlinear models are presented in Table A5, while the models for the lagged specification are shown in Table A6 in the appendix. The nonlinear and lagged specifications yield results that are generally consistent with the baseline models (7)–(12). Across both alternative specifications, the coefficient on AI innovation capacity remains negative in all the models, while significant effects are confirmed for EU-14 and EU-13 (specifications with control variables) only in the nonlinear form. At the same time, the squared term of AI innovation capacity is statistically insignificant across all nonlinear specifications, providing insufficient empirical support for a nonlinear relationship over the analyzed period. Therefore, the baseline linear specification appears to provide a parsimonious approximation of the relationship. However, this conclusion should be interpreted with caution, as the sample's relatively short time dimension may limit the statistical power of the nonlinear tests. The lagged specifications further support the robustness of the main findings, although the estimated delayed effects are weaker, suggesting that the results are not driven solely by the contemporaneous model structure.

The marginal effects presented in Table A7 further support the robustness of the baseline findings. For the EU-27 and EU-13 economies, the effects of AI innovation capacity remain close to zero and statistically insignificant across the selected levels of digital transformation. In contrast, the strongest conditional pattern is observed for the EU-14 economies, where the marginal effects are positive and increase with the DESI levels. So in the controlled nonlinear specification, the effect becomes statistically significant at the 75th percentile of DESI. The lagged specifications yield weaker and insignificant marginal effects. Nevertheless, their direction remains broadly consistent with the baseline and nonlinear models, indicating that the main conclusions are not driven solely by the contemporaneous specification. Overall, the marginal effects confirm the stability of the results across alternative specifications and show that the AI-energy intensity relationship is conditional on the level of digital transformation and differs across groups of economies.

5. Discussion and Conclusions

This study examined the relationship between artificial intelligence innovation capacity and energy intensity in the European Union, with particular attention to the moderating role of digital transformation. The main objective was to determine whether AI-related innovation contributes to reducing energy intensity in EU economies and whether this relationship depends on the level and pace of digitalization. The empirical design made achieving this objective possible by estimating panel models for the EU-27 and for two groups of countries differing in digital maturity: the EU-14 and EU-13.

The results suggest that the relationship between AI innovation capacity and energy intensity is conditional on the level of digital transformation and differs across EU economies. Although the coefficients on AI innovation capacity generally indicate negative association with energy intensity, the marginal effects reveal a more nuanced pattern. In the heterogeneous EU-27 sample, the marginal effects are statistically insignificant, suggesting that average estimates may mask differences between economies at different stages of digital transformation. In the EU-14, the marginal effect becomes stronger as DESI increases and is statistically significant at higher levels of digitalization; however, its positive sign indicates that AI-related innovation is associated with higher, rather than lower, energy intensity. This might suggest that, in digitally advanced economies, the energy demand of digital and computing infrastructure may partly offset potential efficiency gains (Olson, 2024; Solnørdal & Thyholdt, 2019). In the EU-13, the marginal effects remain statistically insignificant, possibly reflecting lower digital maturity and a weaker capacity to translate AI-related innovation into measurable energy-saving outcomes (Mo & Liu, 2026). The results thus provided partial support for the first hypothesis, namely “AI innovation capacity contributes to reducing energy intensity across EU economies”, and upheld the second hypothesis, which said that “The relationship between AI innovation capacity and energy intensity is moderated by the level of digital development, such that the marginal effect of digitalization (DESI) on energy intensity changes with its level".

The moderating role of digitalization became more evident after the acceleration of digital transformation associated with the COVID-19 pandemic, but it remains visible only in economies with a higher level of digital maturity (EU-14). The expansion of digital tools, remote work, digital services, and enterprise-level technology adoption may have strengthened the relationship between AI-related innovation and energy intensity. However, this effect should not be interpreted as an automatic improvement in energy efficiency, since the diffusion of AI and digital technologies also requires energy-intensive digital and computational infrastructure. That means the third hypothesis, "The pandemic-induced structural shift amplifies the moderating effect of digital development on the relationship between AI innovation capacity and energy intensity, due to accelerated digital transformation," was partially supported.

This study highlights the importance of energy intensity as a key indicator of energy transformation. Energy intensity reflects not only the amount of energy required to generate the economic output, but also the technological, structural, and organizational capacity of an economy to decouple growth from energy consumption (Croner & Frankovic, 2018; Deichmann et al., 2018; IEA, 2021). Therefore, reducing energy intensity should be considered a central dimension of the green and digital transition.

