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Digital Infrastructure as a Catalyst for Low-Carbon Development: A Panel Data Analysis of the European Union

Ani Stoykova^{1,*} ¹ Department of Finance and Accounting, South-West University “Neofit Rilski”, Bulgaria

Abstract: This study examines how digital infrastructure expansion shaped carbon intensity across the EU-27 member states from 2015 to 2021. Using a fixed-effects panel model with white diagonal robust standard errors, the research tests for an Environmental Kuznets Curve pattern in digital adoption. The results of the empirical analysis confirm an inverted U-shaped relationship between fixed broadband penetration and carbon intensity, reaching an inflection threshold at approximately 24.8 subscriptions per 100 residents. Initial infrastructure build-outs raise emissions due to added power requirements. Once networks cross this 24.8 threshold, structural efficiency gains and automated energy monitoring reduce overall carbon intensity. These findings indicate that while early-stage digital expansion initially correlates with higher energy demand, advanced digitalization is associated with lower carbon intensity, reflecting structural efficiency and better energy control. Furthermore, the analysis highlights the key contribution of renewable energy and economic development in reducing the European Union’s (EU) environmental impact. Additional channels and heterogeneity analyses indicate that broadband connectivity is positively associated with renewable energy deployment and that its decarbonization effect is significantly stronger in countries with higher digital maturity. These findings support a coordinated “Twin Transition” policy framework, aligning digital investments directly with the EU’s 2050 climate neutrality targets.

Keywords: digitalization, carbon intensity, Environmental Kuznets Curve (EKC), EU-27, green transition

1. Introduction

Industrial digitalization is changing the way production and consumption are organized and is becoming an important factor in the development of the modern world economy. The spread of digital technologies contributes to increased productivity and a more efficient use and allocation of resources, which gradually changes the structure of economic activities. The acceleration of digital integration in the European Union (EU) has not only positive impacts, but its impact on the environment must also be considered. First, significant material and energy resources are needed to operate data centers, and the growing digital infrastructure requires significant material and energy resources. These resources create their own ecological footprint. Second, this same infrastructure can create opportunities for more precise monitoring of ecosystems and the creation of effective measures to limit emissions.

This tension highlights a core question in the EU’s climate strategy: does digital connectivity drive decarbonization, or does it introduce an emerging set of environmental liabilities? Recent scholarship further illustrates this duality. As Wang et al. [1] argue, the digital transition consists of two distinct vectors: industrial digitalization and digital industrialization. Industrial

digitalization, which is the integration of digital instruments into traditional industries, can successfully reduce carbon intensity through energy optimization. On the other hand, digital industrialization, which is the expansion of the high-tech sector, may initially lead to an increase in overall emissions due to its substantial energy demands. The authors examine whether the current connectivity goals are supporting the decarbonization of traditional sectors or expanding energy-intensive digital industries in EU-27 countries.

Digitalization is increasingly seen as a strategic path for company transformation that goes beyond physical infrastructure. Lin et al. [2] observe this change not simply as another technical improvement. According to the authors, it is a deeper transformation, in which the digitalization and “greening” of the economy begin to develop in an increasingly close relationship. The use of information and digital solutions to achieve environmental goals expands the capabilities of enterprises and, to a certain extent, reduces the limitations associated with traditional models of production and management. In this sense, digital transformation can also help sectors with high carbon intensity in adapting to the requirements of the international decarbonization process. This process is of particular importance for the EU, which links its climate policies to the implementation of Sustainable Development Goal 13 – “Climate Action.” Eurostat data [3] show that between 1990 and 2023, net greenhouse gas emissions in the EU decreased by 35.5%. However, the progress made remains insufficient to

*Corresponding author: Ani Stoykova, Department of Finance and Accounting, South-West University “Neofit Rilski”, Bulgaria. Email: ani_qankova_st@swu.bg

reach the 55% reduction target set for 2030, which implies a significant acceleration of the process in the coming years. In this context, the carbon intensity of gross domestic product (GDP) is a particularly relevant indicator, as it allows to assess the number of emissions associated with a unit of economic output produced. This metric plays a central role in this trajectory. Estonia and Slovenia lead by example among EU member states. Both countries achieve a substantial drop in per capita emissions. The obtained results confirm the need for profound structural changes.

Traditional environmental policies can no longer deliver the necessary emissions reductions on their own. This need is also reflected in the EU's 2050 Long-Term Strategy, whose main objective is to make Europe the first climate-neutral continent. The European Green Deal sees the digital and green transitions as interlinked processes. This is where the concept of the "Twin Transition" fits in, combining the development of digital technologies with measures to limit the environmental impact. The expansion of high-capacity digital networks is important in this process, as it creates the technical basis for the development of smart electricity grids, more precise production management and better coordination of supply chains. Such applications can be important for limiting emissions, but the mere presence of digital infrastructure does not automatically mean improved environmental performance. This is precisely why the question of the actual impact of "basic" digital infrastructure on carbon intensity remains open for empirical research. Digitalization increases electricity consumption. Simultaneously, it dematerializes economic activity. Based on these dynamics, this research proposes the following two hypotheses:

H₁: Digital infrastructure has a significant impact on carbon intensity in EU-27 countries.

H₂: The relationship between digital infrastructure and carbon intensity follows an inverted U-shaped Environmental Kuznets Curve (EKC).

The recent scientific literature confirms these nonlinear dynamics. Zhang et al. [4] show how digital expansion initially drives up energy demand. Over time, however, efficiency gains begin to cut emissions. As technological and organizational experience accumulates, the effects of higher efficiency may gradually start to be reflected in emissions. Wu et al. [5] also draw attention to the role of digital tools in the spread of technological effects and the formation of industrial concentrations, pointing out similarities with the development of initiatives such as the German "Industrie 4.0."

In this study, attention is focused on the physical digital infrastructure and its relationship to decarbonization processes in the EU-27 countries. The analysis focuses on the spread of broadband access and the density of secure servers as two indicators through which the development of digital infrastructure is monitored. Unlike the composite indices used in some existing studies, including the Digital Economy and Society Index, this one does not include social, educational, and other characteristics of digital development. Thus, a narrower focus is placed on technical connectivity. The main question is whether the expansion of this infrastructure is linked to a process of "Strong Decoupling" in the context of Sustainable Development Goal 13. To this end, a fixed-effects panel model was estimated for the period 2015–2021, which examines the relationship between digital development and carbon intensity in the EU-27.

In most economic literature, digitalization and the environment are often viewed through the opposition between two main effects: the additional burden associated with digital technologies and the potential benefits of increased efficiency. The

present analysis starts from this setting but looks more specifically at the channels through which the development of broadband infrastructure can affect environmental performance.

The structural transition (structural improving effect) is the first main channel here. The expansion of large-scale network infrastructure accelerates structural economic changes. It moves activities from resource-heavy industries toward high-value digital services and information technologies. Consequently, GDP energy intensity decreases.

The second mechanism operates through firm-level energy optimization. At the business level, the implementation of smart grids, cloud technologies, and automated logistics solutions helps to drastically reduce unnecessary energy consumption and optimize production processes. However, this transfer mechanism is not linear in time. In the initial stages of the digital network, high capital costs and energy needs of operating data centers and network hardware can temporarily increase the environmental burden (economies of scale). Only after a certain critical saturation threshold is passed, technological effects and structural optimization take precedence, leading to a permanent reduction in emissions. In this regard, the main marginal contribution of this study lies in two key aspects: first, the methodological demarcation of physical indicators of digital infrastructure (such as fixed broadband penetration and server density) from broad, composite, and often subjective indices, and second, the empirical measurement of the exact crossing threshold within the EU-27 countries, which provides clearer guidance for future industrial and environmental policies.

