

A New Perspective on Technology, Productivity, and Environmental Sustainability in the European Union

Araştırma Makalesi /Research Article

Mehmet Ali ÇAKIR¹
Mehmet Kutluğhan Savaş ÖKTE²

ABSTRACT This study examines the relationship between economic growth, energy consumption, technology, and productivity intensive technology in the context of environmental degradation across selected European Union countries from 1996 to 2021. Utilizing the cross sectionally augmented autoregressive distributed lag model (CS-ARDL) and the load capacity factor as an environmental proxy, the findings confirm environmental kuznets curve (EKC) hypothesis indicating that economic growth continues to exert pressure on the environment. While energy consumption significantly contributes to environmental degradation, contrary to popular belief, technological advancements alone do not mitigate this issue. Instead, the study highlights that productivity intensive technologies are more effective in reducing environmental degradation. Policy recommendations emphasize the need for green growth strategies, energy efficiency improvements, sectoral energy quotas, and international cooperation in technology sharing. Special attention should be given to ensuring that technological development increases productivity and reduces environmental degradation. The findings contribute to the literature by highlighting the significance of aligning productivity and technological advancement for sustainable environmental outcomes.

Keywords: Economic growth, Technology, Productivity intensive technology, Environmental quality.

Avrupa Birliği’nde Teknoloji, Verimlilik ve Çevresel Sürdürülebilirliğe Yeni Bir Bakış Açısı

ÖZ: Bu çalışma, 1996–2021 yılları arasında seçilmiş Avrupa Birliği ülkelerinde ekonomik büyüme, enerji tüketimi, teknoloji ve verimlilik odaklı teknolojinin çevresel bozulma üzerindeki etkisini incelemektedir. Çalışmada, çevresel gösterge olarak yük kapasite faktörü kullanılarak ve kesitsel olarak genişletilmiş gecikmesi dağıtılmış otoregresif (CS-ARDL) methodu uygulanarak, çevresel kuznets eğrisi (EKC) hipotezi doğrulanmıştır; bu da ekonomik büyümenin çevre üzerindeki baskısını sürdürdüğünü göstermektedir. Enerji tüketiminin çevresel bozulmaya önemli ölçüde katkıda bulunduğu tespit edilirken, yaygın kanının aksine, teknolojik gelişmelerin tek başına bu sorunu azaltmadığı belirlenmiştir. Bunun yerine, çalışmada verimlilik odaklı teknolojilerin çevresel bozulmayı azaltmada daha etkili olduğu vurgulanmaktadır. Politika önerileri, yeşil büyüme stratejileri, enerji verimliliği artırımı, sektörel enerji kotaları ve teknoloji paylaşımında uluslararası iş birliği ihtiyacını öne çıkarmaktadır. Teknolojik gelişmelerin verimliliği artırması ve çevresel bozulmayı azaltması gerektiğine özellikle dikkat edilmelidir. Bu bulgular, sürdürülebilir çevresel sonuçlar için verimlilik ve teknolojik ilerlemenin uyumlu hale getirilmesinin önemini literatüre kazandırmaktadır.

Anahtar Kelimeler: Ekonomik büyüme, Teknoloji, Verimlilik yoğun teknoloji, Çevresel kalite.

Geliş Tarihi / Received: 06/05/2025

Kabul Tarihi / Accepted: 06/07/2025

* 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 at Institute of Social Sciences, Istanbul University, as part of the PhD program in Economics (English).

¹ Research Assistant, Dr., Gümüşhane University, Faculty of Economic and Administrative Sciences, Department of Economics, mehmetali.cakir@gumushane.edu.tr, <https://orcid.org/0000-0001-7878-5192>

² Prof. Dr., Istanbul University, Faculty of Economics, Department of Economics, makte@istanbul.edu.tr, <https://orcid.org/0000-0002-9753-9621>

1. Introduction

Economic activities and energy consumption are closely related to environmental problems. It is almost impossible to conduct economic activities such as transportation and production without energy. Specially, after oil shock in 1970s, energy and environment policies have been one of the major concerns for economies. Although change in energy consumption patterns and resources have some effects on energy consumption and thereby environment, developing world have still provided more than 80 % of their energy needs from either oil or fossil fuel resources (Larcher and Tarascon, 2015). Shafiee and Topal (2009) have estimated that fossil fuel is available approximately up to 2112. According to U.S. Energy Information Administration (EIA), (2016), while industrial sector consumes around 54 % of the world's total delivered energy, residential sector, commercial sector, and transportation will overtake it by 2040. Considering that economic growth and industrial activities are directly tied to energy consumption, energy supply problem must be solved and the literature mainly suggests technology as a solution (Paramati et al., 2022; Wu et al., 2021).

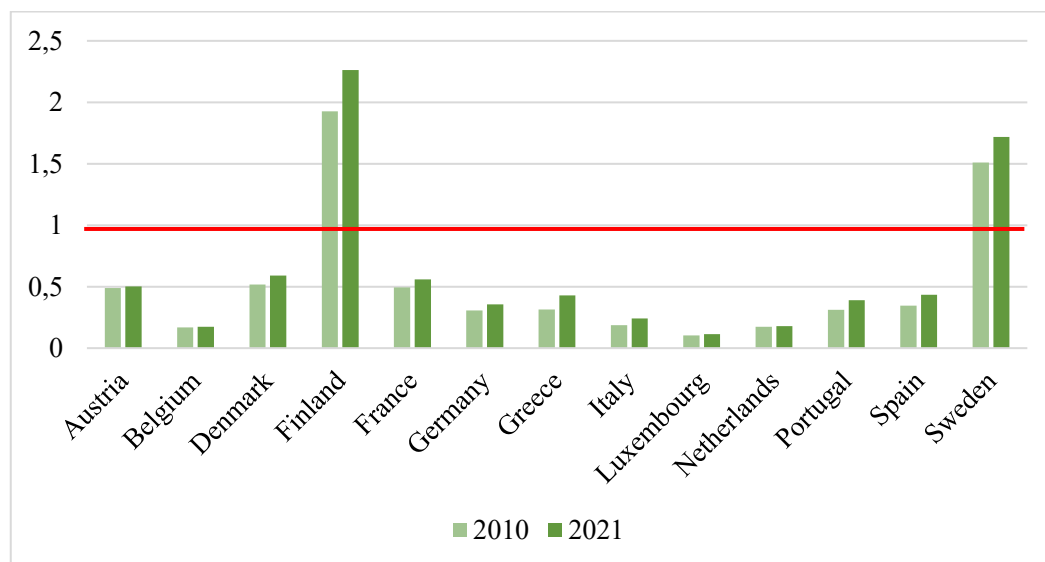
Anser et al. (2020) highlight that negative consequences of energy consumption are key factors to increase health risk of households in the long run. Specially, carbon dioxide (CO₂) emission as a result of energy consumption have positive effect on mortality rate, cardiovascular disease, diabetes mellitus, cancer, and chronic respiratory disease (Rasoulinezhad et al., 2020). In addition to direct effect on human health, energy consumption affects environment. For example, Nathaniel and Bekun (2020) demonstrates that energy consumption has a significant impact on deforestation. On the other hand, forest improves environmental quality by holding large volume of greenhouse gasses, mainly CO₂ and controlling the temperature of surface by providing shades (Azam et al., 2021; Daigneault et al., 2012).

However, while solving the energy problems, the protection of environment and therefore human health must be taken into consideration. Because, environmental pollution is a global challenge that also causes human health problems leading to decrease in economic growth. There is a general consensus in the literature that technology has positive impacts on energy consumption and environment (Adebayo et al., 2022; R. Wang et al., 2020). Technology increases energy efficiency which reduces energy consumption and helps to find different energy sources such as renewable energy sources which mitigate to environmental pollution. However, existing studies including Chen and Lee (2020) and Abid et al. (2022) examining technology and environmental degradation use CO₂ emission as a measurement unit to investigate the effect of technology on environment. Almost all economic activities cause carbon emissions, but also other environmental pollution factors such as deforestation, species extinction or water pollution, and carbon emissions do not capture these. It is known that big technological investments require infrastructure works which can cause environmental

degradation. Moreover, some studies such as Adebayo and Kirikkaleli (2021) show results contrary to the findings in the literature. On the other hand, since it is not required major investment as much as technology, productivity also can be a solution for environmental problems, especially since it requires fewer natural resources to produce the same amount of output. However, it's been ignored in the literature.

