Sosyoekonomi

2026, Vol. 34(69), 189-206

RESEARCH ARTICLE

ISSN: 1305-5577
DOI: 10.17233/sosyoekonomi.2026.03.08
Date Submitted: 05.05.2025
Date Revised: 04.10.2025
Date Accepted: 16.05.2026

Energy Consumption in the EU: The Role of Productivity and Efficiency-Driven Technology[1]

Mehmet Ali ÇAKIR *(https://orcid.org/0000-0001-7878-5192), Gümüşhane University, Türkiye; mehmetali.cakir@gumushane.edu.tr*

Mehmet Kutluğhan Savaş ÖKTE *(https://orcid.org/0000-0002-9753-9621), İstanbul University, Türkiye; mokte@istanbul.edu.tr*

AB'de Enerji Tüketimi: Üretkenlik ve Verimlilik Odaklı Teknolojinin Rolü[2]

Abstract

This study investigates how productivity and productivity-intensive technologies affect energy consumption in selected EU countries from 1996 to 2021. Despite technological progress, fossil fuels still dominate, posing environmental and economic concerns. Using the AMG method, results show that multifactor productivity significantly reduces energy use, while productivity-intensive technologies offer smaller but meaningful reductions. In contrast to prior research linking technology to higher energy demand, this study highlights the importance of efficiency-focused innovation. Findings support the EU's 2030 energy reduction target and suggest policymakers should prioritise productivity-intensive technologies, on-the-job training, and digital tools to decouple growth from energy consumption.

Keywords : Productivity, Productivity Intensive Technology, Energy Consumption, Economic Growth, European Union.

JEL Classification Codes : E20, O47, J24, O11.

Öz

Bu çalışma, 1996-2021 döneminde seçilmiş AB ülkelerinde verimlilik ve verimlilik odaklı teknolojilerin enerji tüketimine etkisini incelemektedir. Teknolojik ilerlemelere rağmen fosil yakıtlar hâlâ baskın kalmakta ve çevresel ile ekonomik sorunlara yol açmaktadır. AMG yöntemiyle elde edilen sonuçlar, çok faktörlü verimliliğin enerji tüketimini önemli ölçüde azalttığını, verimlilik odaklı teknolojilerin ise daha sınırlı ama anlamlı katkılar sağladığını göstermektedir. Teknolojinin enerji talebini artırdığı yönündeki önceki çalışmalardan farklı olarak, bu çalışma verimliliğe odaklanan yeniliklerin önemini vurgulamaktadır. Bulgular, AB'nin 2030 enerji azaltım hedefini desteklemekte ve politika yapıcılara verimlilik odaklı teknoloji, hizmet içi eğitim ve dijital araçlara öncelik verilmesini önermektedir.

Anahtar Sözcükler : Verimlilik, Verimlilik Yoğun Teknoloji, Enerji Tüketimi, Ekonomik Büyüme, Avrupa Birliği.

---

[1] *This article is derived from Mehmet Ali Çakır's doctoral dissertation titled "An Econometric Analysis on Energy, Technology, Environment, and Financial Stability: The Case of Selected EU Countries", completed under the supervision of Prof.Dr. Mehmet Kutluğhan Savaş Ökte, Istanbul University, Institute of Social Sciences, PhD program in Economics, 2025.*

[2] *Bu makale 2025 yılında İ.Ü. Sosyal Bilimler Enstitüsü İktisat Programında Mehmet Ali Çakır tarafından Prof.Dr. Mehmet Kutluğhan Savaş Ökte'nin danışmanlığında hazırlanan "Enerji, Teknoloji, Çevre ve Finansal İstikrar Üzerine Ekonometrik Bir Analiz: Seçilmiş AB Ülkeleri Örneği" başlıklı doktora tezinden üretilmiştir.*

1. Introduction

Technological progress and increased productivity have largely been seen as the drivers of the world's rapid economic growth. Several studies, Bahrini and Qaffas (2019), Nguyen et al. (2020) and Zafar et al. (2019) have found a strong correlation between economic growth and frontier technologies and concluded that technology is one of the main drivers of economic growth. As widely expected, economic growth and technological development are accompanied by increased energy use (Gorus & Aydin, 2019; Rahman & Velayutham, 2020). Similarly, the Energy Information Administration (EIA, 2023) reports that total energy consumption is essentially driven by economic growth, whereas energy consumption per capita is linked to changes in technology policy. As a result, for more than a century, the world's economies have been facing a major challenge: technological and economic development that drives energy consumption.

Besides, though Naimoglu (2021) and Zhang et al. (2020) show the effectiveness of energy-saving technologies in reducing energy consumption, the EIA (2023) report indicates that total energy consumption has been trending upwards. Even though there are many reasons for the dichotomy between the effectiveness of energy-saving technologies and the increase in overall energy consumption, Liu et al. (2019), Safarzadeh et al. (2020), and Stern (2020) have explained it through the rebound effect. Although technological innovation may contribute to long-term efforts to reduce energy use, it may increase short-term pressure on energy use through the rebound effect. Given the dependence of economies on fossil fuels, the upward trend in energy consumption has accelerated the negative impacts of energy use (Khan et al., 2021; Abbasi et al., 2022; Onifade, 2023). Therefore, achieving the net-zero emission target of the Paris Agreement with the help of technology is crucial.

Technological progress is driving the globalisation of industries and fostering international trade, while global integration and trade, in turn, accelerate the diffusion of technology (Grossman & Helpman, 2015). An increase in trade inevitably leads to higher energy consumption due to increased production of goods and transport (Al-mulali & Sheau-Ting, 2014; Topcu & Payne, 2018). Trade has a significant impact on urbanisation, transforming cities into centres of attraction and production (Blaydes & Paik, 2021). As a result, trade, production processes, urbanisation, and the diffusion of technology all impact energy consumption. For the period 2021-2024, the EU allocated 15.1% of its total budget, around €208.1 billion, to digital technologies within the framework of the Horizon Europe Programme (European Commission, 2025a). Also, the Digital Europe report (2024) states that Europe is losing competitiveness in technology, particularly against the USA and China, and that the most immediate risk is missing out on productivity gains. Likewise, Bergeaud (2025) highlights that the EU has experienced productivity weaknesses since 1995, which have widened the productivity gap between the EU and the USA. If the EU ignores productivity losses and focuses solely on technology, energy consumption may increase, making it unlikely that the EU's 2030 11.7% reduction target will be achieved (European Commission, 2023). Therefore, the study will clarify the overlooked linkage between energy consumption, productivity, and technology.