2. Literature Review

The fundamental reorganization of the connection between economic growth and environmental impact within the EU can be defined as a pursuit of climate neutrality, not only as a technical shift. Romeo [6] quantifies the scale of EU net-zero goals. Maintaining a modest 3% annual GDP growth alongside climate targets requires cutting carbon intensity by 11.8% every year. Minor policy changes are insufficient. Reaching net-zero demands deep technological innovation alongside economic restructuring. Ahamer [7] notes that energy systems should be transformed due to the implementation of the EU Green Deal. Technological trends must directly align and connect with broader sustainability shifts. Researchers apply decomposition analysis in order to examine these dynamics. Based on the Kaya Identity, Dell'Aversano et al. [8] analyze the main drivers of global emissions, including those in the EU. They find that efficiency gains are often offset by population and GDP growth. As energy and carbon intensity are highly sensitive to policies under Sustainable Development Goal 13, technical efficiency remains an important factor in decoupling economic growth from emissions. The decoupling achieved in Europe between economic growth and emissions provides a good basis for assessing future trends. It can also be used as a starting point for developing future projections. Bianco et al. [9] find the presence of a "strong decoupling," where carbon emissions decrease with simultaneous GDP growth. The authors use the Logarithmic Mean Divisia Index and the Tapio methodology to examine emissions in the EU-27 for the period 1995–2019. The factor decomposition also shows an important trend. While socio-economic factors contribute to increasing emissions, technical improvements, especially those related to energy and carbon intensity, have the opposite effect.

Supporting this trend, Scarlat et al. [10] record a 48% drop in low-voltage electricity carbon intensity between 1990 and 2019.

Cleaner power generation forms the bedrock of the EU Twin Transition.

Digitalization intersects closely with circular economy practices. Ahmad et al. [11] demonstrate that artificial intelligence (AI) enhances circular economy decarbonization across EU industries. Besseau et al. [12] highlight how high-resolution electricity data clarifies energy technology emissions. Digital tools improve not only efficiency but also monitoring, resource tracking, and renewable grid integration. In summary, these studies suggest that digitalization can support low-carbon development far beyond mere energy efficiency gains. It enables advanced monitoring, resource management, and integration of renewable energy into increasingly complex energy grids.

Lin and Carter [13] examine the relationship between AI and the circular economy across the EU-27. Applying second-generation econometric models, the authors validate pairing digital innovation with circular practices. This combination cuts carbon intensity far better than traditional growth policies. Digital connectivity serves as the “foundational layer,” unlocking AI-driven efficiency in high-emission economies with limited decarbonization options.

Digital dividends are different for the different geographic regions. Quirós-Sánchez and Perote [14] create a new NUTS-2 Digital Index. This index measures regional digital capacity. The researchers establish a persistent “digital breach” between North-Western and South-Eastern European regions although they prove a strong positive relationship between connectivity and GDP per capita. This leads to the assumption that regional absorptive capacity dictates how strongly digital connectivity acts. Targeted infrastructure investments thus become very important for balanced eco-economic growth. At the same time, this digital-green transition reshapes the core drivers of regional inequality.

Remuzgo et al. [15] analyze CO₂ emission inequality in the EU-27 and find that traditional factors like GDP per capita are becoming less influential than the carbon intensity of electricity and technology-driven factors. They argue that digital infrastructure is now the essential medium for synchronized decarbonization and technology transfer. This highlights a shift in policy focus: to reduce regional disparities, the EU must prioritize digital cohesion over simple financial subsidies.

Environmental governance increasingly involves digital tracking of emissions. Mohamed et al. [16] show that corporate decarbonization is supported by green technologies, energy efficiency, and circular economy principles. Digital tools transform compliance requirements not only into a regulatory obligation but also into an opportunity for more efficient use of resources. They are also complemented by the operation of market mechanisms. Kaplan Donmez [17] confirms that instruments such as carbon taxes and participation in Emissions Trading Systems support structural decarbonization. Digital connectivity reinforces these fiscal instruments. High-resolution accounting and real-time verification allow for a more precise internalization of the social costs of carbon for the period 2015–2021.

Finally, the literature suggests that the transition must account for the diverse energy landscapes of the Member States. Cheng et al. [18] utilize panel quantile regression to show that the determinants of carbon intensity, including non-fossil energy and economic growth, impact countries differently based on their initial emission levels. They find a U-shaped relationship between non-fossil energy and intensity, suggesting that the efficiency of the transition is highly dependent on the existing infrastructure. In this context, digital connectivity can be defined as a stabilizing factor. It optimizes energy consumption patterns without

taking into account the national starting conditions and expanding the definition of energy security. Radovanović et al. [19] show that EU energy security is no longer focused on supply only, but it evolves into a multidimensional concept encompassing environmental and social sustainability. Their results reveal that carbon intensity and GDP per capita are the main factors for achieving this sustainable energy security. Former Eastern Bloc countries face heavy import reliance. The authors claim that modern digital infrastructure is a crucial mechanism to mitigate the environmental costs stemming from economic expansion.

The evidence that the environmental consequences of digitalization depend directly on the stage and form of technological progress is provided in recent studies. Wang et al. [20] establish that the digital economy is capable of reducing harmful carbon emissions through scale, structural, and technical effects, while simultaneously highlighting the importance of technological advancement and shifts in the economic structure. Empirical work by Zhang et al. [21] demonstrates that digital infrastructure lowers carbon emission intensity while producing spatial spillovers. They identify industrial upgrading, resource dependency, and green innovation as key transmission channels. In a complementary study, Hao et al. [22] find that digital technologies can reduce energy consumption intensity, though these impacts vary across specific sectors and regions. These insights directly inform our framework. They confirm that evaluating digital infrastructure requires looking beyond direct effects to consider underlying mechanisms and regional structural conditions.

The theoretical perspective can be further developed by considering digitalization, renewable energy, and circularity as interconnected components of the low-carbon transition. Basu et al. [23] framework economic growth, circular economy, and net-zero targets as mutually reinforcing pillars of sustainability. They stress the combined power of renewable substitution, material recycling, and direct pollution reduction. Israr et al. [24] show that the contribution of renewable energy to reducing carbon emissions depends significantly on the level of national income and stage of development. More developed economies achieve stronger emission reductions. Advanced economies, in particular, achieve much stronger abatement results. Therefore, digital infrastructure should be considered in the context of the broader energy and economic conditions in individual countries.

The relationship between digital connectivity and carbon intensity can be viewed through three main channels: technological efficiency, structural transformation, and energy substitution. Broadband infrastructure can reduce carbon intensity through the use of digital tools in production, transport, and energy management. This increases operational efficiency and can limit the amount of energy needed per unit of output. On the other hand, digital connectivity can support structural transformation through the development of knowledge-intensive activities, digital services, and a more efficient allocation of resources. The third channel is related to energy substitution. Improving the monitoring and management of networks through digital tools can accelerate the transition away from systems with high dependence on fossil fuels. This shows that the environmental impact of broadband connectivity is not necessarily immediate and may differ between countries. The expansion of digital infrastructure itself requires additional energy and material resources, which in the initial stages can create additional pressure on the environment.

Recent empirical studies further emphasize the importance of renewable energy innovation, green technological innovation, decentralized energy governance, and climate policy in supporting the transition toward lower carbon development [25–28].

In conclusion, the existing literature outlines a clear direction—from a historical decoupling based on the transition to alternative fuels and tax policies to a contemporary stage in which digital connectivity is being established as a key tool for reducing carbon intensity. Despite the obvious technical and economic advantages of this “Twin transition,” the challenge of overcoming the digital divide remains critical to ensure an effective and fair process for all regions in the EU.

Despite the available research, the existing literature review often fails to systematically summarize the differences in the samples used, economic models, and inflection points considered in previous studies on the digital EKC hypothesis. Most previous studies rely on broad composite indices that mix education, institutional factors, and technology, making comparisons across samples difficult to apply. The present study fills this significant scientific gap by deliberately isolating physical indicators of broadband infrastructure and completely abandoning general indices. This targeted approach achieves a direct link between the literature review and the empirical part, clarifying the contradictory results to date on the environmental impact of digitalization within the EU-27.