As economic growth triggers energy consumption and lead to pollution, the Environmental Kuznets Curve (EKC) developed by Panayotou (1993) by inspiring the study of Kuznets (1955) has been used to show how income and pollution move simultaneously. The Kuznets hypothesis suggests that income growth causes pollution until it reaches a certain point, after which it reduces pollution and improves environmental quality, and draws an inverted u-shape. Although Panayotou (1993) used rate of deforestation as an environmental pollution proxy in his pioneer study, in subsequent studies (Alola and Ozturk, 2021; Dogan and Inglesi-Lotz, 2020), CO₂ emissions have been used more common as a proxy. However, focusing only on CO₂ emissions in environmental economics studies tends to neglect the impact of other pollutants. Thus, Rees (1992) and Ulucak and Bilgili (2018) used the ecological footprints (EF) as a proxy. The EF measures air, water and soil pollution and is a more comprehensive proxy than CO₂ emissions, which measures only have air pollution.

Figure 1: Sustainability Performance of the Countries



Source: (Global Footprint Network Database)

On the other hand, Pata and Balsalobre-Lorente (2022) indicate that both EF and CO₂ emission show human demand for natural resources and for better understanding of environmental sustainability, supply side of natural resources should be considered. They suggest that the Load Capacity Factor (LCF) evaluates both supply and demand side of environmental sustainability and helps to recognize

the true value of environmental sustainability. The LCF is calculated as biocapacity over EF and while biocapacity represents supply side, EF represents demand side of environmental sustainability (Siche et al., 2010). When the ratio of biocapacity to EF equals 1, environmental sustainability is in equilibrium. If the ratio is less than 1, environmental sustainability is out of balance and unsustainable (Pata, 2021). The LCF therefore provides information on both the current state of environmental sustainability and the future state and trend of environmental sustainability. Although the trend has been increasing, Figure 1 shows that most countries are still far from the sustainability limit. To increase the number of countries that exceed the sustainability limit, radical solutions are required. Thus, the purpose of this study is to investigate the effect of economic growth, energy consumption, technology and productivity on environment in the frame of EKC in specific European Union (EU) countries from 1996 to 2021 applying Cross-Sectionally Augmented Auto Regressive Distributed Lagged Model (CS-ARDL) to identify how sustainability limit can be achieved. The EU's Research and Development (R&D) budget has grown significantly, increasing from 0.67% of GDP in 2010 to 2.27% of GDP in 2021 (Eurostat, 2022; Science, Technology and Innovation in Europe, 2010). However, according to report of European Central Bank (2024), a 1 % increase in technological improvement leads to around 0.01% increase productivity. Hence, this case in the EU is a clear example of the differences in the effects of technology and productivity on environment.

The main contribution of this study can be summarized as follows: First, this study will fill the gap in the literature by showing whether the effects of technology and productivity variables, which are often used interchangeably, are the same on the environment. Technology variables are used continuously in the literature, but since productivity is considered to be at least as important as technology for sustainable green growth and environment, the results of this study will be an important finding in terms of sustainable environment. Second, previous studies in the literature have used CO₂ emissions or EF indicators to measure environmental degradation. However, those indicators only demand side of the natural resources. Thus, only some parts of environmental degradation have been able to measured. Using LCF proxy helps to measure both demand and supply side of natural resources and provide more comprehensive measurement. Last, previous studies only focused on country specific result such as China Japan and the United States. Using panel techniques and focusing on EU provide a different perspective for governments, organizations, and companies.

The structure of the study as follows: Section 2 summarizes the previous literature and highlights the differences of the study. Section 3 provides information about data, methodology and empirical findings. Section 4 concludes the study with conclusion and policy recommendation.

2. Literature

2.1. The Environmental Kuznets Curve Hypothesis

The EKC hypothesis has been widely applied to analyze the link between environmental degradation and economic growth. According to this theory, as income rises, pollution levels initially increase. However, beyond a certain income threshold, further economic growth no longer leads to higher pollution; instead, environmental quality begins to improve, forming an inverted U-shaped curve (Grossman and Krueger, 1991). Panayotou (1993) has extended this framework, expressing the model in a mathematical form

$$Y_{it} = \alpha_i + \beta_1 X_{1it} + \beta_2 X_{2it} + \beta_3 X_{3it} + \beta_4 Z_i \mu_{it} \quad (1)$$

Let Y represent the proxy for environmental pollution, X s denote income-related variables, and Z capture other income-related factors that could influence pollution levels. The term α is constant, while β values are the coefficients that determine the nature of the relationship between X and Y . The subscripts i and t refer to the unit and time dimensions, respectively, and μ is the error term. The specific values of β coefficients define the functional structure of how income variables impact environmental pollution. When β_1 is greater than zero, and β_2 and β_3 equal to zero, the linear relationship between variables X and Y is increasing. and when β_1 is less than zero, and β_2 and β_3 equal to zero, the relationship between variables X and Y is characterized by a linear decrease. The relationship between X and Y is inverted U-shape when β_1 is greater than zero, β_2 is less than zero, and β_3 equals to zero. On the other hand, the relationship is U-shape when β_1 is less than zero, β_2 is greater than zero and β_3 equals to zero. (Sarkodie and Strezov, 2019). The model has been used with many different variables for different regions. For example, Shahbaz et al. (2013) have used CO₂ emission as an pollutant proxy and investigated EKC hypothesis for Türkiye. On the other hand, Ansari (2022) has used EF for ASEAN countries. Other environmental pollutant variables used for EKC hypothesis are; greenhouse gas (GHG) emissions, CO₂, methane (CH₄), nitrous oxide (N₂O), and noise pollution (Ali et al., 2021; Xu et al., 2020).

However, those environmental pollutant proxies have limited power to measure environmental degradation. Using more comprehensive proxy utilization provides more realistic results on environmental degradation, especially for supply side of de environmental sustainability. Thus, modifying EKC hypothesis with LCF proxy gives more realistic results for environmental sustainability. Hence, since the calculation of LCF is biocapacity over EF, the signs of income coefficients in the classical EKC hypothesis will be inverse and the shape will be U-shape in the case where EKC is valid. To summarize, the β s in the equation (1) will be $\beta_1 < 0$, $\beta_2 > 0$ and $\beta_3 = 0$ in the case where EKC with LCF is valid, and this situation is opposite while using other pollutant variables with EKC.

Environmental consequences of economic activities have been widely investigated to improve environmental sustainability. The maintenance and preservation of the

ecological balance play crucial role. Humans have been carbonizing the world more than two thousand years and causing climate change. Hence, previous studies have been mostly focused on CO₂ emissions in the environmental effects of economic activities. As related literature, some pioneering studies have been examined. Altıntaş and Kassouri (2020) have used CO₂ emission as a pollutant proxy for fourteen European countries from 1990 to 2014. Their study has not validated the EKC hypothesis for related countries. Similarly, Frodyma et al. (2022) have focused on CO₂ emission in the application of the EKC hypothesis in the Europe from 1970 to 2017. They have also rejected EKC hypothesis for the Europe. Kar (2022) has reached the similar results, which is rejecting the EKC hypothesis, for Baltic countries from 1990 to 2018 using CO₂ emission as a proxy. In contrast to these studies, there are studies that confirm the validity of the EKC hypothesis. For example, Jóźwik et al. (2021) have validated the EKC hypothesis for Central Europe from 1995 to 2016 using CO₂ emission proxy. Saqib and Benhmad (2021) have supported validity of EKC hypothesis for Europe from 1995 to 2015. However, EF have been used as an environmental pollutant proxy in their study. Saqib et al. (2023) have also confirmed the validation of the EKC hypothesis for European countries from 1990 to 2020 using ecological footprint indicator. Moreover, Gormus and Aydin (2020) have not confirmed the EKC hypothesis with ecological footprint indicator for some Europe countries naming Denmark, Finland, Germany, the Netherlands, Sweden, the UK, and Switzerland for the period from 1990 to 2015.

CO₂ emission is one of the useful and common environmental degradation indicators. However, it has limited power to show environmental consequences of economic activities, since economic activities not only cause CO₂ emission but also other pollutants. Although EF consist of 60 % carbon related sub-components, it is much more reliable to measure environmental degradation (Global Footprint Network, 2017). Thus, studies focusing on Europe and using CO₂ emissions as an indicator have mostly rejected the validation of the EKC hypothesis. However, using EF as an indicator in the studies shows that the EKC hypothesis is still valid in Europe, despite some conflicting results. Hence, the more comprehensive indicator used in this study, the LCF, clarifies whether or not Europe has reached peak pollution levels. Validation of the EKC hypothesis with CO₂ emission for G7 economies has been checked by Liu et al. (2022) and the hypothesis has been confirmed for only France. On the other hand, the similar validation has been conducted by Ahmad et al. (2021), but using EF indicator and the EKC hypothesis has been validated for all members in G7. In another CO₂ emission and EF comparison study, Ajmi and Inglesi-Lotz (2021) have tested the EKC hypothesis for Tunisia from 1965 to 2013. The EKC hypothesis with CO₂ emissions has been rejected, but the EKC hypothesis with EF has been validated. These results show that an increase in income does not lead to an increase in CO₂ emissions, but does lead to an increase in EF.