Figure: 1
Diagram of the Impact of Technology and Productivity on Energy Consumption

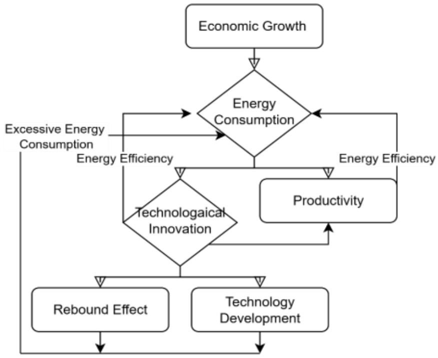
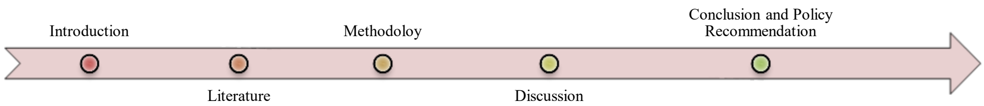


Figure 1 shows the basic relationship between energy and productivity and how they affect energy consumption in an economy. While productivity has a direct effect on energy consumption through energy efficiency, the impact of technological innovation is less straightforward. Technological innovation can lead to energy efficiency. However, the technology development process and the rebound effect may also result in excessive energy consumption. At the same time, technology can boost productivity. Technology and productivity share a complex, inseparable relationship: any increase in productivity intricately influences economic growth, yet energy-efficiency studies have mostly focused on technology. However, studies such as Santos et al. (2021) show that productivity improvements can lead to both economic growth and greater energy efficiency. Considering this perspective, productivity is highly valued for its ability to minimise not only energy input but also other resources such as labour, capital, and raw materials, while maintaining equivalent economic outcomes in production processes (Hasanov & Mikayilov, 2021). Ultimately, this will reduce energy consumption and, in turn, environmental pollution. Due to mixed and conflicting results, further investigation is necessary in this field. Hence, this study aims to investigate how technological advancements and shifts in productivity influence energy consumption across specific EU countries. Changes in energy consumption from 1996 to 2021 have been examined using the Augmented Mean Group (AMG) approach, with technology, productivity, trade, urbanisation, and economic growth rate as explanatory variables.

The literature contains numerous studies on energy efficiency and use. However, the study is intended to fill several gaps in the literature. The first contribution clarifies how technology and productivity drive energy consumption. Instead of prior studies that focused on innovation, communication, transportation, and renewable technologies, this study has focused on total technology spending. Also, by multiplying technology by productivity, a productivity-intensive technology variable has been created to compare technology and productivity in terms of energy usage. Technological innovation is a controversial topic in the literature. Developing new technologies with excessive resources may result in innovations that are never used or that provide benefits lower than their investment costs. Therefore, this study suggests focusing on productivity when developing new technologies to allocate investment budgets and enhance energy efficiency effectively. This method helps fill a gap in the literature by addressing the overlooked role of productivity in maximising the impact of technological investments. Another expected contribution is to focus on a new sample. The literature has been overwhelmingly supportive of studies on China, Japan, and the USA. However, studies on technology and productivity in the EU have generally been overlooked. To conclude, the findings of this study on energy consumption will make significant contributions to the literature by clarifying mixed results, comparing technology and productivity, and focusing on EU economies. The study's structure is illustrated in Fig. 2.

Figure: 2
Structure of the Study



2. Literature

Energy is a widely debated topic that intersects with all areas of economics, and, as a finite resource, researchers focus on extending its availability. Basically, there are two ways to overcome this hurdle: discovering new energy sources and using existing ones more efficiently. From a general perspective, while technology plays a role in both approaches, productivity is primarily associated with efficiency. Hence, existing literature tends to focus mainly on technology and its impact on energy consumption. For example, information communication technology (ICT) is one of the most widely covered topics in the literature regarding energy consumption, and some milestone studies have been explained, such as Ishida (2015), who has focused on the contributors to energy consumption in Japan from 1980 to 2010, applying Autoregressive Distributed Lag (ARDL). The results show that ICT can reduce energy consumption in Japan. He has emphasised that an increase in ICT developments does not lead to an increase in real GDP, but it does lead to energy efficiency, especially fuel efficiency in transport. This relationship has been approved by Han et al. (2016) for China from 1985 to 2014, only for the short term. The Partial Least Squares (PLS) results indicate a U-shaped relationship between ICT and energy consumption in China. It has been stated that the reason for this relationship may be the use of high-skilled workers, enabled by ICT, rather than low-skilled workers. A similar study has been conducted by Dehghan Shabani and Shahnazi (2019) for the Iranian economy from 2002 to 2013 using the Dynamic Ordinary Least Squares (DOLS) method. They indicate that while ICT increases energy consumption in the industrial sector due to a weaker substitution effect, it improves energy efficiency in the transportation sector through dematerialisation. Usman et al. (2021) have researched the same phenomena in a broader country sample, Bangladesh, India, Pakistan, and Sri Lanka, from 1990 to 2018 using the ARDL technique. Interestingly, India is the only country to achieve both energy efficiency and economic growth thanks to ICT. However, ICT causes energy consumption in Sri Lanka. Unlike most of the literature, Ren et al. (2021) concluded that ICT increases energy consumption through economic growth in China, using Ordinary Least Squares (OLS) for the period 2006-2017. Verma et al. (2022) concluded that ICT enhances energy consumption in the South Asian Association for Regional Cooperation, using the Driscoll-Kraay method.