3. Data and Methodology

3.1. Data

This study uses a panel dataset for the 27 EU member states (EU-27). The original dataset covers the period 2015–2024; however, due to missing observations for several variables (such as Renewable Energy and R&D Expenditure) in the most recent years, the effective estimation sample used in the regression analysis is 2015–2021. This results in a balanced panel of 27 countries over 7 years (189 observations). The data were primarily sourced from the World Bank Open Data [29].

All continuous variables are transformed using natural logarithms to facilitate elasticity interpretation and reduce scale differences and potential skewness in the data. In EViews 12, the natural logarithmic transformation is implemented using the *LOG()* function. Accordingly, the empirical models use

$\ln(ci)$, $\ln(bb)$, $\ln(ss)$, $\ln(rd)$, $\ln(gdppc)$, and $\ln(ren)$. The control variables $\ln(gdppc)$, $\ln(ren)$, $\ln(ss)$, and $\ln(rd)$ are included to account for differences in economic development, renewable energy use, digital infrastructure security, and research and development activity (Table 1).

The results of the descriptive statistics are presented in Table 2. The descriptive statistics are applied to the natural logarithms of all six variables in the balanced panel data of 189 observations for the period 2015–2021. In order to ensure robust econometric estimation, the natural logarithmic transformation effectively stabilizes the variance of data and reduces potential heteroscedasticity. The results of skewness statistics show limited to moderate asymmetry across all of the variables, while the differences between means and medians are generally moderate. The standard deviation values confirm moderate variation both between countries and over time for indicators under consideration, which provides a reliable basis for the subsequent econometric modeling. The Jarque–Bera test rejects normality for $\ln(rd)$ and $\ln(ss)$, whereas normality is not rejected for the remaining variables at the 5% significance level.

3.2. Methodology

The analysis follows a two-stage approach using panel least squares (PLS) in EViews 12.

Stage 1 applies the baseline linear model. First, we estimate a linear relationship to identify the general impact of digital and economic factors on carbon intensity:

$$\ln(ci_{it}) = \beta_0 + \beta_1 \ln(bb_{it}) + \beta_2 \ln(gdppc_{it}) + \beta_3 \ln(ren_{it}) + \beta_4 \ln(rd_{it}) + \beta_5 \ln(ss_{it}) + \alpha_i + \varepsilon_{it} \quad (1)$$

Stage 2 applies the nonlinear EKC model. To test the EKC hypothesis, the squared term $[\ln(bb_{it})]^2$ is introduced. This allows to identify a potential turning point (TP) where digitalization shifts from an energy-consuming to an energy-saving phase:

$$\ln(ci_{it}) = \beta_0 + \beta_1 \ln(bb_{it}) + \beta_2 [\ln(bb_{it})]^2 + \beta_3 \ln(gdppc_{it}) + \beta_4 \ln(ren_{it}) + \beta_5 \ln(rd_{it}) + \beta_6 \ln(ss_{it}) + \alpha_i + \varepsilon_{it} \quad (2)$$

Table 1
Description of variables and model role

Variable	Indicator name	Dependent/independent	Long definition
$\ln(ci)$	Carbon intensity of GDP (kg CO_2 per constant 2021 US\$ of GDP)	Dependent	CO_2 emissions from agriculture, energy, waste, and industry per constant 2021 USD of GDP.
$\ln(bb)$	Fixed broadband subscriptions (per 100 people)	Independent	Fixed high-speed Internet subscriptions per 100 people.
$[\ln(bb)]^2$	Broadband squared	Independent	The squared term used to test the nonlinear EKC hypothesis.
$\ln(gdppc)$	GDP per capita (constant 2015 US\$)	Control	Total income per capita in constant 2015 USD.
$\ln(ren)$	Renewable energy consumption (% of total final energy consumption)	Control	Share of renewable energy in total final energy consumption.
$\ln(ss)$	Secure Internet servers (per 1 million people)	Control	Number of distinct Transport Layer Security/Secure Sockets Layer (TLS/SSL) certificates per 1 million people.
$\ln(rd)$	Research and development expenditure (% of GDP)	Control	Gross domestic expenditure on research and development as % of GDP.

Table 2
Descriptive statistics of the variables

	$\ln(bb)$	$\ln(ci)$	$\ln(gdppc)$	$\ln(rd)$	$\ln(ren)$	$\ln(ss)$
<i>Mean</i>	3.48	-1.418	10.189	0.348	2.978	9.612
<i>Median</i>	3.459	-1.441	10.148	0.3	2.868	9.872
<i>Maximum</i>	3.864	-0.018	11.616	1.25	4.059	12.533
<i>Minimum</i>	2.944	-2.643	8.891	-0.832	1.723	5.89
<i>Std. Dev.</i>	0.199	0.603	0.618	0.564	0.526	1.354
<i>Skewness</i>	-0.267	0.142	0.218	-0.144	0.018	-0.47
<i>Kurtosis</i>	2.558	2.61	2.448	2.086	2.358	2.896
<i>Jarque-Bera</i>	3.787	1.835	3.895	7.237	3.251	7.046
<i>Probability</i>	0.151	0.4	0.143	0.027	0.197	0.03
<i>Sum</i>	657.724	-268.037	1925.738	65.717	562.905	1816.578
<i>Sum Sq. Dev.</i>	7.46	68.334	71.831	59.839	52.094	344.596
<i>Observations</i>	189	189	189	189	189	189

Where:

$\ln(ci_{it})$ – Natural logarithm of carbon intensity for country i in year t ;

$\ln(bb_{it})$ – Natural logarithm of fixed broadband subscriptions;

$[(\ln(bb_{it}))^2]$ – Squared natural logarithm of fixed broadband subscriptions;

$\ln(gdppc_{it})$ – Natural logarithm of GDP per capita;

$\ln(ren_{it})$ – Natural logarithm of renewable energy consumption;

$\ln(rd_{it})$ – Natural logarithm of research and development expenditure;

$\ln(ss_{it})$ – Natural logarithm of secure internet servers;

α_i – Country-specific fixed effects;

ε_{it} – Idiosyncratic error term.

To ensure the statistical validity of the empirical findings, a multi-step estimation procedure was conducted using EViews 12. Before performing the main regression, a correlation analysis was carried out to examine the linear relationships between the variables and to check for potential multicollinearity issues. The following diagnostic tests were subsequently applied to select the most appropriate panel estimation technique:

- 1) Hausman Test: This test was applied to determine the choice between fixed effects and random effects models. The null hypothesis (H_0 : Random effects are consistent and efficient) was tested against the alternative (H_1 : Fixed effects are preferred).
- 2) Cross-Sectional Dependence (CD) Test: Given the high degree of economic integration within the EU-27, the Pesaran CD test was employed to identify potential interdependencies (contemporaneous correlation) in the residuals across the different member states.
- 3) Model Estimation: Based on the diagnostic results, the final parameters were estimated using the PLS method, incorporating the necessary adjustments to account for the identified panel characteristics.

To determine the specific threshold at which the impact of digitalization on carbon intensity shifts from an energy-intensive phase to an energy-saving phase, the TP is calculated. Mathematically, starting from the quadratic specification of the Stage 2 model (Equation 2), the conditional expectation function is differentiated with respect to the core independent variable $\ln(bb_{it})$ to

capture the marginal effect. This point represents the vertex of the quadratic function and is derived by taking the first derivative and setting it to zero:

$$\frac{\partial \ln(ci_{it})}{\partial \ln(bb_{it})} = \beta_1 + 2\beta_2 \ln(bb_{it}) = 0 \quad (3)$$

Solving this first-order condition for $\ln(bb_{it})$ yields the logarithmic threshold, which in its original units (subscriptions per 100 people) is then obtained by exponentiating the result:

$$TP = e^{\left(-\frac{\beta_1}{2\beta_2}\right)} \quad (4)$$

Before the TP ($\ln(bb) < TP$): The linear term β_1 dominates, suggesting that the initial expansion of digital infrastructure (construction of data centers, broadband networks, and hardware production) leads to an increase in carbon intensity due to high energy demand.

After the TP ($\ln(bb) > TP$): The quadratic term β_2 takes precedence. At this stage, the efficiency gains from digitalization, such as smart grids, teleworking, and optimized industrial processes, outweigh the energy footprint of the Information and Communication Technologies (ICT) sector, resulting in a net reduction of carbon intensity.