However, Ayad et al. (2024) have made the same comparison for the Middle East and North Africa (MENA) region and found different results compared to study of Ajmi and Inglesi-Lotz (2021). The EKC hypothesis with CO₂ has been valid, but using EF in the EKC hypothesis have shown that increase in income does not increase in EF. Acaroğlu et al. (2023) have reached the same results for Türkiye. While they have confirmed existing of the EKC hypothesis with CO₂ emission, the hypothesis with EF has been rejected.

A few studies have focused on environmental effect of economic activities by using LCF. Wang et al. (2024) have used LCF proxy for testing the EKC hypothesis for Brazil, Russia, India, China, South Africa (BRICS) countries. They have confirmed that the EKC hypothesis is valid for BRICS. Sun et al. (2024) have also tested the EKC hypothesis with LCF for China and they have confirmed the findings of Wang et al. (2024). The EKC hypothesis with LCF has been tested for Türkiye by Caglar et al. (2024) and the results show that the hypothesis is valid.

To summarize, the importance of this study in terms of environmental sustainability is demonstrated by the fact that LCF, which makes both supply and demand side measurements, is used as a proxy for environmental sustainability. Since previous studies have used a less comprehensive proxy, the relationship between environmental pollution and economic growth may not be explained correctly. Moreover, the EKC hypotheses tested with the LCF have focused on developing countries and the European countries have been neglected. Hence, this study makes an importance contribution to the related literature.

2.2. Environment, Energy Consumption, Technology and Productivity

Energy is one of the essential components of economic activities and is required as a basic input for all production activities. However, energy consumption is associated with environmental degradation, especially due to its role in carbon emissions (Xia et al., 2022; Zafar et al., 2021). Hence, the balance between economic growth required more energy consumption and environmental sustainability is a very thin line. Adedoyin et al. (2020) has investigated the effects of economic growth and energy consumption on environmental degradation in EU countries for the period from 1997 to 2014 using the Fully Modified and Dynamic Ordinary Least Squares (FMOLS and DOLS) models. The results of the models show that economic growth and energy consumption cause environmental degradation. Osobajo et al. (2020) have made broader research on the effect of economic growth and energy consumption on CO₂ emission in 70 countries including European countries from 1994 to 2013 using Granger causality test. The Granger causality test results show that economic growth has a bi-directional relationship with CO₂ emissions and energy consumption has a uni-directional relationship with CO₂ emission. Mohsin et al. (2022) have also used Granger causality test to investigate the links among economic growth, energy consumption and CO₂ emission in Europe countries from 1971 to 2016. Based on the test results, economic growth and energy consumption Granger cause CO₂ emission. Unlike

previous studies, Destek et al. (2018) have used broader proxy, EF, to capture more environmental effects of economic growth and energy consumption in European countries from 1980 to 2013. Fully Modified Ordinary Least Square (FMOLS) results show that economic growth and energy consumption cause to increase in EF. Saqib and Benhmad (2021) have also used EF as an environmental degradation proxy to examine how economic growth and energy consumption affect environment in European countries for the period from 1995 to 2015 applying Dumitrescu and Hurlin test. The test results show that there is a one-way causality from economic growth to EF and there is a two-way causality between energy consumption and EF. The more comprehensive analysis covering 120 countries including European countries from 1995 to 2014 has been conducted by Li et al. (2022) using 3E model. Results of the model show that while energy consumption leads economic growth, environmental degradation is raised as result of increase in EF duo to energy consumption.

In addition to panel groups studies covering Europe as a whole, there are also country specific studies. Alper et al. (2022) have claimed that economic growth and energy consumption cause to raise in EF in Germany during the periods from 1970 to 2017 using Fourier bootstrap ARDL model. Similarly, the ARDL analysis for Italy has been conducted by Javed et al. (2023) show that energy consumption, which is renewable energy consumption, mitigates EF, but economic growth enhances EF. Adebayo et al. (2022) have focused on Portugal to analyze how energy consumption, which is renewable energy consumption, and economic growth impact on environment from 1980 to 2019 using wavelet analysis. Findings of the study show that while renewable energy consumption leads to increase environmental quality, economic growth cause a decrease in environmental quality.

The existing literature broadly agrees that economic growth and energy consumption have an adverse effect on environment. Since energy consumption cannot be avoided and economic growth cannot be compromised, efforts have been made to minimize their damage to the environment. The first and most common solution that comes to mind is technology and technological innovations. Therefore, the literature has evolved in this direction. For example, Balsalobre-Lorente et al. (2018) have focused on the effect of innovation on environmental degradation using CO₂ proxy in Germany, France, Italy, Spain, and the United Kingdom (European Union 5) during the period from 1985 to 2016 using the EKC model. The findings of the study show that innovation improves environmental quality by reducing CO₂ emissions. Chen and Lee (2020) have examined how technological innovation impacts CO₂ emissions in 96 countries during the period from 1996 to 2018 using Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model. The results show that technological innovation helps to reduce CO₂ emissions only in high-income, high-technology, and high-CO₂ emission countries. In globally, technological innovation has no effect on CO₂ emissions. Mongo et al. (2021) have focused on the effect of innovation on CO₂ emissions in EU countries for the period from 1991 to 2014 using ARDL model. They show that

innovation reduces CO₂ emissions in the long run. Bilgili et al. (2023) have examined the effect of research and development on environment degradation in Europe countries from 1990 to 2021 using Method of Moments Quantile Regression (MMQR) method. They show that research and development on both renewable, non-renewable energy and energy efficiency increases environmental quality by cutting CO₂ emissions.

Although the effects of technological innovation are often measured in terms of CO₂ emissions, their impact on environment, especially during development processes, is much greater than CO₂ emissions. A more inclusive proxy, EF, is used in the literature to analyze this impact. One such study by Adedoyin et al. (2020) has used EF as an environmental proxy and investigated the effect of research and development on environment in Europe from 1997–2014 using FMOLS method. The results show that research and development enhance environmental quality in Europe by reducing EF. Wang et al. (2023) have used EF to measure the impact of technological innovations on environment in Europe from 1994 to 2020. The Augmented Mean Group (AMG) test results show that technological innovation mitigates EF level and enhances environmental quality. Zhen et al. (2023), approaching the issue from a technological efficiency perspective, have showed that technological efficiency has a positive effect on environmental quality by reducing EF in Europe using CS-ARDL methods. In a country specific research, Javed et al. (2023) have investigated the effect of green technology innovation on environment in Italy from 1994–2019 using ARDL methods. The results show that green technology innovation mitigates EF and increases environmental quality.

However, it may not be correct to think of technological innovation as a complete solution to environmental degradation. The report of IEA (2019) indicates while electric vehicles contributes to reduce local air pollution, without decarbonizing the power sectors, usage of electric vehicles actually increases overall CO₂ emissions. Empirical studies also show that not all technological innovation or technology enhance environmental sustainability. For example, Koçak and Ulucak (2019) have examined the effects of research and development expenditures on CO₂ emission between the years from 2003 to 2015 using STIRPAT model in OECD economies. The findings show that research and development expenditures for energy efficiency and fossil energy cause to increase in CO₂ emission. Cheng et al. (2019) have investigated the effects of technology on environment in BRICS economies between 2000 to 2013 using OLS methods. They show that technology causes to raise in CO₂ emission and environmental degradation. Mongo et al. (2021) have indicated that in the short run, innovation tends to increase CO₂ emission in Europe from 1994 to 2014 as a result of ARDL model application, but this effect disappears in the long run. Existing literature has measured technology with monetary measurement proxies in technology measurements and studies mostly focus on developing countries.