In addition to ICT, environmental technology is another technology proxy commonly used in the literature. Paramati et al. (2022) have addressed the subject using environmental technology as a proxy. They have focused on OECD countries from 1990 to 2014 using the AMG method. The findings indicate that environmental technology mitigates energy consumption, because the majority of economies depend on high-energy-intensive sectors. However, the findings of Paramati et al. (2022) have not been confirmed by Shinwari et al. (2024) for Belt and Road Initiative countries during 2000-2021. The Driscoll-Kraay method shows that green environment-related technology increases energy consumption. They suggest that this may be due to the rebound effect and technological developments that increase energy demand. Wang et al. (2023) investigated the causal relationship between energy consumption and technological innovation in the EU from 1995 to 2020 using the Dumitrescu-Hurlin test. The findings indicate a bidirectional causality between energy consumption and technology. Likewise, using generalised least squares (GLS) regression, Alofaysan et al. (2024) found that green technology innovation is associated with energy efficiency in the EU during 2011-2020.

Anser et al. (2024) have also focused on the same problem using a different technology proxy, patent applications. The GMM method shows that technological improvements have increased energy efficiency in BRIC economies over the period 1990 - 2023. However, these findings are contrary to those of Jiang and Khan (2023) for Belt and Road Initiative countries from 1995 to 2019. They have also used patent applications and the GMM method, but they indicated that technological improvements cause more energy consumption. They indicate that innovation needs more energy sources.

The literature has primarily focused on technology as a solution to energy problems. It is widely accepted that technology can address these issues on both demand and supply sides. For example, developing new energy sources such as solar power can help solve supply-side problems, while enhancing energy efficiency through innovations like energy-efficient vehicles can address demand-side challenges. However, it must be remembered that both solutions offer more energy or materials. Therefore, developing solutions to the energy problem that do not rely on increased material consumption could represent a significant advancement. Studies such as Román-Collado and Colinet (2018), Hasanov and Mikayilov (2021), and Qianqian et al. (2025) have strictly suggested that productivity mitigates energy consumption. Román-Collado and Colinet (2018) have investigated the link between labour productivity and energy consumption in Spain from 2000 to 2013 using the LMDI-I method.

The show that labour productivity mitigates energy consumption in Spain. They suggested that this may be related to reduced working hours. However, during a low-unemployment-rate situation, an increase in productivity has an adverse effect on energy consumption. Given the close relationship between technology and productivity, this study proposes productivity-intensive technology as a solution to energy problems and seeks to fill a gap in the literature. The other contribution is that, while most existing research has focused on the role of technology in energy consumption, the specific relationship between productivity and energy consumption has received much less attention, particularly in Europe. Unlike previous studies that primarily investigate Asian, Middle Eastern, or global samples, this research specifically examines the European region, thereby filling a geographical gap in the literature. By highlighting the overlooked link between productivity, technology, and energy efficiency, the study provides a more comprehensive understanding of how Europe can achieve its energy and environmental targets and fill the gap in the literature.

3. Data, Methodology and Findings

3.1. Data

This study includes 13 EU countries for which ‘Total Productivity’ (MFP) data is available in the OECD database: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Italy, Luxembourg, the Netherlands, Portugal, Spain, and Sweden. Although these countries have different levels of development, they share similar characteristics in terms of energy consumption, the dependent variable, and can be considered homogeneous. Although Eurostat provides data for all EU countries, its MFP data was not used because it is still in a raw and experimental format, making it less reliable. The study covers the period from 1996 to 2021, providing a consistent and complete dataset. Details on the data sources and variables are in Table 1.

Table: 1
Definitions and Sources of the Variables

Variables	Symbol	Unit of Measurement	Source
Total Energy Consumption	lnTEC	Fossil, nuclear, and renewable energy consumption per capita (kWh)	Our World in Data
Economic Growth	lnGDP	GDP per capita (US $)	World Bank-WDI
Multifactor Productivity	lnMFP	Overall efficiency (labour and capital) 2015=100	OECD
Trade	lnTRD	Trade (% of GDP)	World Bank-WDI
Urbanization	lnURB	Urban population to rural population ratio	World Bank-WDI
Patent Applications	lnPAT	Total (residents+ nonresidents)	WIPO statistics database
Productivity*Patent Applications	lnMFP*lnPAT	Numeric	Author’s Calculations

To demonstrate the influence of productivity-intensive technology, 2 models have been created. Model 1 in equation (1) is used to show the relationship between total energy consumption (TEC), economic growth (GDP), urbanisation (URB), trade (TRD), and total productivity (MFP). In Model 2 (equation 2), the number of patent applications is added to test whether technological change affects total energy use. In both models, i stands for the country, and t stands for the year. The symbol ε shows the error term in the equations.

Model: 1

$$lnTEC_{it} = \alpha_0 + \alpha_1 lnGDP_{it} + \alpha_2 lnURB_{it} + \alpha_3 lnTRD_{it} + \alpha_4 lnMFP_{it} + \varepsilon_{it} \quad (1)$$

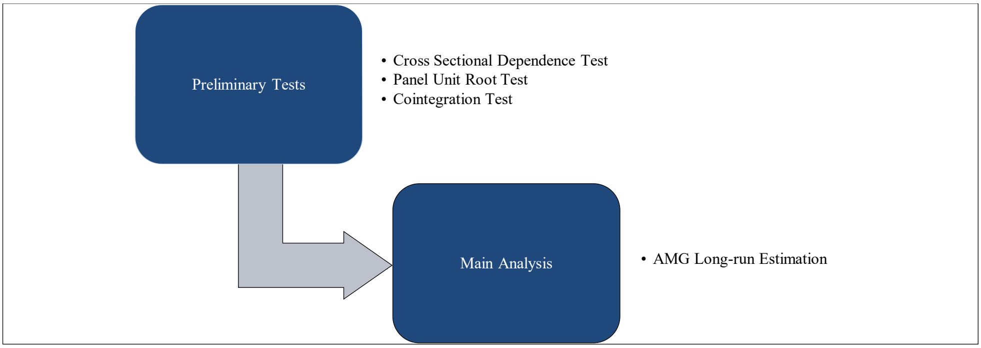
Model: 2

$$lnTEC_{it} = \alpha_0 + \alpha_1 lnGDP_{it} + \alpha_2 lnURB_{it} + \alpha_3 lnTRD_{it} + \alpha_4 lnMFP * lnPAT_{it} + \varepsilon_{it} \quad (2)$$

3.2. Methodology and Findings

Before applying econometric tests to examine the relationships among the variables, preliminary tests must be conducted to ensure more reliable results. These tests help determine the most appropriate econometric method for the study. The study's methodological framework is shown in Figure 2.