Recognizing the strategic importance of reducing energy intensity, the EU and its member states have increasingly been embedding energy-efficiency objectives in climate, industrial and innovation policies. The revised Energy Efficiency Directive sets a binding target to reduce final energy consumption by 11.7% by 2030, while national initiatives in countries such as Sweden, Germany, France and Spain link energy-efficiency improvements with industrial modernization, digital energy management and decarbonization (Directive (EU) 2023/1791 of the European Parliament and of the Council of 13 September 2023 on energy efficiency and amending Regulation (EU) 2023/955 (recast)). These developments show that reducing energy intensity is increasingly often treated not only as an energy policy goal, but also as a strategic instrument for strengthening competitiveness, industrial resilience, and environmental sustainability in the low-carbon transition.

Support for AI research, patenting, data infrastructure and industrial AI applications may improve energy performance, especially in energy-intensive sectors. Digital infrastructure is a necessary condition for transforming AI innovation into energy-efficiency gains. Investment in broadband networks, cloud infrastructure, data interoperability, cybersecurity, digital skills and smart energy systems is therefore essential (Colangelo et al., 2025; Olson, 2024). Less digitally advanced EU economies require targeted support to reduce the digital-energy efficiency gap. In particular, policies should support SMEs in adopting AI and digital energy management tools and strengthen the diffusion of technology between the more and the less digitally advanced member states. Policies supporting AI and digital transformation should be aligned with renewable energy deployment, energy-efficient digital infrastructure and rebound-effect monitoring. This highlights the twin transition as an integrated agenda linking AI innovation, digital maturity and energy transformation.

This study has several limitations. First, the empirical analysis is based on a relatively short panel, mainly due to the availability of comparable DESI and AI patent data for EU countries. Therefore, the results should be interpreted primarily as short-term conditional associations rather than long-term causal effects. Second, AI innovation capacity is measured using AI-related patents, which capture innovation activity but not the actual implementation of AI technologies across sectors. Similarly, the aggregate DESI index reflects the overall digital maturity but does not identify which specific dimensions of digital transformation (human capital, connectivity, integration of digital technology and digital public services) are most relevant for the AI–energy intensity relationship. Third, the potential endogeneity cannot be fully ruled out. Although country fixed effects control for unobserved time-invariant differences between economies, they do not eliminate reverse causality or omitted time-varying factors. For instance, economies with different levels of energy intensity may also differ in their incentives and capacity to invest in AI-related innovation. Therefore, the results should be interpreted as conditional associations rather than definitive causal effects. Finally, there were some common shocks, such as the COVID-19 pandemic, the energy crisis and accelerated digital transformation in the analyzed period, which may affect the interpretation of the results. These issues suggest that future studies should be expanded to include longer time series, alternative indicators of digitalization and different approaches, such as dynamic, nonlinear or threshold-based panel models.

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Appendix A

Table A1. Literature covering the potential AI's impact on energy intensity, energy efficiency, CO2 emissions and energy consumption

Author(s)	Country/sector/ research sample	Key findings	Energy changes through			
			EI	EE	EC	CI
(L. Liu et al., 2021)	China/ industrial sectors	Reduction of energy intensity (AI ↑ by 1% then EI ↓ by 0.0244%) Boosting applications of AI can significantly reduce energy intensity by both increasing production value and reducing energy consumption.	X		X	
(Zhang et al., 2022)	China, time series 2008-2019, OLS and WLS	Increasing industrial AI reduces energy intensity by lowering energy consumption. There is a significant scale effect at the enterprise level: for large enterprises, the AI effect on energy intensity is greater, with larger reductions.	X		X	
(Huang et al., 2022)	Chinese firms' level analysis – panel from 2001 to 2012	Robot adoption in the production process promotes intelligent production and improves energy efficiency, mainly by advancing production technology and increasing output.		X		