On the other hand, focusing on technology as a solution to environmental degradation may not always be the solution, as shown in the literature. In fact, the processing of technological innovation may require more factors of production and it may result in an increase in the demand for natural resources. However, to mitigate environmental degradation and enhance environmental sustainability, it may not be sufficient only to decelerate pollution level. At the same time, reducing demand for natural resources is also important. Hence, productivity is therefore important, whether it is the achievement of more production with the same amount of inputs or the preservation of existing production by reducing total inputs. Surprisingly, the existing literature is relatively weak about productivity and environment. The investigation on energy productivity by Kirikkaleli et al. (2022) shows that energy productivity in Cyprus from 1990 to 2018 using nonlinear autoregressive distributed lag (NARDL) leads to decrease in CO₂ emissions and enhances environmental quality. Addai et al. (2022) have also investigated the effect of energy productivity on environment in Germany from 1990 to 2019 using Fourier ARDL approach. The results show that energy productivity mitigates CO₂ emissions. Addai et al. (2023) have examined that the impact of energy productivity on environment in the Netherlands between 1990 and 2019 using Fourier ARDL method. They indicate that energy productivity leads to decrease in CO₂ emissions. Mushafiq and Prusak (2023) have focused on the impact of resource productivity and environmental quality in Europe from 2000 to 2020 using ARDL model. According to the findings, resource productivity triggers to reduction in CO₂ emissions and increase environmental quality. Chen et al. (2023) have examined how material productivity impacts environment in 17 emerging economies from 1995 to 2019 using Driscoll Kraay estimation method. The results show that material productivity reduces CO₂ emissions. Addai and Kirikkaleli (2023) have also researched the effect of energy productivity on environmental degradation in Poland between 1990 to 2019 Fourier ARDL method. The findings support the findings of Kirikkaleli et al. (2022), Addai et al. (2022) and Addai et al. (2023) that energy productivity mitigates CO₂ emissions. Also, economies to fully utilize their productive capacity can also reduce environmental damage. In this regard, Oluc et al. (2023) have conducted the study about the effect of productivity capacity on environmental degradation in OECD economies from 2000 to 2018 using the pooled mean group (PMG). The findings show that improved productive capacity mitigates environmental degradation by reducing CO₂ emissions.

To summarize, the relevant literature is mostly dominated by the use of CO₂ emissions and EF as environmental pollutant proxies. These proxies have limited power to measure the pollutant and the supply side of nature is not captured by these proxies. Hence, real environmental effect of developed economies has not been shown and studies mostly orients to developing economies. Using LCF can real environmentally effect of developed economies. Also, whether the technology that has been shown as a solution to environmental pollution is really a solution should be tested with the broader environmental proxy, LCF. The literature has also

ignored technology intensive efficiency. The fact that this study focuses on European countries, uses a broader environmental proxy and focuses on technology efficiency will help fill the gaps in the literature.

3. Data Methodology and Discussion

3.1. Model and Data

The econometric model used in the study has been show in the equation (2). Dependent variable in the model is the *LCF* that shows total environmental quality. *GDP* represents economic growth and GDP^2 is the square of *GDP*. It has been added to model the check whether the EKC hypothesis is valid or not. *TEC* in the model shows total energy consumption. *PAT* is the number of patents that indicates technological innovation and $MFP * PAT$ shows productivity intensive technological innovation. In the equation α_0 is constant parameter and $\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5$ are slope coefficients. *i* and *t* refer to unit and time dimension and ε represents error term.

Model:

$$\ln LCF_{it} = \alpha_0 + \alpha_1 \ln GDP_{it} + \alpha_2 \ln GDP_{it}^2 + \alpha_3 \ln TEC_{it} + \alpha_4 \ln PAT_{it} + \alpha_5 \ln MFP * \ln PAT_{it} + \varepsilon_{it} \quad (2)$$

Table 1: Definitions and Sources of the Variables

| Variables | Symbol | Unit of measurement | Source |
|---------------------------|--------------------|--|--------------------------|
| Load Capacity Factor | ln LCF | Biocapacity divided by ecological footprint (Global hectares per person) | Global Footprint Network |
| 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 |
| Square of Economic Growth | lnGDP ² | Square of GDP per capita (US \$) | Author's Calculations |
| Multifactor Productivity | lnMFP | overall efficiency (labor and capital) 2015=100 | OECD |
| Patent Applications | lnPT | Total (residents+ nonresidents) | World Bank-WDI |
| Productivity*Patent | lnMFP*lnPAT | Numeric | Author's Calculations |

Thirteen of the EU-27 countries with Total Factor Productivity (MFP) data in the OECD Database have been selected: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Italy, Luxembourg, the Netherlands, Portugal, Spain and Sweden. Despite Eurostat having data for all countries in its database, the MFP data set has not been used as it is unreliable due to the fact that it is raw and still at an

experimental stage. Although these countries have varying levels of development, they share similar characteristics in terms of environmental sustainability, as they are subject to the same European Commission regulations, which also define the dependent variable, making them relatively homogeneous. Detail information regarding the sources of data and variables has been presented in Table 1.

3.2. Methodology

3.2.1. Testing for Cross-Sectional Dependence

In panel data methods, which have developed rapidly in recent years, the results of the test for cross-sectional dependence have become very important. The results obtained from the cross-sectional dependence test provide preliminary information on the tests to be performed in panel data analysis. In addition, the presence of dependence among the countries used in the panel indicates that any shock affecting one country may also affect other countries due to globalization and liberalization. Therefore, if there is dependence between the cross-sections used in the panel, tests that take into account cross-sectional dependence should be used in the analysis. In this sense, a number of tests have been developed to test cross-sectional dependence.

One of these tests is the LM test developed by Breusch and Pagan (1980). The Breusch-Pagan (1980) LM test is a test that can be used when $T > N$. The null hypothesis of the LM test is “there is no correlation between the residuals” and it shows the χ^2 distribution for $T \rightarrow \infty$ when N is constant (Pesaran, 2004):

$$LM = T \sum_{i=1}^{N-1} \sum_{j=i+1}^N \hat{\rho}_{ij}^2 \sim \frac{\chi^2_{N(N-1)}}{2} \quad (3)$$

The CD_{LM} test developed by Pesaran (2004) can also be used in the $T > N$ case. The CD_{LM} test statistic is asymptotically standardized for $T \rightarrow \infty$ and then for $N \rightarrow \infty$ (Pesaran, 2004):

$$CD_{LM} = \sqrt{\frac{1}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^N (T \hat{\rho}_{ij}^2 - 1) \sim N(0,1) \quad (4)$$

3.2.3. PANIC Unit Root Test

Following the examination of cross-sectional dependence and homogeneity in the study, the subsequent phase is to evaluate whether the units exhibit a unit root or not. The results of the cross-sectional dependency test indicate that the use of second-generation unit tests, which account for cross-sectional dependency, is essential. Thus, PANIC test has been used in the study and its null hypothesis is units are non-stationary against the alternative hypothesis which is some units are stationary (Bai and Ng, 2004).

The factor model in the intercept case can be shown as follow:

$$X_{it} = c_i + \lambda_i' F_t + e_{it} \quad (5)$$

Where, $x_{it} = \Delta X_{it}$, $f_t = \Delta F_t$, $z_{it} = \Delta e_{it}$ are the differences and first difference form is shown in equation 6.

$$x_{it} = \lambda'_i f_t + z_{it} \quad (6)$$

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

$$\Delta \hat{e}_{it} = d_{i0} \hat{e}_{it-1} + d_{i1} \Delta \hat{e}_{it-1} + \dots + d_{ip} \Delta \hat{e}_{it-p} + error \quad (7)$$

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

$$\Delta \hat{F}_t = c + \delta_0 \hat{F}_{t-1} + \delta_1 \Delta \hat{F}_{t-1} + \dots + \delta_p \Delta \hat{F}_{t-p} + error \quad (8)$$

As a result;

For the models $ADF_{\hat{e}}^c(i)$ and $ADF_{\hat{F}}^c(i)$ have been test by $p_{\hat{e}}^c(i)$ and $p_{\hat{F}}^c(i)$ can be calculated with the formulation shown below:

$$p_{\hat{e}}^c = \frac{-2 \sum_{i=1}^N \log p_{\hat{e}}^c(i) - 2N}{\sqrt{4N}} \xrightarrow{d} N(0,1) \quad (9)$$

$$p_{\hat{e}}^{\tau} = \frac{-2 \sum_{i=1}^N \log p_{\hat{e}}^{\tau}(i) - 2N}{\sqrt{4N}} \xrightarrow{d} N(0,1) \quad (10)$$

The calculated statistics values of $p_{\hat{e}}^c(i)$ and $p_{\hat{e}}^{\tau}(i)$ compares with the values at table critical values to test that null hypothesis. The null hypothesis is all units are non-stationary, while the alternative hypothesis is some units are stationary (Tıraşoğlu, 2017).