Figure: 3
Framework of the Methodology



3.2.1. Cross-Sectional Dependency (CSD) Test

The CSD test is one of the most important diagnostic tests for determining whether events or shocks in one unit affect other units in the dataset. Analysing data without accounting for CSD leads to biased or inconsistent estimates in panel data models. In this study, BP_{LM} and CD_{LM} tests have been used to assess CSD. For improved readability, we have provided a detailed explanation of the tests in the Appendix. The null hypothesis of the tests states that there is no CSD in the series. The findings indicate the presence of CSD in the model. Therefore, second-generation panel unit root tests need to be applied. Table 2 shows both BP_{LM} and CD_{LM} test results.

Table: 2
CSD Test Results

Variables	BP_{LM}	CD_{LM}
lnTEC	394.368***	25.330***
lnMFP	145.801***	5.428***
lnTRD	140.191***	4.979***
lnURB	190.432***	9.002***
lnPAT	117.892***	3.194***
lnMFP*lnPAT	127.828***	3.989***

**** represents 1% significance level.*

3.2.2. PANIC Unit Root Test

Based on the CSD test findings, the PANIC unit root test has been applied as a second-generation unit root test. The null hypothesis is that all units are non-stationary, and the alternative hypothesis is that some units are stationary. A detailed explanation of the tests has been included in the Appendix to enhance readability. The unit root test results are shown in Table 3.

Table: 3
PANIC Test Results

Variables	Test	Level	1st Difference
lnTEC	$Z_{\hat{e}}^{c}$	-2.3704	8.8651***
	$P_{\hat{e}}^{c}$	8.9068	89.9271***
lnMFP	$Z_{\hat{e}}^{c}$	-1.8710	5.0037***
	$P_{\hat{e}}^{c}$	12.5080	62.0823***
lnTRD	$Z_{\hat{e}}^{c}$	-1.6621	5.5672***
	$P_{\hat{e}}^{c}$	14.0142	66.1453***
lnURB	$Z_{\hat{e}}^{c}$	0.7199	1.5972*
	$P_{\hat{e}}^{c}$	31.1914	37.5175*
lnPAT	$Z_{\hat{e}}^{c}$	-2.2115	6.0102***
	$P_{\hat{e}}^{c}$	10.0529	69.3401***
lnMFP*lnPAT	$Z_{\hat{e}}^{c}$	-1.5780	7.0496***
	$P_{\hat{e}}^{c}$	14.6212	76.8351***

****, **, and * indicates 1 %, 5%, and 10 % significance level.*

3.2.3. LM Panel Cointegration Test

To continue the long-run econometric analysis in the study, it is necessary to check whether the series are cointegrated. For this purpose, the LM bootstrap panel cointegration test can be applied in the case of CSD. The presence of cointegration across all cross-sectional units is the null hypothesis, and the absence of cointegration across some cross-sectional units is the alternative hypothesis. To improve readability, we have added a detailed explanation of the tests in the Appendix. The results presented in Table 4 indicate that the variables in the models exhibit a long-run cointegrating relationship.

Table: 4
Panel Cointegration Test Results

Test	Model 1			Model 2		
	Statistic	Asymp. p-value	Bootstrap p-value	Statistic	Asymp. p-value	Bootstrap p-value
LM^{+}	4.959	0.000	0.994	4.565	0.000	0.998

Bootstrap p-values are based on 10,000 bootstrap replications.

3.2.4. Augmented Mean Group (AMG) Long-Run Estimation

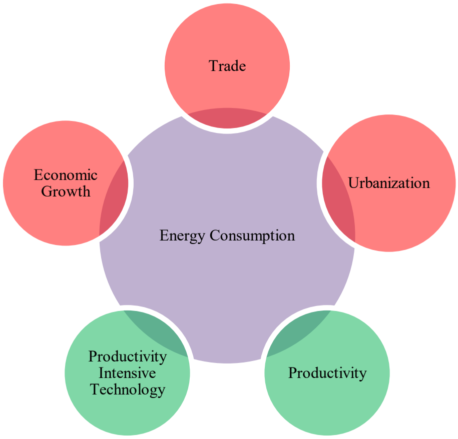
AMG estimation has been designed for use in CSD models and heterogeneous models. We have applied the AMG test since our series exhibits CSD. For improved readability, we have provided a detailed explanation of the tests in the Appendix. The AMG estimation results are presented in Table 5, and the p-value from the Wald test, which assesses the overall significance of the models, indicates that both Model 1 and Model 2 are statistically significant.

Table: 5
AMG Long-run Estimation Results

Variables	Model 1 $lnTEC_{it} = \alpha_0 + \alpha_1 lnGDP_{it} + \alpha_2 lnURB_{it} + \alpha_3 lnTRD_{it} + \alpha_4 lnMFP_{it} + \varepsilon_{it}$		Model 2 $lnTEC_{it} = \alpha_0 + \alpha_1 lnGDP_{it} + \alpha_2 lnURB_{it} + \alpha_3 lnTRD_{it} + \alpha_4 lnMFP * lnPAT_{it} + \varepsilon_{it}$	
	Values	**P-value**	**Values**	**P-value**
lnGDP	0.713	0.000	0.558	0.000
lnURB	0.349	0.072	0.485	0.006
lnTRD	0.372	0.010	0.264	0.018
lnMFP	-1.488	0.000	-	-
lnMFP*lnPAT	-	-	-0.086	0.071
Wald chi2	295.47	0.000	672.09	0.000

The results of Models 1 and 2 are presented in Table 5. While Model 1 states the influence of productivity on total energy consumption, Model 2 highlights the impact of productivity-intensive technology on total energy consumption. The findings of the Model 1 show that economic growth, urbanisation, and trade boost energy consumption in European Countries. More specifically, a 1% increase in lnGDP causes a 0.713% increase in lnTEC. Similarly, a 1% increase in lnURB and lnTRD increases lnTEC by 0.349% and 0.372%, respectively. However, marginal factor productivity is the only variable that mitigates energy consumption in European Countries. A 1% increase in lnMFP leads to a -1.488% decrease in lnTEC. As in Models 1 and 2, economic growth, urbanisation, and trade boost energy consumption in European Countries. To be specific, 1% increase in lnGDP, lnURB and lnTRD causes a rise in lnTEC by 0.558%, 0.485% and 0.264%, respectively. A 1% increase in lnMFP*lnPAT reduces lnTEC by 0.086%. It shows that productivity-intensive technology mitigates energy consumption in European Countries. The summary of the findings is shown in Figure 4.