(Kopka & Grashof, 2022)	Germany, analysis on the regional level (NUTS-3), panel data for the years 2005-2015	AI's impact on energy use varies by a region's technology and industry. "Dirty industries" consume more energy with AI. Regions with green technology see no significant AI effect. Central regions experience a moderate, decreasing AI impact.			x	
(J. Liu et al., 2022)	Chinese industrial sector (13 categories) - time series 2005-2016	AI adoption significantly reduces carbon intensity, with greater effects in labor-intensive and technology-intensive industries than in capital-intensive sectors. To amplify AI's impact on reducing carbon intensity, diversified policies should be implemented in line with industry characteristics.				x
(Li et al., 2022)	Panel of 35 countries – time span from 1993-2017	The use of industrial robots is actively reducing carbon intensity, and this effect is further enhanced by green total factor productivity and energy efficiency.	X			x
(Gyamfi et al., 2023)	Panel of 26 EU economies for the years 1990-2019	AI contributes to energy efficiency by optimizing the energy use, while promoting the transition towards renewable sources, thereby reducing energy intensity and consumption.	X	x	x	
(Xie & Wang, 2024)	China, panel model for 30 Chinese provinces between 1997 and 2019	The findings indicate that AI technologies have the capacity to substantially reduce carbon emissions, with this effect being particularly evident in regions characterized by advanced digital infrastructure and substantial level of economic development.				x
(Lee et al., 2024)	Panel of 64 countries – time span 2005-2019	Along with the progressing AI development, the scale of energy transformation is gradually growing at the national level. The direct impact of digitalization on the energy transition is negative, but, as a moderating factor, it accelerates the positive influence of AI on it.				x
(Podrecca et al., 2024)	Global dataset of 5,919 granted patents filed between 2011 and 2023	The key findings indicate that while AI patents in manufacturing predominantly support operational efficiency, only a limited share of them directly targets energy management and carbon reduction. This suggests that AI's environmental potential is emerging but has not been fully utilized yet.			x	x
(Gao & Wang, 2025)	Panel of 52 countries – time span 2000-2019	AI mitigates energy vulnerability through accelerating changes in the structure of the industry to improve energy efficiency and reduce energy intensity, catalyzing green innovation technology and optimizing governance capability	X	x		
(Lyu et al., 2025)	China – time series analysis (01.2013-06.2023)	Bi-directional Granger causality relation between AI and CE (clean energy index). AI offers intelligent solutions that enhance efficiency, optimize energy management and foster innovation within the CE sector.		x		

Source: author's work based on literature review.

Table A2. Proxy variables describing AI

Type	Autor(s)	Operationalization
Industrial robots / automation-based proxies	(Graetz & Michaels, 2018)	AI-related technological adoption, using country-level robot density data from the International Federation of Robotics (IFR), with robot diffusion serving as a proxy for the influence of intelligent automation on productivity growth.
	(L. Liu et al., 2021)	The authors used AI variables, measured as: (1) the number of installed industrial robots; (2) the stock of industrial robots.
	(Acemoglu & Restrepo, 2022)	Proxy AI-driven technological change using the stock of industrial robots per thousand workers, treating robots as physical embodiments of task-based automation and intelligent execution systems at a workplace.
	(Zhang et al., 2022)	AI is measured by the stock of industrial robots.
	(J. Liu et al., 2022)	AI is measured by the number of industrial robot installations in China's industrial sectors.
	(Li et al., 2022)	Industrial robot application intensity is a proxy variable of intelligent production.
	(Lee et al., 2024)	AI is measured as the stock of industrial robots.
	(Gao & Wang, 2025)	AI is measured on the basis of: (1) the stock of robot usage, and (2) the installation of new robots in companies.
Firm-level AI/robot adoption	(Huang et al., 2022)	To measure the degree of a firm's robot implementation, the researchers used three indicators: (1) a dummy variable to describe whether the firm uses robots in production, (2) the number of robots used by the firm in the production process, and (3) the value of robots used by the firm.
AI indices	(Lyu et al., 2025)	China's AI industry is characterized by the Artificial Intelligence Concept Index, which captures key dimensions of AI development – technology, policy and market implementation.
AI patent-based proxies	(Kopka & Grashof, 2022)	AI knowledge of regions is operationalized using a patent dataset, in which authors calculated the AI share as the cumulative number of AI patents at the regional level, divided by the total number of patent families originating in that region.
	(Xie & Wang, 2024)	AI is measured as (1) the quantity of AI patents, (2) the operational stock of industrial robots, and (3) the increase in the number of industrial robots.
AI-green patent-based proxies	(Podrecca et al., 2024)	The authors use AI-enhanced patent activity in the manufacturing sector, focusing on inventions that integrate AI techniques into climate-oriented process optimization and energy efficiency.
	(Biggi et al., 2025)	AI is proxied by identifying patents that combine artificial intelligence components – such as machine learning and neural networks – with green technologies, using CPC codes and keyword mapping.
	(Chun & Hwang, 2025)	AI is proxied by the density and interaction of national-level AI and green technology patent portfolios, capturing the extent to which AI-related patents intersect with green innovation capacity in each country

Note. The table summarizes selected proxy variables used in the literature to measure AI development, AI adoption and AI innovation capacity. The proxies can be grouped into robot-based measures, firm-level adoption indicators, composite AI indices and patent-based measures.
Source: author's work based on literature review.