To enhance the econometric outputs derived from EViews 12, the analysis was supplemented with advanced diagnostic and predictive visualizations developed in Python via the Seaborn and Matplotlib libraries. These graphical tools were specifically utilized to offer a more profound spatial and functional perspective on the panel data dynamics. In particular, a nonlinear EKC regression mapping was constructed to model the relationship between $\ln(bb_{it})$ and $\ln(ci_{it})$, thereby illustrating the predicted trajectory of the Digital EKC and pinpointing the threshold at which digital infrastructure maturity begins to facilitate carbon-intensity mitigation. Furthermore, to investigate potential CD, a diagnostic heatmap was generated from the model's residuals. This visualization provides a clear inspection of the correlation coefficients between the error terms of the EU-27 member states, effectively uncovering clusters of countries that may be influenced by synchronized economic or environmental shocks.

To examine a potential channel through which broadband connectivity affects carbon intensity, renewable energy is considered as an intermediate factor. The mechanism analysis is based on two complementary fixed-effects equations. The first

examines whether broadband connectivity is associated with renewable energy:

$$\ln(\text{ren}_{it}) = \alpha + \theta \ln(\text{bb}_{it}) + \gamma' X_{it} + \alpha_i + \varepsilon_{it} \quad (5)$$

The second examines whether renewable energy is associated with carbon intensity after controlling for broadband connectivity:

$$\ln(\text{ci}_{it}) = \alpha + \beta \ln(\text{bb}_{it}) + \delta \ln(\text{ren}_{it}) + \gamma' X_{it} + \alpha_i + \varepsilon_{it} \quad (6)$$

where ren_{it} denotes renewable energy, bb_{it} represents broadband connectivity, ci_{it} denotes carbon intensity, X_{it} is the vector of control variables, α_i represents country fixed effects, and ε_{it} is the error term. Evidence supporting the proposed mechanism is obtained when broadband connectivity is significantly associated with renewable energy and renewable energy is significantly associated with lower carbon intensity after controlling for broadband connectivity.

A heterogeneity analysis was applied to examine whether the relation between broadband connectivity and carbon intensity differs according to the level of digital maturity. An interaction term between broadband connectivity and a dummy variable for high digital maturity was included in the analysis. Countries were classified into two main groups based on the country-specific mean and median values of the relevant index. The first group comprises countries with a high level of digital maturity, and the second group comprises those with a low level of digital maturity. Countries with a mean value equal to or above the corresponding median were classified as high-digital-maturity countries and were included in the first group, while the remaining countries were assigned to the low-digital-maturity group. The heterogeneous effect was estimated by extending the baseline fixed-effects model with an interaction term between broadband connectivity and the high-digital-maturity indicator:

$$\ln(\text{ci}_{it}) = \alpha + \beta_1 \ln(\text{bb}_{it}) + \beta_2 [\ln(\text{bb}_{it}) \times \text{HighTech}_i] + \gamma' X_{it} + \alpha_i + \varepsilon_{it} \quad (7)$$

where ci_{it} denotes carbon intensity, bb_{it} represents broadband connectivity, HighTech_i is a time-invariant dummy variable equal to one for countries classified as having high digital maturity and zero otherwise, X_{it} represents the vector of control variables, α_i denotes country fixed effects, ε_{it} is the error term.

In this specification, β_1 represents the effect of broadband connectivity for the low-digital-maturity group, while β_2 captures the difference in the broadband effect between the low- and high-digital-maturity groups. Therefore, the total effect of broadband connectivity for the high-digital-maturity group is calculated as:

$$\beta_{\text{HighTech}} = \beta_1 + \beta_2 \quad (8)$$

The statistical significance of the total effect for the high-digital-maturity group was assessed using a Wald test of the following null hypothesis:

$$H_0 : \beta_1 + \beta_2 = 0 \quad (9)$$

The model was estimated using country fixed effects and white diagonal standard errors and covariance with degrees-of-freedom correction.

4. Results

4.1. Correlation analysis

Prior to estimating the regression models, a Pearson correlation analysis (Table 3) was conducted to evaluate the strength and direction of the linear relationships between the variables. This diagnostic step is crucial for identifying potential multicollinearity and ensuring the structural integrity of the model.

Table 3 reports the correlation matrix for the EU-27 panel. All independent and control variables show an inverse relationship with carbon intensity ($\ln(\text{ci})$). The strongest negative correlation occurs between GDP per capita and carbon intensity ($r = -0.811$), confirming that economic growth links directly to lower emissions per unit of output. Fixed broadband subscriptions ($\ln(\text{bb})$) also exhibit a moderate negative correlation with carbon intensity ($r = -0.577$). This offers preliminary support for environmental benefits of digital connectivity. It should be noted that none of the correlation coefficients between independent variables exceed the critical values of 0.80 or 0.90. However, some variables, such as $\ln(\text{gdppc})$ and $\ln(\text{bb})$, show a moderate positive correlation ($r = 0.577$). This result provides grounds for concluding that multicollinearity does not pose a significant risk to the reliability of the regression analysis and allows for a precise estimation of the parameters. The variable $\ln(\text{ren})$ for renewable energy shows a weak linear correlation with carbon intensity ($r = -0.058$), which supports the need to apply a fixed-effects regression model to effectively control for unobserved institutional and country-specific factors.

To quantitatively verify the absence of multicollinearity and complement the correlation analysis, variance inflation factor (VIF) tests were conducted. The resulting VIF values for all explanatory variables ranged between 1.20 and 4.33, remaining well below the conventional critical threshold of 5.0. These values do not indicate severe multicollinearity among the explanatory variables (Table 4).

4.2. Diagnostic test results

Several diagnostic tests are applied in order to determine the most appropriate estimation technique for the panel data.

Table 3
Correlation matrix of the variables

Variable	$\ln(\text{ci})$	$\ln(\text{bb})$	$\ln(\text{gdppc})$	$\ln(\text{rd})$	$\ln(\text{ren})$	$\ln(\text{ss})$
$\ln(\text{ci})$	1.000					
$\ln(\text{bb})$	-0.577	1.000				
$\ln(\text{gdppc})$	-0.811	0.577	1.000			
$\ln(\text{rd})$	-0.405	0.473	0.570	1.000		
$\ln(\text{ren})$	-0.058	-0.132	-0.100	0.210	1.000	
$\ln(\text{ss})$	-0.226	0.420	0.330	0.309	0.112	1.000

Table 4
Variance inflation factors results

Variable	Coefficient	Uncentered	Centered
	Variance	VIF	VIF
C	1.540963	89860.97	NA
$\ln(bb)$	0.008877	6212.588	2.666269
$\ln(ss)$	4.32E-05	227.7205	4.328371
$\ln(rd)$	0.002961	20.01805	1.202429
$\ln(gdppc)$	0.014035	84831.54	2.274093
$\ln(ren)$	0.004214	2168.389	1.349441

The results of the Hausman test are summarized in Table 5. The results show that the fixed-effects model should be employed. As the p -value of 0.0020 is significantly below the 5% threshold, the null hypothesis that random effects are consistent is rejected. This indicates that country-specific error terms are linked with the explanatory variables. Consequently, the fixed-effects model is the most reliable method for incorporating the specific institutional and economic frameworks of the EU-27 member states.

Table 5
Hausman test for model selection

Test summary	Chi-sq. statistic	Chi-sq. $d.f.$	Prob.
Cross-section random	18.9030	5	0.0020

The results of CD tests are presented in Table 6. The residual analysis confirms that the EU-27 member states do not operate in isolation, displaying strong evidence of CD. All four diagnostic tests, including the Breusch–Pagan Lagrange Multiplier (LM), Pesaran scaled LM, Bias-corrected scaled LM, and the Pesaran CD test, reject the null hypothesis of no cross-sectional correlation at the 1% significance level. A Pesaran CD statistic of 3.82 ($p = 0.0001$) suggests that environmental or economic shocks in one EU country tend to affect neighboring economies. Such findings justify the move away from standard estimators toward methods that remain robust in the presence of cross-country dependencies.