3.2.4. Panel Cointegration Test

In the present study, the existence of a cointegration relationship between the series is examined using the LM Bootstrap panel cointegration test of Westerlund and Edgerton (2007). The test allows for autocorrelation and heteroscedasticity in the cointegration equation under the assumption of cross-sectional dependence. In addition, the endogeneity problem can be eliminated by using the FMOLS method.

$$LM_N^+ = \frac{1}{NT^2} \sum_{i=1}^N \sum_{t=1}^N w_i^{-2} S_{it}^2 \quad (11)$$

Where (S_{it}^2) is the partial sums of error terms estimated by FMOLS method and (w_i^{-2}) is the long-run variances. In the Westerlund and Edgerton (2007) panel cointegration test, the LM_N^+ statistic, asymptotic probability value and bootstrap probability value are obtained. The null hypothesis of the test is “there is cointegration between the series” (Westerlund and Edgerton, 2007:186). In case of cross-sectional dependence, bootstrap probability values are taken into account.

3.2.5. Long Run Estimation (CS-ARDL)

The Cross-Sectional Augmented Auto-Regressive Distributed Lag (CS-ARDL) method developed by Chudik et al. (2016) is an estimator that takes into account

cross-sectional dependence, heterogeneity and endogeneity problems. It is the ARDL version of the Dynamic Common Correlated Estimator based on lagged stochastic variables and lagged cross-sectional averages and individual assessments (Chudik and Pesaran, 2015).

Although the slope coefficients are heterogeneous, this technique allows for average group evaluations. The mean group version of CS-ARDL techniques is based on adding cross-sectional averages (representing unobservable common components and lags) to the ARDL evaluations of each cross-section (Khan et al., 2022). Moreover, this estimator can be used when the series are cointegrated at I(0) and I(1) or when some of the series are I(0) and some are I(1). This method, which can estimate short and long run coefficients separately, is calculated according to equation (12):

$$\Delta Y_{it} = \beta_0 + \beta_1 \sum_{i=1}^a \Delta Y_{i,t-1} + \beta_2 \sum_{i=0}^b \Delta X_{i,t-l} + \beta_3 \sum_{i=0}^c \Delta \bar{Z}_{i,t-1} + \varepsilon_{i,t} \quad (12)$$

Where β_0 denotes the constant term and Δ indicates that the difference is taken. a, b and c denote the lag length. Y_{it} denotes the dependent variable in the model and X_{it} denotes the independent variables in the model. $\bar{Z}_{i,t}$ represents the cross-sectional means of the dependent and independent variables $\bar{Z}_{i,t} = \Delta \bar{Y}_{i,t}, \bar{X}_{i,t}$.

3.2.6. Empirical Findings

The purpose of this study is to examine the impact of economic growth, energy consumption, technology, and productivity on environment and to test whether the EKC hypothesis is valid in case of load capacity factor usage. Hence, the most appropriate econometric method is CS-ARDL as it allows both tests at the long run analysis. However, before using the CS-ARDL method, some preconditions that allow the use of this model should be met. Hence, first cross-sectional dependence, then homogeneity, Unit Root Test and Cointegration Tests have been conducted. The LM test developed by Breusch-Pagan (1980) and the CD_{LM} test developed by Pesaran (2004) have been applied the variables and the results have been demonstrated in Table 2.

Table 2: Cross-Sectional Dependence Test Results

| Variables | Breusch-Pagan LM | Pesaran CD_{LM} |
|--------------------|------------------|-------------------|
| lnLCF | 183.348*** | 8.435*** |
| lnTEC | 394.368*** | 25.330*** |
| lnGDP | 277.240*** | 15.952*** |
| lnGDP ² | 277.967*** | 16.010*** |
| lnPAT | 117.892*** | 3.194*** |
| lnMFP*lnPAT | 127.828*** | 3.989*** |

The findings in Table 2 show that both test supports rejection of null hypothesis, which is no cross-sectional dependence. Based on these results, second-generation

unit root tests can be applied the variables. Hence, the CIPS test developed by Pesaran (2007) has been used and the results has been shown in Table 3.

Table 3: PANIC Unit Root Test Results

| Variables | Test | Level | 1st Difference |
|--|------------------|---------|----------------|
| lnLCF | Z_{ϵ}^c | -0.7688 | 10.1027*** |
| | P_{ϵ}^c | 20.4559 | 98.8519*** |
| lnTEC | Z_{ϵ}^c | -2.3704 | 8.8651*** |
| | P_{ϵ}^c | 8.9068 | 89.9271*** |
| lnGDP | Z_{ϵ}^c | -1.3570 | 4.6801*** |
| | P_{ϵ}^c | 16.2147 | 59.7490*** |
| lnGDP ² | Z_{ϵ}^c | -1.2279 | 6.1381*** |
| | P_{ϵ}^c | 17.1452 | 70.2625*** |
| lnPT | Z_{ϵ}^c | -2.2115 | 6.0102*** |
| | P_{ϵ}^c | 10.0529 | 69.3401*** |
| lnMFP*lnPAT | Z_{ϵ}^c | -1.5780 | 7.0496*** |
| | P_{ϵ}^c | 14.6212 | 76.8351*** |
| ***, **, and * represents 1 %, 5%, and 10 % significance level | | | |

The results in Table 3 show that all variables are stationary at first difference level. Hence, in the next test applications to check heterogeneity and cross-sectional dependence to proceed CS-ARDL test. The model results must be heterogen and cross-sectional dependence to use CS-ARDL test.

Table 4: LM Panel Cointegration Results

| Test | Model | | |
|-----------------|-----------|--------------------|-----------------------|
| | Statistic | Asymp. Probability | Bootstrap Probability |
| LM ⁺ | 10.381 | 0.000 | 1.000 |

The asymptotic and bootstrap probability values of the LM test have been shown in Table 4. The findings show that the null hypothesis that is cointegration exists cannot be rejected for the model. Hence, the series in the model have a cointegrated relationship in the long run.

After testing the applicability of the CS-ARDL method by applying pioneer tests, it was determined that the prerequisites for the application of the CS-ARDL method were met and it was decided to apply the method. The results of CS-ARDL estimation can be seen in Table 5.

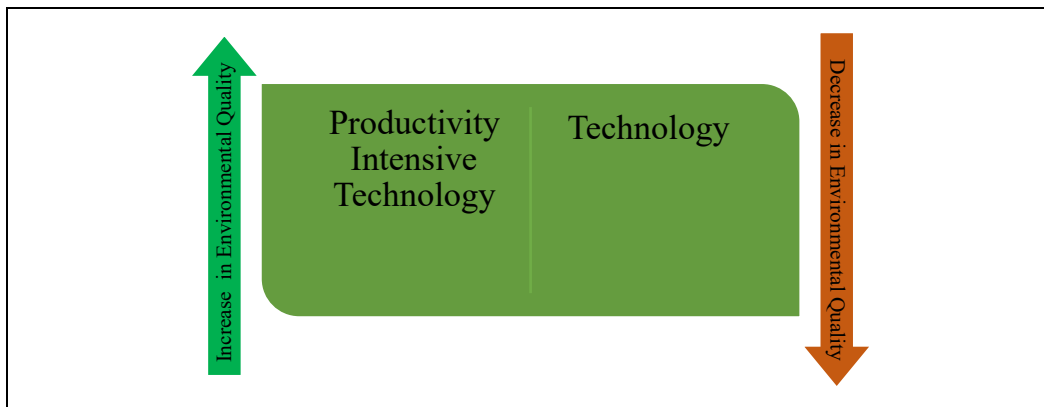
Table 5: The Results of CS-ARDL Estimation

| Model | | |
|--|--------------------|-------------|
| $\ln LCF_{it} = \alpha_0 + \alpha_1 \ln GDP_{it} + \alpha_2 \ln GDP_{it}^2 + \alpha_3 \ln TEC_{it} + \alpha_4 \ln PAT_{it} + \alpha_5 \ln MFP * \ln PAT_{it} + \varepsilon_{it}$ | | |
| Long run | coefficient | prob |
| lnGDP | -10.129 | 0.005 |
| lnGDP ² | 1.015 | 0.010 |
| lnTEC | -0.233 | 0.026 |
| lnPAT | -0.700 | 0.001 |
| lnMPC * lnPAT | 0.374 | 0.000 |

Table 5 shows the results of CS-ARDL methods in the long-run. According to results, the effect of lnGDP on lnLCF is statistically significant and negative in the long-run. A one percent change in lnGDP leads to a decrease of 10.401 percent in lnLCF by 10.129 percent in the long run. This result indicates that economic growth causes environmental degradation in Europe. However, lnGDP² that is added to model whether the EKC hypothesis is valid or not has a significant positive effect on lnLCF. This indicates that the EKC hypothesis with LCF is valid in Europe.