Figure: 4
The Summary of the Estimation Results



4. Discussions

It is well known that global energy demand has been steadily increasing. Although innovative technologies have diversified energy sources, fossil fuels still account for the majority of global energy consumption. In energy-importing countries, this puts serious pressure on their economies. The European Commission (2025) stated that the EU paid €604 billion in 2022 for energy imports. In addition to diversifying energy sources, innovative technologies can also mitigate energy consumption by improving energy efficiency. However, this general perspective is sometimes rejected by studies such as Dehghan Shabani and Shahnazi (2019), Usman et al. (2021), Ren et al. (2021), and Verma et al. (2022). The argument in these studies is that technology increases energy consumption: either because it drives economic growth and, in turn, energy consumption, or because technological development itself generates high energy demand. Therefore, this study aims to offer alternative approaches in the literature for mitigating energy consumption by focusing on productivity, to enhance cost, material, and environmental efficiency.

According to OECD (2023), multifactor productivity also encompasses changes in management practices, brand identity, organisational changes, general knowledge, network effects, and spillovers from production factors, alongside the overall efficiency in utilising labour and capital inputs. Based on these definitions, restricting energy consumption without high energy demand in technological processes or the overall economy is achievable. To increase productivity in this case, little or no extra resources are needed. Our findings indicate that increased productivity mitigates energy consumption, and the study presents results consistent with the few studies in the literature that address this issue: Román-Collado and Colinet (2018), Hasanov and Mikayilov (2021), and Qianqian et al. (2025). There are also reservations that productivity increases may increase energy consumption in some cases, such as a low-unemployment-rate case or a leading-excessive-growth-rate case. In such cases, our findings show that productivity-intensive technologies can mitigate energy consumption and serve as solutions to this problem. Our findings on productivity-intensive technology and energy consumption contrast with those of Dehghan Shabani and Shahnazi (2019), Usman et al. (2021), Ren et al. (2021), and Verma et al. (2022), who primarily focus on technology. In contrast, our study emphasises that technologies should also prioritise productivity to be environmentally friendly. Although this per-unit effect appears modest, its cumulative impact over time and across sectors could be substantial. Even small reductions in energy intensity, when scaled, may translate into meaningful energy and emissions savings, reinforcing the role of productivity-intensive technologies as a pathway toward sustainable energy use in Europe. In particular, energy-intensive sectors such as manufacturing, heavy industry, and transport can significantly reduce fuel consumption through digitalisation and efficiency improvements.

The report of the European Commission (2022) on energy consumption states that the EU has a plan to reduce energy consumption by 2030, providing energy efficiency by 13%. To achieve this target, the report highlights the importance of behavioural awareness, public-sector energy savings, and the adoption of digitalisation and smart technologies. Thus, the definition of multifactor productivity of OECD (2023) and the aim of the European Commission (2022) show significant overlap. In addition, the European Commission (2023) has set a target of achieving a minimum 55% reduction in CO_2 emissions by 2030. However, Çakır and Ökte (2025) indicate that while technology exacerbates environmental degradation, productivity-intensive technology improves environmental quality in the EU. Therefore, focusing on productivity-intensive technology to mitigate energy consumption in the EU has also provided positive environmental externalities. To summarise, our findings indicate that productivity mitigates energy consumption, and productivity-intensive technology can help mitigate energy consumption when productivity does not, as in cases of low unemployment rates that lead to excessive growth.

5. Conclusion and Policy Recommendations

It is widely recognised that global energy demand continues to rise. Although technological advancements have diversified energy sources, fossil fuels still dominate the global energy supply. While energy source diversification is crucial, the efficient use of energy resources is even more critical for extending the lifespan of these limited resources. In light of this, the present study offers valuable insights by focusing on selected EU countries: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Italy, Luxembourg, the Netherlands, Portugal, Spain, and Sweden, over the period from 1996 to 2021. Based on the AMG test results, multifactor productivity significantly reduces energy consumption. Moreover, productivity-intensive technology also contributes to reducing energy use, though to a lesser extent than multifactor productivity alone. Nevertheless, economic growth emerges as the main driver behind increasing energy demand in both models. Urbanisation and trade are also found to positively influence energy consumption.

The models show that economic growth, urbanisation, and trade have a positive effect on energy consumption. Thus, policymakers should be boosting renewable energy, as outlined in the REPowerEU plan of the European Commission (2022). By replacing excessive energy demand with renewable energy sources, Europe can reduce its dependence on Russian energy supplies. This shift will directly weaken the connection between energy and trade. Policymakers should develop policies to decouple economic growth from energy consumption. In light of our findings, productivity-intensive technology can help decouple economic growth from energy consumption. The EU should prioritise productivity-intensive technologies to achieve the same output with less energy. Policymakers should monitor and evaluate each technological innovation, and if it is productivity-intensive, it can be supported with a grant or tax reduction. Policymakers should encourage productivity-intensive innovation in high-energy-demand sectors such as transport, manufacturing, and construction, where marginal efficiency gains can deliver significant reductions in total energy use. Also, our findings show that productivity mitigates energy consumption in the EU. Based on these results, policymakers should centralise productivity in the policies. Those policies, energy savings and efficiency, are also in line with the REPowerEU plan objectives. Policymakers should also be aware that productivity can be increased without technological investment. As the OECD (2023) report states, management practices, brand identity, organisational changes, general knowledge, network effects, and spillovers from production factors are the main determinants of multifactor productivity. Management practices, general knowledge and organisational changes can be enhanced through in-service training. Therefore, the EU should encourage firms to provide such training by providing public funds. Brand identity, network effects, and spillovers from production factors can be enhanced through technology, such as the use of platforms and digital tools that increase in value with user participation, like customer apps or integrated service ecosystems, as well as through knowledge sharing, automation, and cross-departmental collaboration. Therefore, the EU should encourage technological investments by prioritising productivity-intensive technologies.