Table A3. Two clusters of EU economies based on the median of the DESI index

Cluster 0 – EU13	**Cluster 1 – EU14**
Belgium, Bulgaria, Czechia, Greece, Croatia, Italy, Cyprus, Latvia, Hungary, Poland, Portugal, Romania, Slovakia	Denmark, Germany, Estonia, Ireland, Spain, France, Lithuania, Luxembourg, Malta, the Netherlands, Austria, Slovenia, Finland, Sweden

Source: author's work.

Table A4. Marginal effects of AI innovation capacity on energy intensity, conditional on digital transformation, based on models (7)–(12)

Model	G	C	P	l_desi	me	se	95% ci
7	EU-27	No	P25	3.6053	-0.0105	0.009	[-0.029; 0.007]
			P50	3.7821	-0.0032	0.009	[-0.020; 0.014]
			P75	3.9259	0.0028	0.009	[-0.015; 0.021]
8	EU-27	Yes	P25	3.6053	-0.0028	0.009	[-0.021; 0.015]
			P50	3.7821	0.0029	0.008	[-0.014; 0.019]
			P75	3.9259	0.0075	0.009	[-0.010; 0.025]
9	EU-14	No	P25	3.7792	0.0063	0.014	[-0.020; 0.033]
			P50	3.886	0.0151	0.014	[-0.013; 0.043]
			P75	4.0021	0.0247	0.016	[-0.006; 0.055]
10	EU-14	Yes	P25	3.7792	0.0151	0.013	[-0.010; 0.039]
			P50	**3.886**	**0.0234**	**0.013**	**[-0.002; 0.049]**
			P75	**4.0021**	**0.0325**	**0.014**	**[0.005; 0.061]**
11	EU-13	No	P25	3.4086	-0.0155	0.010	[-0.036; 0.005]
			P50	3.6008	-0.0093	0.009	[-0.027; 0.009]
			P75	3.7081	-0.0058	0.010	[-0.024; 0.013]
12	EU-13	Yes	P25	3.4086	-0.0086	0.010	[-0.028; 0.011]
			P50	3.6008	-0.0006	0.009	[-0.018; 0.017]
			P75	3.7081	0.0039	0.009	[-0.014; 0.022]

Note. Bolded results indicate statistically significant effects, G stands for a group of economies, C for control variables, P for percentiles and me/se represents marginal effect/standard error.
Source: author's work based on calculations.

Table A5. Regression results of energy intensity models (NL) for the EU-27, EU-14 and the EU-13 for the whole sample, including squared AI innovation capacity (robustness check)

Variable	NL1	NL2	NL3	NL4	NL5	NL6
	EU-27	EU-27	EU-14	EU-14	EU-13	EU-13
$AIP_{i,t}$	−0.1406 (0.1105)	−0.0757 (0.3474)	−0.291** (0.0410)	−0.2515* (0.0560)	−0.1201 (0.1756)	−0.1574* (0.0600)
$AIP_{i,t}^2$	0.0016 (0.6082)	0.0038 (0.1890)	0.0012 (0.7949)	0.0025 (0.5480)	0.0012 (0.8347)	−0.0011 (0.8391)
$DESI_{i,t}$	1.621** (0.014)	0.575 (0.363)	−0.789*** (0.000)	−0.574*** (0.0002)	−0.330*** (0.0000)	−0.233*** (0.0018)
$DESI_{i,t}^2$	−0.282*** (0.0026)	−0.1198 (0.1786)	–	–	–	–
$ACC_{i,t}$	0.0348 (0.1594)	0.0172 (0.4436)	0.0770* (0.0570)	0.0672* (0.0697)	0.0303 (0.2247)	0.0441* (0.0656)
RD_{it}	–	0.181***	–	0.1861*	–	0.057
K_{it}	–	0.024	–	0.0431	–	−0.031

UR_{it}	−	0.099**	−	0.116*	−	0.128**
$FOSIL_{it}$	−	0.641***	−	0.612***	−	0.4142*
$RENEW_{it}$	−	−0.0978	−	−0.149*	−	−0.03
(R^2)	0.9814	0.9856	0.9826	0.9871	0.9793	0.9826

Note. *, **, *** − significance at 10%, 5% and 1%, respectively; p-values in parentheses.
Source: author's work based on calculations.