The effect of lnTEC on ln LCF is negative and statically significant in the long-run. A 1% increase in lnTEC causes to a reduction of 0.233 % in lnLCF in the long-run. This effect indicates that energy consumption causes environmental pollution in Europe.

lnPAT significantly and negatively influences lnLCF in the long-run. This shows that technological innovation in Europe causes environmental degradation by reducing load capacity in the long-run. A 1% increase in lnPAT causes to a reduction of 0.700 % in lnLCF in the long-run.

Figure 2: Sustainability Outcomes of Technology vs. Productivity Intensive Technology

The impact of lnMFP*lnPAT on ln LCF is positive and statistically significant in the long-run. A 1% increase in lnMFP*lnPAT leads to an increase of 0.374 % in lnLCF in the long-run. lnMFP*lnPAT is the only variable in the model that

enhances environmental quality in the Europe. While technology causes environmental degradation in Europe in the long-run. Productivity intensive technology helps to increase environmental quality in Europe. This result emphasizes the importance of productivity.

3.3. Discussion

This study investigated the effect of economic growth, energy consumption, technology and productivity on environment in the frame of the EKC hypothesis in selected European Union (EU) countries. Although at first glance it seems that there are many studies on this subject, there are serious gaps in the literature and this study can fill the gaps. First, while previous studies have already examined the validation of the EKC hypothesis in Europe, the studies have mainly been based on CO₂ emission and ecological footprint variables. In addition, the literature shows that while the EKC hypothesis is generally invalid in studies using CO₂, or past the turning point, there are few cases where the EKC hypothesis is valid in studies using ecological footprint. Hence, the validity of the EKC hypothesis has been tested with a more inclusive variable, load capacity. The findings show that the EKC hypothesis is valid and it is thought that the inclusiveness of the environmental pollution variable used plays an important role in this. Because load capacity measures environmental degradation as well as environmental improvement. Although the stabilization of environmental degradation is considered as a pollution station, we cannot talk about environmental sustainability without environmental improvement. The findings of the study show that income growth in Europe is still causing environmental degradation and the turning point has not been reached. In this respect, the findings of the study for Europe are supported by studies such as Józwiak et al. (2021), Saqib and Benhmad (2021) and Saqib et al. (2023).

Second, in addition to economic growth, energy consumption has an adverse consequence on environment and there is a high degree of consensus on this issue in the existing literature and the findings of this study also prove that. The studies in the literature such as Adedoyin et al. (2020), Chen and Lee (2020), Zhen et al. (2023), Javed et al. (2023), and Wang et al. (2023) suggest technology as a solution for this problem. However, the findings of this study cannot support this view. The reason why this study does not support the findings in the literature can be due to two reasons. First, CO₂ emissions and ecological footprint variables has been mostly used in the previous studies and these variables have limited power to catch real effect of environmental degradation. Hence, using load capacity can show the real effect of technology on environment. The other reason can be measurement of technology an innovation. Because research and development expenditure has been mostly used as a technology and innovation proxy. However, this proxy is an input variable in the technology process. This study has focused on output of the technology process and used number of patents to measure real output of technological process. Findings of this study do not support the findings of Adedoyin et al. (2020), Chen and Lee (2020), Zhen et al. (2023), Javed et al. (2023),

and Wang et al. (2023). This study only supports of the findings of Mongo et al. (2021) for the short-run.

Finally, this study has created a productivity intensive technology variable to measure the impact of productivity. The study found that this variable plays a role in improving environmental quality. This finding is in line with the works of Kirikkaleli et al. (2022), Addai et al. (2022), Addai et al. (2023), Mushafiq and Prusak (2023) and Addai and Kirikkaleli (2023) although they did not use exactly the same variable. This result shows us the importance of productivity in increasing environmental quality and shows that technological innovations should be productivity-centered, otherwise it will cause environmental degradation.

4. Conclusion and Policy Recommendation

Environmental pressures on economies have been increasing in the world. These environmental pressures have many impacts on human health, species, natural resources and production factors. However, it is thought that developed economies have ended this problem and it is perceived more as a problem of developing economies. Hence, this study investigated the effect of economic growth, energy consumption, technology and productivity on environment in the frame of the EKC hypothesis in selected European Union (EU) countries from 1996 to 2021 applying Cross-Sectionally Augmented Auto Regressive Distributed Lagged Model (CS-ARDL). The use of load capacity factor as an environmental proxy has led to a more detailed measurement of environmental degradation. Thus, the EKC hypothesis is confirmed, showing that income growth in Europe still causes environmental degradation. Energy consumption has also been identified as another factor causing environmental degradation.

On the other hand, the impact of technology, which is presented in the literature as a solution to environmental degradation, has been analyzed and it has been found that contrary to the literature, technology is not a solution to environmental degradation, but a contributing cause. One of the most important reasons for this is that previous studies in the measurement of technology have generally used input, i.e. investment, but since it is actually healthier to use output instead of input, this study uses the number of patents as the output of technology.

The productivity analysis, which is one of the most important contributions of the study, shows that productivity reduces environmental destruction. Contrary to the findings in the literature, it is determined that it is not technology that reduces environmental destruction, but productivity-intensive technology created by the combination of productivity and technology reduces environmental destruction.

As it is shown that economic growth still causes environmental degradation; therefore, policymakers should prioritize green growth. Consequently, during economic growth, energy consumption restrictive actions should be taken, sectoral analyses should be made and sectors with low energy consumption should be revitalized, for example tourism. In particular, the technology sector should be re-

examined, and the impact of the technology developed on other ecological footprints should be examined, not only as a measure of carbon emission reduction. In addition to reducing pollution, the ability of the technology to increase biocapacity will not only prevent environmental degradation, but will also lead to environmental improvement, and policy makers should pay attention to this. Productivity improvements should be emphasized in the evaluation of technological outputs by policymakers. Focusing on productivity increase in the technology development process, importance should be given to the effect of both the technology development process and the obtained technological outputs on productivity. Otherwise, technology will do nothing but increase environmental degradation. In addition, bulleted policy recommendations for policymakers are listed below;

- Investments in Research and Development activities should be encouraged, and tax exemption and grant support can be provided to companies investing in this area.
- Public cooperation with private companies should be increased, public facilities should be used in coordination with private companies for large infrastructure works required for Research and Development studies
- Energy efficiency should be increased in buildings and transportation in private and public enterprises, thereby reducing total energy consumption. For this, energy can be priced gradually and less use can be encouraged
- In addition, a sectoral quota should be set and consumption above this quota should be taxed and environmental protection activities can be carried out with this income.
- Since the process of technology development is cost and resource intensive, cooperation in international technology sharing should be enhanced to reduce the environmental impact of technology development.
- Productivity should be emphasized in the technologies developed, support for non-productive technologies that cause both energy consumption and environmental degradation should be reduced and extra taxation should be introduced
- Also, taking into account the spillover effect of environmental pollution, care should be taken to prevent pollution in neighboring countries, sharing information, technology and funds.

References

Abid, A., Mehmood, U., Tariq, S., and Haq, Z. U. (2022). The effect of technological innovation, FDI, and financial development on CO₂ emission: Evidence from the G8 countries. *Environmental Science and Pollution Research*, 29(8), 11654–11662.

Acaroğlu, H., Kartal, H. M., and García Márquez, F. P. (2023). Testing the environmental Kuznets curve hypothesis in terms of ecological footprint and CO₂

emissions through energy diversification for Turkey. *Environmental Science and Pollution Research*, 30(22), 63289–63304.

Addai, K., and Kirikkaleli, D. (2023). Insights from Poland on the long-run effect of energy productivity on environmental degradation: A Fourier ARDL-based approach. *Environmental Science and Pollution Research*, 30(23), 63453–63463.

Addai, K., Kirikkaleli, D., and Altuntaş, M. (2023). Energy productivity and environmental degradation in the Netherlands: Evidence from the novel Fourier-based estimators. *Environmental Science and Pollution Research*, 30(30), 75943–75956.

Addai, K., Ozbay, R. D., Castanho, R. A., Genc, S. Y., Couto, G., and Kirikkaleli, D. (2022). Energy Productivity and Environmental Degradation in Germany: Evidence from Novel Fourier Approaches. *Sustainability*, 14(24), 16911.

Adebayo, T. S., and Kirikkaleli, D. (2021). Impact of renewable energy consumption, globalization, and technological innovation on environmental degradation in Japan: Application of wavelet tools. *Environment, Development and Sustainability*, 23(11), 16057–16082.