Data restriction is the biggest limitation in the study. Thus, future studies can modify econometric methods using machine learning techniques that can handle short-term time-series data to cover the entire sample. Further study should also focus on sectoral-level productivity and technology. Specifically, productivity-intensive technology options should be investigated in energy-intensive sectors.

References

Abbasi, K.R. et al. (2022), “Analyze the environmental sustainability factors of China: The role of fossil fuel energy and renewable energy”, *Renewable Energy*, 187, 390-402.

Al-mulali, U. & L. Sheau-Ting (2014), “Econometric analysis of trade, exports, imports, energy consumption and CO2 emission in six regions”, *Renewable and Sustainable Energy Reviews*, 33, 484-498.

Alofaysan, H. et al. (2024), "The effect of digitalization and green technology innovation on energy efficiency in the European Union", *Energy Exploration & Exploitation*, 42(5), 1747-1762.

Anser, M.K. et al. (2024), "Energy consumption, technological innovation, and economic growth in BRICS: A GMM panel VAR framework analysis", *Energy Strategy Reviews*, 56, 101587.

Bahrini, R. & A.A. Qaffas (2019), "Impact of Information and Communication Technology on Economic Growth: Evidence from Developing Countries", *Economies*, 7(1), 21.

Bai, J. & S. Ng (2004), "A PANIC Attack on Unit Roots and Cointegration", *Econometrica*, 72(4), 1127-1177.

Baltagi, B.H. (2008), *Econometric analysis of panel data* (4^{th} ed), John Wiley & Sons.

Bergeaud, A. (2025), *The Past, Present and Future of European Productivity*, European Central Bank.

Blaydes, L. & C. Paik (2021), "Muslim Trade and City Growth Before the Nineteenth Century: Comparative Urbanization in Europe, the Middle East and Central Asia", *British Journal of Political Science*, 51(2), 845-868.

Breusch, T.S. & A.R. Pagan (1980), "The Lagrange Multiplier Test and its Applications to Model Specification in Econometrics", *The Review of Economic Studies*, 47(1), 239-253.

Bulut, A.E. & M. Tunç (2025), "Do Financial and Technological Innovations Enhance Environmental Quality? Empirical Evidence from the EU Countries", *Sosyoekonomi*, 33(65), 315-334.

Çakır, M.A. & M.K.S. Ökte (2025), "A New Perspective on Technology, Productivity, and Environmental Sustainability in the European Union", *Uluslararası Ekonomi ve Yenilik Dergisi*, 11(2), 369-395.

Choi, I. (2001), "Unit root tests for panel data", *Journal of International Money and Finance*, 20(2), 249-272.

Dehghan Shabani, Z. & R. Shahnazi (2019), "Energy consumption, carbon dioxide emissions, information and communications technology, and gross domestic product in Iranian economic sectors: A panel causality analysis", *Energy*, 169, 1064-1078.

Digitaleurope (2024), *The EU's Critical Tech Gap: Rethinking economic security to put Europe back on the map*, <https://cdn.digitaleurope.org/uploads/2024/06/DIGITALEUROPE-EU-CRITICAL-TECH-GAP-REPORT_WEB_UPDATED.pdf>, 02.03.2025.

Eberhardt, M. & S. Bond (2009), "Cross-section dependence in nonstationary panel models: A novel estimator", *MPRA Paper* 17692, University Library of Munich, Germany.

EIA (2023), *Annual Energy Outlook*, <https://www.eia.gov/outlooks/aeo/pdf/AEO2023_Narrative.pdf>, 02.03.2025.

European Commission (2022), *REPowerEU Plan*, <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=COM%3A2022%3A230%3AFIN&qid=1653033742483>, 02.03.2025.

European Commission (2023), *Delivering the European Green Deal*, <https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/european-green-deal/delivering-european-green-deal_en>, 02.03.2025.

European Commission (2025a), *Digital tracking*, <https://commission.europa.eu/strategy-and-policy/eu-budget/performance-and-reporting/horizontal-priorities/digital-tracking_en#:~:text=Connecting%20Europe%20Facility.-,Supporting%20the%20development%20and%20deployment%20of%20digital%20technologies%20and%20research,EUR%204.7%20billion%20to%20research>, 02.03.2025.

European Commission (2025b), *Energy prices and costs in Europe*, <https://energy.ec.europa.eu/data-and-analysis/energy-prices-and-costs-europe_en#:~:text=The%20report%20warns%20about%20the,drain%20on%20the%20European%20economy>, 02.03.2025.

Gorus, M.S. & M. Aydin (2019), "The relationship between energy consumption, economic growth, and CO2 emission in MENA countries: Causality analysis in the frequency domain", *Energy*, 168, 815-822.

Grossman, G.M. & E. Helpman (2015), "Globalization and Growth", *American Economic Review*, 105(5), 100-104.

Han, B. et al. (2016), "Effect of information and communication technology on energy consumption in China", *Natural Hazards*, 84(S1), 297-315.

Hasanov, F.J. & J.I. Mikayilov (2021), "The impact of total factor productivity on energy consumption: Theoretical framework and empirical validation", *Energy Strategy Reviews*, 38, 100777.

Ishida, H. (2015), "The effect of ICT development on economic growth and energy consumption in Japan", *Telematics and Informatics*, 32(1), 79-88.

Jiang, Y. & H. Khan (2023), "The relationship between renewable energy consumption, technological innovations, and carbon dioxide emission: Evidence from two-step system GMM", *Environmental Science and Pollution Research*, 30(2), 4187-4202.

Khan, I. et al. (2021), "The impact of natural resources, energy consumption, and population growth on environmental quality: Fresh evidence from the United States of America", *Science of The Total Environment*, 754, 142222.

Liu, H. et al. (2019), "An improved approach to estimate direct rebound effect by incorporating energy efficiency: A revisit of China's industrial energy demand", *Energy Economics*, 80, 720-730.