Table 6
Residual cross-section dependence tests

Test	Statistic	$d.f.$	Prob.
Breusch–Pagan LM	745.8156	351	0.0000
Pesaran scaled LM	14.9014		0.0000
Bias-corrected scaled LM	12.6514		0.0000
Pesaran CD	3.8210		0.0001

4.3. Baseline regression results

To address heteroskedasticity, the baseline models were estimated using white diagonal heteroskedasticity-consistent standard errors. These standard errors provide robustness to heteroskedasticity across panel units. However, the residual diagnostics also reveal statistically significant CD among EU-27 countries. Therefore, the results should be interpreted with this remaining

cross-sectional interdependence in mind. Table 7 presents the results of the fixed-effects panel regression for the EU-27 member states. The model exhibits a substantial explanatory power, evidenced by an Adjusted R -squared of 0.992. This high value suggests that the variations in digitalization, economic growth, and renewable energy consumption provide a 99.2% explanation for the changes in carbon intensity throughout the member states.

The results of the baseline model show that digitalization and economic growth are associated with lower carbon intensity in the EU. The coefficient of fixed broadband subscriptions ($\ln(bb)$) is negative and statistically highly significant ($\beta = -0.2919$, $p = 0.0023$). This means that a 1% increase in broadband penetration corresponds to a 0.29% reduction in carbon intensity. The result shows that the expansion of digital connectivity in the EU is associated with more efficient resource management and, in particular, with the dematerialization of economic processes. Similarly, the coefficient for GDP per capita ($\ln(gdppc)$) shows a strong negative influence on carbon intensity ($\beta = -0.4395$, $p = 0.0003$). This indicates that as EU countries progress economically, their economies become more carbon efficient. One possible reason is the structural changes toward the service sector and the introduction of higher environmental standards. Renewable energy consumption ($\ln(ren)$) stands out as a significant factor in reducing intensity ($\beta = -0.4171$, $p = 0.0000$). The high statistical significance of this parameter highlights the importance of decarbonizing the regional energy mix, which is also a key focus of the European Green Deal. Research and development expenditure ($\ln(rd)$), although significant only at the 10% level ($p = 0.0672$), also shows a negative relationship with carbon intensity ($\beta = -0.1003$). This result suggests that technological innovations can contribute to increasing environmental efficiency, although their full effect appears with some delay. In contrast, secure internet servers ($\ln(ss)$) show a statistically insignificant effect ($p = 0.1763$). This reveals that active broadband connectivity is more important for environmental outcomes than just the technical security of the infrastructure. The Durbin–Watson statistic shows a slight positive serial correlation, which is common in macro panel data. To account for potential heteroscedasticity and to increase the reliability of the statistical inference, robust white diagonal standard errors were used in the estimation. Furthermore, white diagonal robust standard errors [30] are preferred over a two-way fixed-effects framework to avoid excessive loss of degrees of freedom in the short-balanced panel ($T = 7$) while ensuring consistent and reliable statistical inference in the presence of cross-sectional heteroscedasticity.

4.4. Mechanism analysis

Two fixed-effects models were applied to examine whether renewable energy indicates a possible transmission channel between broadband connectivity and carbon intensity. The first model tests the relation between broadband connectivity and renewable energy, while the second model incorporates renewable energy into the carbon-intensity equation. The results are presented in Table 8.

The first specification provides evidence of a significant positive relationship between broadband connectivity and renewable energy. The coefficient of $\ln(bb)$ is positive and statistically significant ($\theta = 0.3212$; $p = 0.0209$), indicating that higher broadband connectivity is associated with greater renewable energy deployment. The second specification shows that renewable energy is negatively and significantly associated with carbon intensity ($\delta = -0.4171$; $p < 0.001$).

Table 7
Fixed effects panel regression results (baseline model)

Variable	Coefficient	Std. error	<i>t</i> -statistic	Prob.
C	5.4391	1.2414	4.3815	0.0000
ln(<i>bb</i>)	−0.2919	0.0942	−3.0985	0.0023
ln(<i>ss</i>)	−0.0089	0.0066	−1.3583	0.1763
ln(<i>rd</i>)	−0.1003	0.0544	−1.8430	0.0672
ln(<i>gdppc</i>)	−0.4395	0.1185	−3.7101	0.0003
ln(<i>ren</i>)	−0.4171	0.0649	−6.4247	0.0000
<i>R</i> -squared: 0.9919		<i>F</i> -statistic: 621.32		Prob(<i>F</i> -stat):0.0000
Adjusted <i>R</i> -squared: 0.9903		Durbin–Watson: 0.9013		Observations: 189
<i>R</i> -squared: 0.9919		<i>F</i> -statistic: 621.32		Prob(<i>F</i> -stat): 0.0000

Table 8
Mechanism analysis: the role of renewable energy

Variable	(1) ln(<i>ren</i>)	(2) ln(<i>ci</i>)
ln(<i>bb</i>)	0.3212** (0.0209)	−0.2919*** (0.0023)
ln(<i>ren</i>)	—	−0.4171*** (0.0000)
ln(<i>ss</i>)	0.0359*** (0.0042)	−0.0089 (0.1763)
ln(<i>rd</i>)	0.1767** (0.0450)	−0.1003* (0.0672)
ln(<i>gdppc</i>)	−0.0636 (0.7529)	−0.4395*** (0.0003)
Constant	2.1015 (0.2999)	5.4391*** (0.0000)
Country fixed effects	Yes	Yes
Observations	189	189
Adjusted <i>R</i> ²	0.9596	0.9903

Note: Coefficients are reported with *p*-values in parentheses. White diagonal standard errors and covariance, degrees-of-freedom corrected. *** *p* < 0.01, ** *p* < 0.05, * *p* < 0.10.

After including renewable energy in the model, the coefficient of broadband connectivity (ln(*bb*)) remains negative and statistically significant ($\beta = -0.2919$; $p = 0.0023$). The results are consistent with the role of renewable energy as a potential transmission channel linking broadband connectivity to lower carbon intensity.

4.5. Heterogeneity analysis based on digital maturity

To investigate whether the effect of broadband connectivity on carbon intensity varies with the level of digital maturity, the baseline fixed-effects model was extended by including an interaction term between ln(*bb*) and the high-digital-maturity group. The estimation results are reported in Table 9.

The results indicate a clear difference in the broadband–carbon intensity relationship between the two digital-maturity groups. For countries with low digital maturity, the coefficient of broadband connectivity (ln(*bb*)) is negative but statistically insignificant ($\beta_1 = -0.1142$; $p = 0.2234$). In contrast, the interaction term is negative and statistically significant, indicating that the broadband–carbon intensity relationship is significantly more negative in high-digital-maturity countries. The total effect for the high-digital-maturity group is -0.5758 and is statistically significant according to the Wald test.

The interaction coefficient is negative and statistically significant ($\beta_2 = -0.4615$; $p = 0.0013$). This indicates that the effect of broadband connectivity is significantly more negatively associated

with carbon intensity in high-digital-maturity countries. The total effect for the high-digital-maturity group is obtained by summing the coefficient of ln(*bb*) and the interaction coefficient:

$$\begin{aligned}\beta_{HighTech} &= \beta_1 + \beta_2 \\ \beta_{HighTech} &= -0.1142 + (-0.4615) = -0.5758\end{aligned}$$

The statistical significance of this combined effect is confirmed by the Wald test. The null hypothesis that the total effect is equal to zero is strongly rejected ($F(1,156) = 19.6526$; $p < 0.001$). Therefore, broadband connectivity has a statistically significant negative association with carbon intensity in the high-digital-maturity group. The results suggest that the environmental effect of broadband connectivity is conditional on the broader level of digital development. While broadband connectivity alone does not exhibit a statistically significant effect in the low-digital-maturity group, its association with lower carbon intensity becomes considerably stronger in economies characterized by higher digital maturity.