Adebayo, T. S., Oladipupo, S. D., Adeshola, I., and Rjoub, H. (2022). Wavelet analysis of impact of renewable energy consumption and technological innovation on CO2 emissions: Evidence from Portugal. *Environmental Science and Pollution Research*, 29(16), 23887–23904.

Adedoyin, F. F., Alola, A. A., and Bekun, F. V. (2020). An assessment of environmental sustainability corridor: The role of economic expansion and research and development in EU countries. *Science of The Total Environment*, 713, 136726.

Ahmad, M., Jiang, P., Murshed, M., Shehzad, K., Akram, R., Cui, L., and Khan, Z. (2021). Modelling the dynamic linkages between eco-innovation, urbanization, economic growth and ecological footprints for G7 countries: Does financial globalization matter? *Sustainable Cities and Society*, 70, 102881.

Ajmi, A. N., and Inglesi-Lotz, R. (2021). Revisiting the Kuznets curve hypothesis for Tunisia: Carbon dioxide vs. Ecological footprint. *Energy Sources, Part B: Economics, Planning, and Policy*, 16(5), 406–419.

Ali, S., Yusop, Z., Kaliappan, S. R., and Chin, L. (2021). Trade-environment nexus in OIC countries: Fresh insights from environmental Kuznets curve using GHG emissions and ecological footprint. *Environmental Science and Pollution Research*, 28(4), 4531–4548.

Alola, A. A., and Ozturk, I. (2021). Mirroring risk to investment within the EKC hypothesis in the United States. *Journal of Environmental Management*, 293, 112890.

Alper, A. E., Alper, F. O., Ozayturk, G., and Mike, F. (2022). Testing the long-run impact of economic growth, energy consumption, and globalization on ecological footprint: New evidence from Fourier bootstrap ARDL and Fourier bootstrap Toda–Yamamoto test results. *Environmental Science and Pollution Research*, 30(15), 42873–42888.

Altıntaş, H., and Kassouri, Y. (2020). Is the environmental Kuznets Curve in Europe related to the per-capita ecological footprint or CO2 emissions? *Ecological Indicators*, 113, 106187.

Ansari, M. A. (2022). Re-visiting the Environmental Kuznets curve for ASEAN: A comparison between ecological footprint and carbon dioxide emissions. *Renewable and Sustainable Energy Reviews*, 168, 112867.

Anser, M. K., Hanif, I., Vo, X. V., and Alharthi, M. (2020). The long-run and short-run influence of environmental pollution, energy consumption, and economic activities on health quality in emerging countries. *Environmental Science and Pollution Research*, 27(26), 32518–32532.

Ayad, H., Shuaib, M., Hossain, Md. E., Haseeb, M., Kamal, M., and Ur Rehman, M. (2024). Re-examining the Environmental Kuznets Curve in MENA Countries: Is There Any Difference Using Ecological Footprint and CO2 Emissions? *Environmental Modeling & Assessment*. <https://doi.org/10.1007/s10666-024-09977-7>

Azam, M., Liu, L., and Ahmad, N. (2021). Impact of institutional quality on environment and energy consumption: Evidence from developing world. *Environment, Development and Sustainability*, 23(2), 1646–1667.

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

Balsalobre-Lorente, D., Shahbaz, M., Roubaud, D., and Farhani, S. (2018). How economic growth, renewable electricity and natural resources contribute to CO2 emissions? *Energy Policy*, 113, 356–367.

Bilgili, F., Balsalobre-Lorente, D., Kuşkaya, S., Alnour, M., Önderol, S., and Hoque, M. E. (2023). Are research and development on energy efficiency and energy sources effective in the level of CO2 emissions? Fresh evidence from EU data. *Environment, Development and Sustainability*.

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

Caglar, A. E., Destek, M. A., and Manga, M. (2024). Analyzing the load capacity curve hypothesis for the Türkiye: A perspective for the sustainable environment. *Journal of Cleaner Production*, 444, 141232.

Chen, F., Ali, S., Ma, J., Arshad, S., and Ahmad, S. (2023). Material productivity and environmental degradation: Moderating role of environment-related technologies in achieving carbon neutrality. *Gondwana Research*, 117, 155–168.

Chen, Y., and Lee, C.-C. (2020). Does technological innovation reduce CO2 emissions? Cross-country evidence. *Journal of Cleaner Production*, 263, 121550.

Cheng, C., Ren, X., Wang, Z., and Yan, C. (2019). Heterogeneous impacts of renewable energy and environmental patents on CO2 emission—Evidence from the BRIICS. *Science of The Total Environment*, 668, 1328–1338.

Chudik, A., Mohaddes, K., Pesaran, M. H., and Raissi, M. (2016). Long-Run Effects in Large Heterogeneous Panel Data Models with Cross-Sectionally Correlated Errors. In G. GonzÁlez-Rivera, R. C. Hill, & T.-H. Lee (Eds.), *Advances in Econometrics* (Vol. 36, pp. 85–135). Emerald Group Publishing Limited.

Chudik, A., and Pesaran, M. H. (2015). Common correlated effects estimation of heterogeneous dynamic panel data models with weakly exogenous regressors. *Journal of Econometrics*, 188(2), 393–420.

Daigneault, A., Sohngen, B., and Sedjo, R. (2012). Economic Approach to Assess the Forest Carbon Implications of Biomass Energy. *Environmental Science & Technology*, 46(11), 5664–5671.

Destek, M. A., Ulucak, R., and Dogan, E. (2018). Analyzing the environmental Kuznets curve for the EU countries: The role of ecological footprint. *Environmental Science and Pollution Research*, 25(29), 29387–29396.

Dogan, E., and Inglesi-Lotz, R. (2020). The impact of economic structure to the environmental Kuznets curve (EKC) hypothesis: Evidence from European countries. *Environmental Science and Pollution Research*, 27(11), 12717–12724.

EIA. (2016). *International Energy Outlook 2016*. [https://www.eia.gov/outlooks/ieo/pdf/0484\(2016\).pdf](https://www.eia.gov/outlooks/ieo/pdf/0484(2016).pdf)

European Central Bank. (2024). *Digitalisation and productivity: A report by the ESCB expert group on productivity, innovation and technological change*. Publications Office. <https://data.europa.eu/doi/10.2866/907812>

Eurostat. (2022). *R&D expenditure*. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=R%26D_expenditure&oldid=551418#:~:text=In%202022%2C%20EU%20research%20and,year%20when%20it%20recorded%202.27%20%25.&text=In%202022%2C%20the%20EU%20spent,compared%20with%202.08%20%25%20in%202012 (Accessed: 01.06.2024).

Frodyma, K., Papież, M., and Śmiech, S. (2022). Revisiting the Environmental Kuznets Curve in the European Union countries. *Energy*, 241, 122899.

Global Footprint Network. (2017). *How Ecological Footprint accounting helps us recognize that engaging in meaningful climate action is critical for our own success*. <https://www.footprintnetwork.org/2017/11/09/ecological-footprint-climate-change/#:~:text=Currently%2C%20the%20carbon%20Footprint%20makes,60%25%20of%20humanity's%20Ecological%20Footprint> (Accessed: 10.05.2024).

Global Footprint Network. (2024). *Global Footprint Network*. https://data.footprintnetwork.org/?_ga=2.133828806.951887049.1748634600-1863298122.1707051840#/ (Accessed: 10.06.2024)

Gormus, S., and Aydin, M. (2020). Revisiting the environmental Kuznets curve hypothesis using innovation: New evidence from the top 10 innovative economies. *Environmental Science and Pollution Research*, 27(22), 27904–27913.

Grossman, G., and Krueger, A. (1991). *Environmental Impacts of a North American Free Trade Agreement* (No. w3914; p. w3914). National Bureau of Economic Research. <https://doi.org/10.3386/w3914>

IEA. (2019). *World Energy Outlook 2019*. <https://www.iea.org/reports/world-energy-outlook-2019> (Accessed: 15.02.2024).

Javed, A., Rapposelli, A., Khan, F., and Javed, A. (2023). The impact of green technology innovation, environmental taxes, and renewable energy consumption on ecological footprint in Italy: Fresh evidence from novel dynamic ARDL simulations. *Technological Forecasting and Social Change*, 191, 122534.

Jóźwik, B., Gavryshkiv, A.-V., Kyophilavong, P., and Gruszecki, L. E. (2021). Revisiting the Environmental Kuznets Curve Hypothesis: A Case of Central Europe. *Energies*, 14(12), 3415.

Kar, A. K. (2022). Environmental Kuznets curve for CO₂ emissions in Baltic countries: An empirical investigation. *Environmental Science and Pollution Research*, 29(31), 47189-47208.