Maddala, G.S. & S. Wu (1999), "A Comparative Study of Unit Root Tests with Panel Data and a New Simple Test", *Oxford Bulletin of Economics and Statistics*, 61(S1), 631-652.

Naimoglu, M. (2021), "Enerji Alanında Yapılan Ar-Ge Harcamalarının Enerji Tüketimi Üzerindeki Etkisi: Almanya Örneği", *Bingöl Üniversitesi Sosyal Bilimler Enstitüsü Dergisi*, 22, 97-118.

Nguyen, T.T. et al. (2020), "Role of information and communication technologies and innovation in driving carbon emissions and economic growth in selected G-20 countries", *Journal of Environmental Management*, 261, 110162.

OECD (2023), *Multifactor Productivity*, OECD.

Onifade, S.T. (2023), "Environmental impacts of energy indicators on ecological footprints of oil-exporting African countries: Perspectives on fossil resources abundance amidst sustainable development quests", *Resources Policy*, 82, 103481.

Paramati, S.R. et al. (2022), "The role of environmental technology for energy demand and energy efficiency: Evidence from OECD countries", *Renewable and Sustainable Energy Reviews*, 153, 111735.

Pesaran, M.H. (2004), "General Diagnostic Tests for Cross Section Dependence in Panels", *SSRN Electronic Journal*, https://doi.org/10.2139/ssrn.572504

Pesaran, M.H. & R. Smith (1995), "Estimating long-run relationships from dynamic heterogeneous panels", *Journal of Econometrics*, 68(1), 79-113.

Qianqian, D. et al. (2025), "Does green innovation mitigate consumption-based carbon emissions? The role of nuclear energy consumption and energy productivity in G-7 nations", *Nuclear Engineering and Technology*, 57(5), 103384.

Rahman, M.M. & E. Velayutham (2020), "Renewable and non-renewable energy consumption-economic growth nexus: New evidence from South Asia", *Renewable Energy*, 147, 399-408.

Reese, S. & J. Westerlund (2016), "Panicca: Panic on Cross-Section Averages", *Journal of Applied Econometrics*, 31(6), 961-981.

Ren, S. et al. (2021), "Digitalization and energy: How does internet development affect China's energy consumption?", *Energy Economics*, 98, 105220.

Román-Collado, R. & M.J. Colinet (2018), "Are labour productivity and residential living standards drivers of the energy consumption changes?", *Energy Economics*, 74, 746-756.

Safarzadeh, S. et al. (2020), "A review of optimal energy policy instruments on industrial energy efficiency programs, rebound effects, and government policies", *Energy Policy*, 139, 111342.

Santos, J. et al. (2021), "Exploring the links between total factor productivity and energy efficiency: Portugal, 1960-2014", *Energy Economics*, 101, 105407.

Shinwari, R. et al. (2024), "Does FDI affect energy consumption in the Belt and Road Initiative economies? The role of green technologies", *Energy Economics*, 132, 107409.

Stern, D.I. (2020), "How large is the economy-wide rebound effect?", *Energy Policy*, 147, 111870.

Tıraşoğlu, M. (2017), *Doğrusal Olmayan Panel Birim Kök Testleri: E7 Ülkelerinde Gelir Yakınsamasının Araştırılması*, İstanbul Üniversitesi.

Topcu, M. & J.E. Payne (2018), "Further evidence on the trade-energy consumption nexus in OECD countries", *Energy Policy*, 117, 160-165.

Usman, A. et al. (2021), "The effect of ICT on energy consumption and economic growth in South Asian economies: An empirical analysis", *Telematics and Informatics*, 58, 101537.

Verma, A. et al. (2022), "Environmental effects of ICT diffusion, energy consumption, financial development, and globalization: Panel evidence from SAARC economies", *Environmental Science and Pollution Research*, 30(13), 38349-38362.

Wang, R. et al. (2023), "Achieving ecological sustainability through technological innovations, financial development, foreign direct investment, and energy consumption in developing European countries", *Gondwana Research*, 119, 138-152.

Westerlund, J. & D.L. Edgerton (2007), "A panel bootstrap cointegration test", *Economics Letters*, 97(3), 185-190.

Zafar, M.W. et al. (2019), "From nonrenewable to renewable energy and its impact on economic growth: The role of research & development expenditures in Asia-Pacific Economic Cooperation countries", *Journal of Cleaner Production*, 212, 1166-1178.

Zhang, M. et al. (2020), "Is Technological Innovation Effective for Energy Saving and Carbon Emissions Reduction? Evidence From China", *IEEE Access*, 8, 83524-83537.

Appendix

Cross-Sectional Dependency (CSD) Test

Two different CSD tests have been applied in the study to assess whether CSD exists among the variables.

The first CSD test is BP_{LM} test, and it was developed by Breusch and Pagan (1980). The formula of the test is shown in equation (1).

$$LM = T\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}^{2} \sim X^{2}_{\frac{N(N-1)}{2}} \quad (1)$$

In this equation, N is constant and $T \rightarrow \infty$ with χ^2 distribution and $\hat{\rho}_{ij}$ shows the sample estimate of pairwise correlation of residuals.

The second test is CD_{LM} and the difference between BP_{LM} and CD_{LM} the test is whether $N \rightarrow \infty$ or not. If $N \rightarrow \infty$, using CD_{LM} is more appropriate (Pesaran, 2004). CD_{LM} test has been calculated based on the equation (2).

$$CD_{LM} = \sqrt{\left(\frac{1}{N(N-1)}\right)}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}(T\hat{\rho}_{ij}^{2} - 1) \sim N(0,1) \quad (2)$$

The null hypothesis for both tests is that there is no cross-sectional dependence in the series. The findings based on equations (1) and (2) show rejection of the null hypothesis and indicate the usage of second-generation panel unit root tests (Baltagi, 2008).