4.6. Fixed-effects regression results

The fixed-effects regression (nonlinear EKC model) results are presented in Table 10. These results provide strong empirical confirmation of the DigitalEKC hypothesis within the EU-27 context. The linear term for digitalization (ln(*bb*)) is positive and significant ($\beta_1 = 4.6053$, $p < 0.01$), while the squared term

Table 9
Heterogeneity of the broadband–carbon intensity relationship by digital maturity

Variable	Coefficient	Std. error	<i>p</i> -value
$\ln(bb)$	−0.1142	0.0935	0.2234
$\ln(bb) \times HighTech$	−0.4615***	0.1411	0.0013
$\ln(ss)$	−0.0080	0.0062	0.2011
$\ln(rd)$	−0.0527	0.0527	0.3191
$\ln(gdppc)$	−0.5211***	0.1243	0.0000
$\ln(ren)$	−0.3866***	0.0645	0.0000
High-digital-maturity total effect	−0.5758***	0.1299	0.0000

Note: Country fixed effects are included. White diagonal standard errors and covariance, degrees-of-freedom corrected. The high-digital-maturity total effect is calculated $(\beta_1 + \beta_2)$. Wald test: $F(1,156) = 19.6526$, $p < 0.001$. *** $p < 0.01$.

Table 10
Fixed effects regression results (nonlinear EKC model)

Variable	Coefficient	Std. error	<i>t</i> -statistic	Prob.
C	−1.8701	1.8383	−1.0173	0.3106
$\ln(bb)$	4.6053	1.2371	3.7227	0.0003
$[(\ln(bb))^2]$	−0.7173	0.1826	−3.9280	0.0001
$\ln(ss)$	−0.0078	0.0062	−1.2607	0.2093
$\ln(rd)$	−0.0620	0.0519	−1.1927	0.2348
$\ln(gdppc)$	−0.5530	0.1171	−4.7211	0.0000
$\ln(ren)$	−0.3792	0.0650	−5.8355	0.0000
<i>R</i> -squared: 0.9925		<i>F</i> -statistic: 646.17	Prob(<i>F</i> -stat): 0.0000	
Adjusted <i>R</i> -squared: 0.9910		Durbin–Watson: 0.9936	Observations: 189	

$[(\ln(bb))^2]$ is negative and significant ($\beta_2 = -0.7173$, $p < 0.01$). This mathematically establishes an inverted U-shaped relationship between digital infrastructure and carbon intensity in the EU-27.

4.7. Testing the digital EKC hypothesis and turning point analysis

The empirical findings from the nonlinear model (Table 10) lend strong support to the Digital Environmental Kuznets Curve (EKC) hypothesis for the EU-27. The mathematical foundation for the inverted U-shaped relationship is established by the positive coefficient of the linear term ($\beta_1 = 4.6053$) alongside the negative coefficient of the squared term ($\beta_2 = -0.7173$) mathematically defines an inverted U-shaped relationship. This non-monotonic dynamic is visually captured in Figure 1, which illustrates how carbon intensity levels evolve in response to expanding digital infrastructure.

According to the TP analysis, the impact of digitalization reaches its peak at approximately 24.78 (~24.8) broadband subscriptions per 100 people. To the left of this threshold, the EU-27 economies experience an “Energy-Intensive Phase,” where the expansion of digital infrastructure correlates with rising carbon intensity. This upward trend is primarily driven by the scale effect, as the energy requirements for network deployment, hardware manufacturing, and the initial power demands of data centers outweigh early efficiency gains. However, once this critical tipping point of 24.8 subscriptions is surpassed, the relationship enters a “Mitigation Phase” where the curve begins a downward

trajectory. At this stage, the technique effect becomes dominant, as widespread digital penetration enables smart grids, optimized logistics, and industrial automation that decouple economic activity from carbon emissions. Given that most member states have already crossed this threshold, further investment in high-speed connectivity is expected to yield increasing environmental dividends, directly supporting the EU’s dual green and digital transition objectives. A residual cross-correlation heatmap was generated in order to provide a more detailed view of the interdependencies within the EU-27 (Figure 2). This visualization maps the correlation coefficients of the residuals between each pair of member states following the fixed-effects estimation.

The heatmap illustrates a complex network of synchronized environmental shocks and shared policy impacts across the EU. The heatmap displays district regional clusters, where dark green (high positive correlation) and dark red blocks (high negative correlation) signify specific groups of countries.

For instance, the Nordic and Baltic countries (Denmark, Estonia, and Finland) respond symmetrically to undetected factors. Such patterns likely reflect highly integrated energy markets and coordinate climate programs in these sub-regions. The Pesaran CD test results are reconfirmed considering the high consistency of significant correlation coefficients which values exceeding the 0.5 threshold. This interdependence certifies that carbon intensity fluctuations in one member state are inextricably connected to its neighbors, primarily due to the deep economic integration of the Single Market and the harmonized nature of EU environmental regulations. Finally, this visual evidence of a relationship between countries provides a strong basis for using

Figure 1
Estimated nonlinear relationship between broadband penetration and carbon intensity

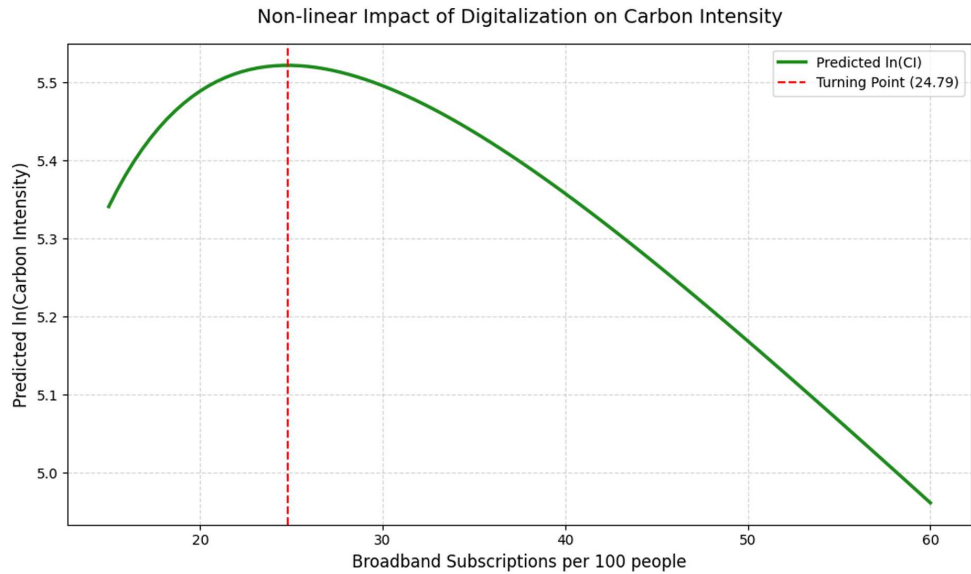
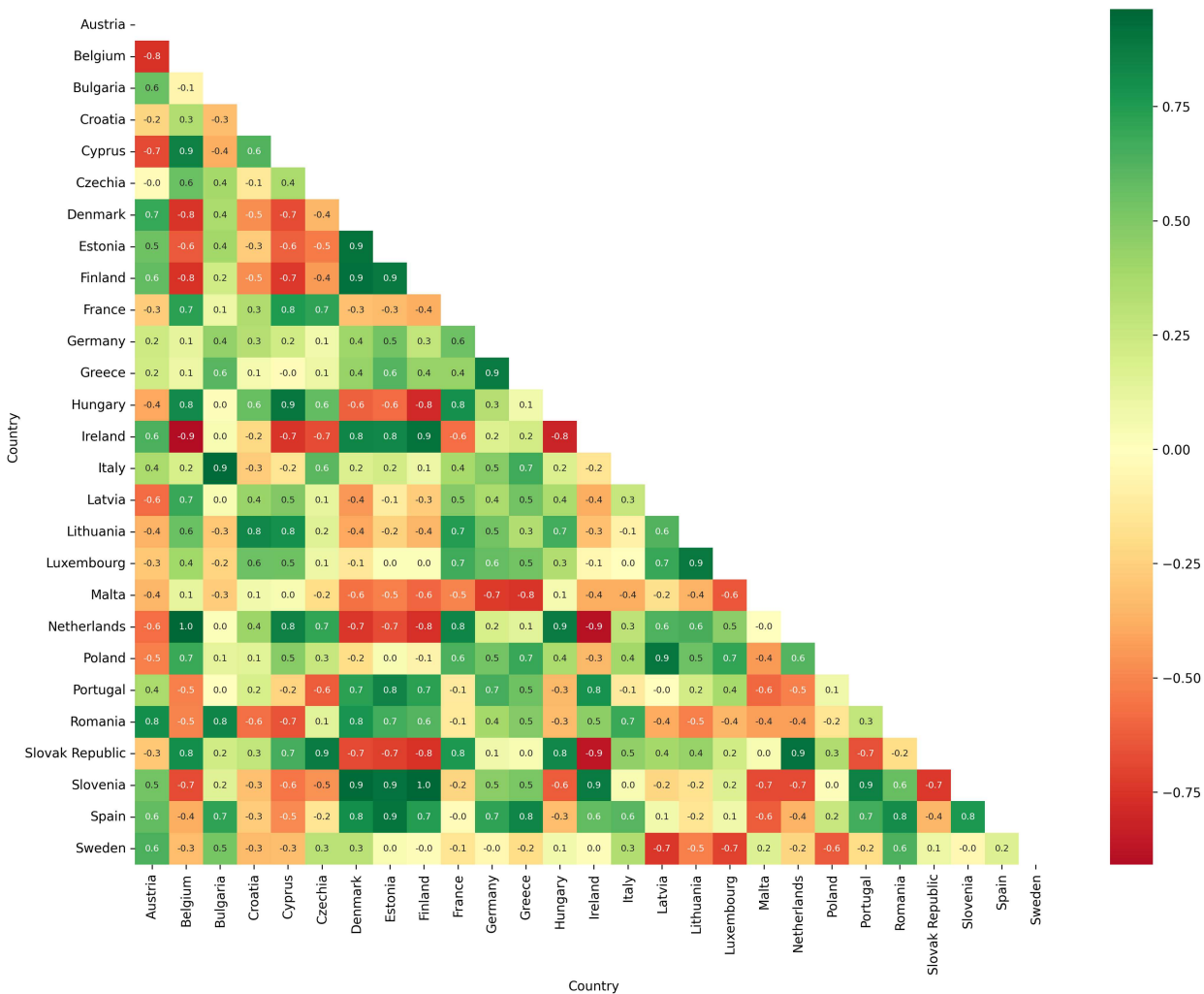