Table A6. Regression results of energy intensity models with lagged variables (LM) for the EU-27, EU-14 and the EU-13 for the whole sample (robustness check)

Variable	LM-1	LM-2	LM-3	LM-4	LM-5	LM-6
	EU-27	EU-27	EU-14	EU-14	EU-13	EU-13
$AIP_{i,t-1}$	−0.0931 (0.1074)	−0.0517 (0.1002)	−0.1781 (0.1742)	−0.1936 (0.1579)	−0.1111 (0.1187)	−0.1443 (0.1162)
$DESI_{i,t-1}$	1.734** (0.8537)	0.244 (0.8164)	−0.646*** (0.1833)	−0.573*** (0.1723)	−0.363*** (0.0610)	−0.273*** (0.0899)
$DESI^2{}_{i,t-1}$	−0.301** (0.1217)	−0.0812 (0.1168)	−	−	−	−
$ACC_{i,t}$	0.0222 (0.0287)	0.0131 (0.0266)	0.0416 (0.0459)	0.0517 (0.0414)	0.0324 (0.0328)	0.0427 (0.0321)
RD_{it}	−	0.2784***	−	0.3636**	−	0.1280
K_{it}	−	0.0736	−	0.0748	−	0.0020
UR_{it}	−	0.1242**	−	0.0988	−	0.1546**
$FOSIL_{it}$	−	0.6943***	−	0.6659***	−	0.6215*
$RENEW_{it}$	−	−0.0980	−	−0.1399	−	−0.0271
R^2	0.9825	0.9866	0.9832	0.9876	0.9781	0.9817

Note. *, **, *** − significance at 10%, 5% and 1%, respectively; standard errors in parentheses.
Source: author's work based on calculations.

Table A7. Marginal effects of AI innovation capacity on energy intensity, conditional on digital transformation, based on non-linear models and models with lagged variables

Type			Non-linear models (NL)			Lagged models (LM)		
G	C	P	l_desi	me/se	95% ci	l_desi	me/se	95% ci
EU-27	No	25	3.605	-0.0078 (0.011)	[-0.029; 0.013]	3.579	-0.0135 (0.011)	[-0.036; 0.009]
		50	3.782	-0.0016 (0.009)	[-0.020; 0.017]	3.741	-0.01 (0.011)	[-0.031; 0.011]
		75	3.926	0.0034 (0.009)	[-0.015; 0.022]	3.871	-0.0071 (0.012)	[-0.030; 0.015]
EU-27	Yes	25	3.605	0.0033 (0.01)	[-0.017; 0.023]	3.579	-0.005 (0.011)	[-0.027; 0.017]
		50	3.782	0.0063 (0.009)	[-0.011; 0.023]	3.741	-0.0029 (0.01)	[-0.023; 0.017]
		75	3.926	0.0088 (0.009)	[-0.008; 0.026]	3.871	-0.0012 (0.011)	[-0.022; 0.019]
EU-14	No	25	3.779	0.0076 (0.015)	[-0.021; 0.036]	3.746	-0.0225 (0.018)	[-0.057; 0.012]
		50	3.886	0.0158 (0.014)	[-0.012; 0.044]	3.851	-0.0181 (0.018)	[-0.053; 0.017]
		75	4.002	0.0247 (0.016)	[-0.006; 0.055]	3.946	-0.0141 (0.019)	[-0.052; 0.024]
EU-14	Yes	25	3.779	0.0178 (0.014)	[-0.009; 0.045]	3.746	0.0003 (0.018)	[-0.036; 0.036]
		50	3.886	0.025 (0.014)	[-0.002; 0.052]	3.851	0.0057 (0.018)	[-0.030; 0.042]
		75	**4.002**	**0.0328 (0.015)**	**[0.004; 0.062]**	3.946	0.0106 (0.019)	[-0.027; 0.049]

EU-13	No	25	3.409	-0.0142 (0.015)	[-0.038; 0.01]	3.394	-0.001 (0.013)	[-0.026; 0.024]
		50	3.601	-0.0084 (0.01)	[-0.027; 0.011]	3.569	0.0047 (0.011)	[-0.017; 0.026]
		75	3.708	-0.0051 (0.009)	[-0.023; 0.013]	3.667	0.0079 (0.011)	[-0.014; 0.029]
EU-13	Yes	25	3.409	-0.0096 (0.012)	[-0.032; 0.013]	3.394	0.0007 (0.013)	[-0.025; 0.027]
		50	3.601	-0.0011 (0.01)	[-0.020; 0.018]	3.569	0.0082 (0.012)	[-0.014; 0.031]
		75	3.708	0.0036 (0.01)	[-0.015; 0.022]	3.667	0.0123 (0.012)	[-0.010; 0.035]

Note. Bolded results indicate statistically significant effects, G stands for a group of economies, C for control variables, P for percentiles and me/se for marginal effect/standard error.
Source: author’s work based on calculations.