PANIC Unit Root Test

The PANIC unit root test, one of the second-generation unit root tests, can be used when CSD is present in at least some of the series (Bai & Ng, 2004; Reese & Westerlund, 2016). The test statistics have been formulated based on the study by Tıraşoğlu (2017), as shown below.

$$X_{it} = D_{it} + \lambda_i' F_t + e_{it} \quad (3)$$

D_{it} is the polynomial trend function, F_t is the common factor vector which has $r\ x\ 1$ dimension, e_{it} is the error term, and X_{it} is the sum of deterministic components. Also, in the model with N variables, there are N idiosyncratic components but a small number of common factors (Bai & Ng, 2004).

The factor model in the intercept case can be rewritten as follows:

$$X_{it} = c_i + \lambda_i' F_t + e_{it} \tag{4}$$

where, $x_{it} = \Delta X_{it}$, $f_t = \Delta F_t$, $z_{it} = \Delta e_{it}$ are the differences, so the model can be rewritten in the first-differenced shape.

$$x_{it} = \lambda_i' f_t + z_{it} \tag{5}$$

Let $ADF_{ê}^{c}(i)$ represent t statistic for testing $d_{i0} = 0$ in the univariate augmented autoregression without deterministic terms.

$$\Delta ê_{it} = d_{i0} ê_{it-1} + d_{i1} \Delta ê_{it-1} + \cdots + d_{ip} \Delta ê_{it-p} + error \tag{6}$$

Let $r = 1$ and $ADF_{\hat{F}}^{c}$ t statistics for testing $\delta_0 = 0$ in the univariate augmented autoregression including intercept.

$$\Delta \hat{F}_t = c + \delta_0 \hat{F}_{t-1} + \delta_1 \Delta \hat{F}_{t-1} + \cdots + \delta_P \Delta \hat{F}_{t-p} + error \tag{7}$$

The model should be rearranged for a linear trend.

$$X_{it} = c_i + \beta_i \, \lambda_i' F_t + e_{it} \tag{8}$$

The model can be rewritten after some arrangement.

$$x_{it} = \lambda_i' f_t + z_{it} \tag{9}$$

where, the variables express the differences which are; $x_{it} = \Delta X_{it} - \overline{\Delta X_i}$, $f_t = \Delta F_t - \overline{\Delta F}$, $z_{it} = \Delta e_{it} - \overline{\Delta e_i}$

Let $ADF_{ê}^{\tau}(i)$ represent t statistic for testing $d_{i0} = 0$ in the univariate augmented autoregression without deterministic terms.

$$\Delta ê_{it} = d_{i0} ê_{it-1} + d_{i1} \Delta ê_{it-1} + \cdots + d_{ip} \Delta ê_{it-p} + error \tag{10}$$

Let $r = 1$ and $ADF_{\hat{F}}^{\tau}$ t statistics for testing $\delta_0 = 0$ in the univariate augmented autoregression including intercept and time trend. Then the model becomes in equation (11)

$$\Delta \hat{F}_t = c_0 + c_{it} + \delta_0 \hat{F}_{t-1} + \delta_1 \Delta \hat{F}_{t-1} + \cdots + \delta_P \Delta \hat{F}_{t-p} + error \tag{11}$$

For the models having trend and intercept, p values combining with $ADF_{ê}^{c}(i)$ and $ADF_{ê}^{\tau}(i)$ have been test by $p_{ê}^{c}(i)$ and $p_{ê}^{\tau}(i)$.

$$p_{\hat{e}}^{c} = \frac{-2\sum_{i=1}^{N}\log p_{\hat{e}}^{c}(i) - 2N}{\sqrt{4N}} \xrightarrow{d} N(0,1) \tag{12}$$

$$p_{\hat{e}}^{\tau} = \frac{-2\sum_{i=1}^{N}\log p_{\hat{e}}^{\tau}(i) - 2N}{\sqrt{4N}} \xrightarrow{d} N(0,1) \tag{13}$$

The test first proposed by Maddala and Wu (1999) for fixed N and Choi (2001) has improved the test for $N \to \infty$ (Bai & Ng, 2004). The obtaining statistics values of $p_{\hat{e}}^{c}(i)$ and $p_{\hat{e}}^{\tau}(i)$ have been compared with the table critical values to test that null hypothesis which is all units are non-stationary against the alternative hypothesis which is some units are stationary.

LM Panel Cointegration Test

The LM bootstrap panel cointegration test developed by Westerlund and Edgerton (2007) has been used in the study. The test formulation is shown below.

$$y_{it} = a_i + x_{it}\beta_i + z_{it} \tag{14}$$

Here, $t = 1, \dots, T$ and $n = 1, \dots, N$ denote the time period and cross-sectional units, respectively. The variable x_{it} has dimension K, may follow a pure random walk process, while z_{it} represents the distributional components of the data. The test statistics of the test is calculated based on equation (15).

$$LM_N^t = \frac{1}{NT^2}\sum_{i=1}^{N}\sum_{t=1}^{N}\hat{\omega}_{\mathrm{i}}^{-2}\, S_{it}^2 \tag{15}$$

Here, the terms S_{it} and ω_{it} represent the partial sum processes of the error term z_{it}, derived using the Fully Modified Ordinary Least Squares (FMOLS) method. The presence of cointegration across all cross-sectional units is the null hypothesis, and the absence of cointegration across some cross-sectional units is the alternative hypothesis.

AMG Long-Run Estimation

The AMG estimation introduced by Eberhardt and Bond (2009) is designed for use in CSD and heterogeneous models. The AMG estimation process begins by applying first differences to the data using time dummy variables for all but one period in a pooled regression (FD-OLS). In the second stage, the model is estimated by including each of the cross-sectional regressions $\hat{\mu}_t$in the first stage. Alternatively, $\hat{\mu}_t$ is different from the dependent variable. This case, on the other hand, shows that a common process is applied to each unit. In the third stage, using the MG approach developed by Pesaran and Smith (1995), the estimations have been applied. The formulation of the estimation is shown below.

$$\Delta Y_{it} = b'\Delta X_{it} + \sum_{t=2}^{T} c_t \Delta D_t + e_t \text{ and } \hat{c}_t \equiv \hat{\mu}_t \tag{16}$$

$$Y_{it} = a_i + b'X_{it} + a_i t\, d_i \hat{\mu}_t + e_{it} \tag{17}$$

$$\hat{b}_{AMG} = N^{-1}\sum_i \widehat{b_\iota} \tag{18}$$