Figure 2
EU-27 residual cross-correlation heatmap



the white diagonal standard errors, ensuring that the reported impact of digitalization is a reliable finding rather than a spurious result caused by unaddressed spatial correlations.

4.8. Comparative discussion of baseline and nonlinear EKC models

The horizontal comparison between the baseline linear model (Table 7) and the nonlinear EKC model (Table 10) shows high robustness of the main macroeconomic and environmental parameters, while highlighting changes in individual coefficients. The coefficients of GDP per capita ($\ln(gdpc)$) and renewable energy consumption ($\ln(ren)$) remain close in both size and statistical significance, confirming their significant role in limiting the carbon intensity in the EU-27. A different picture is observed for research and development expenditure ($\ln(rd)$). While in the baseline linear specification $\ln(rd)$ has a negative but statistically weakly significant effect ($p = 0.0672$), when the squared term of broadband access ($[(\ln(bb))]^2$) is included, its statistical significance disappears. This change may be related to the high structural collinearity and shared variance between technological innovation represented by R&D and the degree of development of digital infrastructure. When including the nonlinear quadratic specification of digitalization, part of the effect that is associated with R&D in the baseline model is captured by the nonlinear components of broadband access. This suggests that R&D retains its importance as a long-term factor of the green transition, but its direct linear effect is more difficult to distinguish when the nonlinear characteristics of digital development are explicitly taken into account in the model.

5. Discussion

Nonlinear model estimates confirm a non-directional relationship between digital infrastructure and carbon intensity across the EU-27 countries. In the quadratic specification, the linear coefficient for fixed broadband subscriptions is positive and statistically significant. Conversely, the coefficient of the squared broadband variable is negative and also statistically significant. This parameter combination confirms an inverted U-shaped relationship. Thus, the impact of digitalization on the environment changes depending on the degree of development of the digital infrastructure. Overall, the fixed-effects panel estimation (2015–2021) confirms core theoretical assumptions. Specifically, Hypothesis H1 is supported, as the results demonstrate that digital infrastructure exerts a statistically significant impact on carbon intensity across the EU-27. Furthermore, Hypothesis H2 is also supported, establishing the existence of a Digital Environmental Kuznets Curve (EKC).

In the initial stage, the expansion of digital infrastructure may be associated with an increase in carbon intensity. The construction of networks, the production and replacement of digital equipment, the operation of data centers, and the increase in electricity consumption create an additional energy burden. At this stage, the so-called scale effect may prevail over the positive effects of technological efficiency. Digitalization therefore creates an environmental trade-off: its infrastructure generates an additional energy and material footprint, while its applications can simultaneously reduce energy and resource use in other sectors. However, as digitalization progresses, the possibilities for automation, optimization of production processes, intelligent energy management, and more efficient use of resources increase. This explains why, beyond a certain level of digital maturity, the direction of the relationship changes.

The estimated threshold of approximately 24.8 fixed broadband subscriptions per 100 people is a particularly important result of the study. It indicates the approximate level at which the positive effect of the initial expansion of infrastructure starts to be offset by the increasing benefits of technological efficiency. This finding supports the concept of digitalization as a process with two sequential effects: initially higher energy consumption and subsequent improvement in resource and energy efficiency. In this sense, digital infrastructure should not only be viewed as an additional source of electricity consumption but also as a foundation for transforming the way economic activities use energy and resources. Beyond this inflection point, the “technique effect” begins to outweigh the “scale effect,” as technological progress facilitates increased resource efficiency and the optimization of industrial processes. The results of this study are consistent with the growing number of international studies that establish digitalization as a dual-edged sword for environmental sustainability. Specifically, the confirmation of the Digital EKC in the EU-27 aligns with the findings of Zhang et al. [3] and Wang et al. [1], who observed similar nonlinear dynamics in global and regional contexts. By validating that the “technique effect” eventually offsets the initial “scale effect,” this research reinforces the consensus that technological maturity is a prerequisite for absolute decoupling.

The additional mechanism and heterogeneity analyses provide further support for the interpretation of the baseline model results. The mechanism analysis indicates that broadband connectivity is positively associated with renewable energy ($\theta = 0.3212$; $p = 0.0209$), while renewable energy is negatively associated with carbon intensity ($\delta = -0.4171$; $p < 0.001$). This finding is consistent with the theoretical argument that digital connectivity can facilitate the monitoring, management, and integration of renewable energy resources. The heterogeneity analysis further shows that the negative association between broadband connectivity and carbon intensity is significantly stronger in countries with higher digital maturity. Taken together, these results suggest that the environmental contribution of digital connectivity depends not only on the expansion of broadband infrastructure itself but also on the complementary technological and energy conditions under which it is deployed.

The analysis of the heterogeneity of the broadband–carbon intensity relationship across different levels of maturity shows that the negative relation between broadband connectivity and carbon intensity is significantly stronger in high-digital-maturity countries. This leads to the assumption that broadband infrastructure can generate greater environmental benefits when it is supported by a broader digital ecosystem, including more advanced digital services, technologies, and capabilities. Thus, the environmental impact of connectivity depends on the ability of economies to use the broadband infrastructure and not only on the availability of broadband infrastructure itself.

The results also show that the impact of digitalization must be viewed within a broader economic context. The coefficient of GDP per capita is negative and statistically significant. This means that in the sample under consideration, a higher level of economic development is associated with a lower carbon intensity. A possible explanation is the higher technological and production efficiency of economies in which higher value-added activities occupy a larger place. These economies also usually have greater opportunities for investment in modern technologies and environmental protection solutions. From this perspective, the effect of digitalization cannot be considered separately from the economic structure. Both the general level of development and the ability of individual economies to introduce and use new technologies are important.

Renewable energy also has a clear importance in the results obtained. The coefficient of renewable energy consumption is negative and statistically significant in both the linear and nonlinear models. Therefore, a higher share of renewable energy sources is associated with a lower carbon intensity. This is also important from the perspective of the link between the digital and green transitions. The expansion of digital infrastructure alone does not guarantee a positive environmental impact if the electricity needed to operate it continues to be produced mainly from carbon-intensive sources. For this reason, the environmental benefits of digitalization may be greater in economies that simultaneously develop their digital infrastructure and reduce the carbon intensity of the energy sector.

The results also show the presence of spatial interdependence between the EU-27 countries. The analysis of residual dependencies suggests that changes in carbon intensity should not be viewed solely as separate national processes. This is understandable given the strong economic integration between Member States, the common internal market, and similar regulatory conditions in the field of digitalization and environmental protection. At the same time, countries differ in terms of their digital maturity, level of economic development, and structure of the energy sector. Therefore, the same policy will not necessarily have the same effect in all countries. Countries with more developed digital infrastructure and greater capacity to deploy modern technologies may realize efficiency gains at an earlier stage. Economies that are still expanding basic digital connectivity may initially face higher energy needs and infrastructure costs. This means that the transition to low-carbon digitalization may unfold differently across EU countries, even within a common European framework. National policies should therefore take into account the specific conditions and differences between individual economies.

The study period is limited to 2015–2021 due to data availability. However, these years do not represent a completely homogeneous stage in the digital and green transition process. In the period 2015–2019, digital connectivity in the EU expanded gradually, in parallel with the development of climate policies. In 2020, the COVID-19 pandemic significantly changed established economic trends and at the same time accelerated the adoption of digital technologies. In 2021, an economic recovery began, accompanied by an increase in industrial activity. Therefore, the estimates obtained reflect different macroeconomic conditions over the period under consideration, rather than a constant baseline situation. With the accumulation of longer panel series, it will be possible to examine these sub-periods separately and to check whether the established dependencies persist in the longer term.

The results can also be seen in the broader context of the concept of the “Twin Transition,” which combines digital and green transformation. Digital technologies create opportunities to support the transition to a low-carbon economy through smart energy grids, automation, digital surveillance, logistics optimization, and more efficient resource management. The link with the circular economy is of particular importance. Digital tools can be used to better track the movement of materials, improve waste management, and use available resources more efficiently. Technologies also facilitate product traceability, enable predictive maintenance, and can extend the useful life of equipment.

From this perspective, the role of digital infrastructure is not limited to the ability to reduce energy consumption. It can also support more rational use of materials and the reduction of waste at the different stages of production and consumption. Thus, digital infrastructure is gradually transforming from an independent

technological element into the basis for broader changes in the way production and economic processes are organized.

Overall, the results are consistent with the main hypothesis of a significant relationship between digital infrastructure and carbon intensity and provide grounds to speak of a nonlinear relationship with an inverted U-curve shape. This means that the impact of digitalization on the environment is not the same at all levels of digital development. It depends on the degree of digital maturity and the conditions under which the digital transition takes place. Therefore, the further development of digital infrastructure should go hand in hand with the decarbonization of energy, increasing energy efficiency and the wider use of digital solutions for resource optimization.

The results on structural differences between countries further show that policies cannot be completely the same for all countries. In economies with a higher degree of digital maturity, attention can be directed to the wider use of modern digital solutions for circular production, smart energy management, and resource optimization. For countries still building their basic digital capacity, the development of reliable ICT infrastructure and the simultaneous integration of renewable energy remain at the forefront. Achieving the EU’s green and digital transition goals therefore requires policies that take into account differences between countries in terms of their digital maturity, rather than applying a one-size-fits-all approach.

6. Conclusions and Policy Implications

6.1. Conclusions

The study shows that digitalization is closely linked to the decarbonization process in the EU-27 countries. The empirical results obtained indicate a significant nonlinear relationship between the development of digital infrastructure and carbon intensity for the analyzed countries. This means that the impact of digital technologies on the environment does not remain unchanged at different levels of digital development. Along with digitalization, the expansion of renewable energy, as well as the general economic characteristics of individual countries, is also of great importance.

The results give reason to assume that digital progress does not automatically lead to lower carbon intensity. Environmental benefits depend to a large extent on the way in which new technologies are combined with the decarbonization of the energy sector, increased efficiency, and more rational use of resources. Additional analyses support this interpretation. They point to a possible role of renewable energy as a mechanism through which digitalization can affect carbon intensity. Higher broadband connectivity is associated with a greater use of renewable energy sources, and a higher share of renewable energy, in turn, is associated with a lower carbon intensity.

Differences between countries in terms of digital maturity are also significant. In countries with a more developed digital environment, the relationship between broadband connectivity and environmental outcomes is more pronounced. This suggests that the presence of digital infrastructure alone is not enough to realize its potential to support the green transition. Complementary technological, economic, and institutional conditions need to exist that allow digital solutions to be used for more efficient energy and resource management.

The results obtained should also be considered in light of some limitations of the empirical analysis. The most significant of these is related to the availability of data, which limits the time

scope of the study and does not allow for tracking processes over a longer period. There are also significant differences between the EU-27 countries in terms of digital maturity, the structure of the economy, and the characteristics of the energy systems. Therefore, digital developments cannot be expected to have exactly the same effects in all Member States.

These limitations highlight several opportunities for future research. The current analysis focuses on the physical side of digital infrastructure through indicators of broadband penetration and density of secure servers. Future research could use more disaggregated indicators and distinguish between different technological strands. Of particular interest is the development of technologies such as AI and edge computing. Their diffusion can support the shift toward more efficient and low-carbon economic models but at the same time can create additional demand for electricity. Tracking these two effects would allow a more precise assessment of whether the new generation of digital technologies is accelerating the transition to a stage of real emission reductions or creating new energy constraints.

6.2. Policy implications

Based on the results obtained, European policies can focus more on the joint development of digitalization and the transition to a low-carbon economy. In EU Member States already in the lower part of the EKC, the expansion of 5G networks and high-capacity digital connectivity should be combined with the development of smart electricity grids. For countries approaching the estimated threshold of 24.8, targeted support through the Cohesion Fund could facilitate the transition to a lower carbon intensity. The spatial interdependence between countries indicates the need for better policy coordination at the EU level. In this context, the Digital Decade Strategy can help better align digital development with the EU's climate goals. This implies that technological progress should be developed in parallel with the decarbonization of the energy sector, higher energy efficiency, and the gradual introduction of circular models in the technology industry.

In order to more directly link the empirical findings to specific policies, the recommendations are differentiated according to the position of Member States in relation to the identified broadband tipping point. In economies where digital infrastructure is still below this threshold, the main question is how to limit the energy costs inherent in the early stages of digitalization. In these countries, it is important that the development of green ICT goes hand in hand with the expansion of broadband networks, data centers, and related infrastructure. This can be supported by renewable energy supply contracts and stricter energy efficiency requirements for hardware and network infrastructure, so as to limit additional emissions when new capacity is built. For economies that have already passed the estimated tipping point, the focus could shift to using digitalization to further reduce carbon intensity. In this case, instead of a major expansion of basic infrastructure, smart grids, advanced software solutions, applications of AI for resource management, and digital transformation in various sectors become more important. Such developments could contribute to more efficient use of energy and resources and to a deeper integration of digital technologies in the decarbonization process.

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Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The author declares that she has no conflicts of interest to this work.

Data Availability Statement

The data that support the findings of this study in Table 1 are openly available from the World Bank's World Development Indicators database at <https://databank.worldbank.org/source/world-development-indicators#>. The data presented in Table 1 were compiled and systematically organized by the author based on the original data obtained from the World Bank.

Author Contribution Statement

Ani Stoykova: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition.

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