Khan, A. A., Khan, S. U., Ali, M. A. S., Safi, A., Gao, Y., Ali, M., and Luo, J. (2022). Role of institutional quality and renewable energy consumption in achieving carbon neutrality: Case study of G-7 economies. *Science of The Total Environment*, 814, 152797.

Kirikaleli, D., Ali, M., Kondozi, M., and Dördüncü, H. (2022). The linear and nonlinear effects of energy productivity on environmental degradation in Cyprus. *Environmental Science and Pollution Research*, 30(4), 9886–9897.

Koçak, E., and Ulucak, Z. Ş. (2019). The effect of energy R&D expenditures on CO₂ emission reduction: Estimation of the STIRPAT model for OECD countries. *Environmental Science and Pollution Research*, 26(14), 14328–14338.

Kuznets, S. (1955). Economic Growth and Income Inequality. *The American Economic Review*, 45(1). <https://www.jstor.org/stable/1811581>

Larcher, D., and Tarascon, J.-M. (2015). Towards greener and more sustainable batteries for electrical energy storage. *Nature Chemistry*, 7(1), 19–29.

Li, R., Wang, X., and Wang, Q. (2022). Does renewable energy reduce ecological footprint at the expense of economic growth? An empirical analysis of 120 countries. *Journal of Cleaner Production*, 346, 131207.

Liu, P.-Z., Narayan, S., Ren, Y.-S., Jiang, Y., Baltas, K., and Sharp, B. (2022). Re-Examining the Income–CO2 Emissions Nexus Using the New Kink Regression Model: Does the Kuznets Curve Exist in G7 Countries? *Sustainability*, 14(7), 3955.

Mohsin, M., Naseem, S., Sarfraz, M., and Azam, T. (2022). Assessing the effects of fuel energy consumption, foreign direct investment and GDP on CO2 emission: New data science evidence from Europe & Central Asia. *Fuel*, 314, 123098.

Mongo, M., Belaïd, F., and Ramdani, B. (2021). The effects of environmental innovations on CO2 emissions: Empirical evidence from Europe. *Environmental Science & Policy*, 118, 1–9.

Mushafiq, M., and Prusak, B. (2023). Resource productivity and environmental degradation in EU-27 countries: Context of material footprint. *Environmental Science and Pollution Research*, 30(20), 58536–58552.

Nathaniel, S. P., and Bekun, F. V. (2020). Environmental management amidst energy use, urbanization, trade openness, and deforestation: The Nigerian experience. *Journal of Public Affairs*, 20(2), e2037.

OECD. (2024). *Multifactor productivity*. <https://www.oecd.org/en/data/indicators/multifactor-productivity.html> (Accessed: 12.01.2024).

Oluc, I., Ben Jebli, M., Can, M., Guzel, I., and Brussaers, J. (2023). The productive capacity and environment: Evidence from OECD countries. *Environmental Science and Pollution Research*, 30(2), 3453–3466.

Osobajo, O. A., Otitoju, A., Otitoju, M. A., and Oke, A. (2020). The Impact of Energy Consumption and Economic Growth on Carbon Dioxide Emissions. *Sustainability*, 12(19), 7965.

Our World in Data. (2024). *Data Catalog*. <https://ourworldindata.org/data> (Accessed: 12.01.2024).

Panayotou, T. (1993). Empirical tests and policy analysis of environmental degradation at different stages of economic development. *International Labour Office*. https://www.ilo.org/public/libdoc/ilo/1993/93B09_31_engl.pdf

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

Pata, U. K. (2021). Do renewable energy and health expenditures improve load capacity factor in the USA and Japan? A new approach to environmental issues. *The European Journal of Health Economics*, 22(9), 1427–1439.

Pata, U. K., and Balsalobre-Lorente, D. (2022). Exploring the impact of tourism and energy consumption on the load capacity factor in Turkey: A novel dynamic ARDL approach. *Environmental Science and Pollution Research*, 29(9), 13491–13503.

Pesaran, M. H. (2004). General Diagnostic Tests for Cross Section Dependence in Panels. *SSRN Electronic Journal*.

Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross-section dependence. *Journal of Applied Econometrics*, 22(2), 265–312.

Rasoulinezhad, E., Taghizadeh-Hesary, F., and Taghizadeh-Hesary, F. (2020). How Is Mortality Affected by Fossil Fuel Consumption, CO2 Emissions and Economic Factors in CIS Region? *Energies*, 13(9), 2255.

Rees, W. E. (1992). Ecological footprints and appropriated carrying capacity: What urban economics leaves out. *Environment and Urbanization*, 4(2), 121–130.

Saqib, M., and Benhmad, F. (2021). Does ecological footprint matter for the shape of the environmental Kuznets curve? Evidence from European countries. *Environmental Science and Pollution Research*, 28(11), 13634–13648.

Saqib, N., Ozturk, I., Usman, M., Sharif, A., and Razzaq, A. (2023). Pollution Haven or Halo? How European countries leverage FDI, energy, and human capital to alleviate their ecological footprint. *Gondwana Research*, 116, 136–148.

Sarkodie, S. A., and Strezov, V. (2019). Effect of foreign direct investments, economic development and energy consumption on greenhouse gas emissions in developing countries. *Science of The Total Environment*, 646, 862–871.

Science, technology and innovation in Europe (2010 ed). (2010). Publications Office of the European Union.

Shafiee, S., and Topal, E. (2009). When will fossil fuel reserves be diminished? *Energy Policy*, 37(1), 181–189.

Shahbaz, M., Ozturk, I., Afza, T., and Ali, A. (2013). Revisiting the environmental Kuznets curve in a global economy. *Renewable and Sustainable Energy Reviews*, 25, 494–502.

Siche, R., Pereira, L., Agostinho, F., and Ortega, E. (2010). Convergence of ecological footprint and emergy analysis as a sustainability indicator of countries: Peru as case study. *Communications in Nonlinear Science and Numerical Simulation*, 15(10), 3182–3192.

Sun, A., Bao, K., Aslam, M., Gu, X., Khan, Z., and Fakhriddinovich Uktamov, K. (2024). Testing load capacity and environmental Kuznets curve hypothesis for

China: Evidence from novel dynamic autoregressive distributed lags model. *Gondwana Research*, 129, 476–489.

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

Ulucak, R., and Bilgili, F. (2018). A reinvestigation of EKC model by ecological footprint measurement for high, middle and low income countries. *Journal of Cleaner Production*, 188, 144–157.

Wang, R., Mirza, N., Vasbieva, D. G., Abbas, Q., and Xiong, D. (2020). The nexus of carbon emissions, financial development, renewable energy consumption, and technological innovation: What should be the priorities in light of COP 21 Agreements? *Journal of Environmental Management*, 271, 111027.

Wang, R., Usman, M., Radulescu, M., Cifuentes-Faura, J., and Balsalobre-Lorente, D. (2023). Achieving ecological sustainability through technological innovations, financial development, foreign direct investment, and energy consumption in developing European countries. *Gondwana Research*, 119, 138–152.

Wang, S., Wasif Zafar, M., Vasbieva, D. G., and Yurtkuran, S. (2024). Economic growth, nuclear energy, renewable energy, and environmental quality: Investigating the environmental Kuznets curve and load capacity curve hypothesis. *Gondwana Research*, 129, 490–504.

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

World Bank-WDI. (2024a). *GDP per capita (current US\$)*. <https://data.worldbank.org/indicator/NY.GDP.PCAP.CD?end=2021&start=1996&view=chart> (Accessed: 12.01.2024).

World Bank-WDI. (2024b). *Patent applications*. <https://data.worldbank.org/indicator/IP.PAT.RESD> (Accessed: 12.01.2024).

Wu, H., Xue, Y., Hao, Y., and Ren, S. (2021). How does internet development affect energy-saving and emission reduction? Evidence from China. *Energy Economics*, 103, 105577.

Xia, W., Apergis, N., Bashir, M. F., Ghosh, S., Doğan, B., and Shahzad, U. (2022). Investigating the role of globalization, and energy consumption for environmental externalities: Empirical evidence from developed and developing economies. *Renewable Energy*, 183, 219–228.

Xu, C., Yiwen, Z., Cheng, B., Li, L., and Zhang, M. (2020). Study on environmental Kuznets Curve for noise pollution: A case of 111 Chinese cities. *Sustainable Cities and Society*, 63, 102493.

Zafar, M. W., Sinha, A., Ahmed, Z., Qin, Q., and Zaidi, S. A. H. (2021). Effects of biomass energy consumption on environmental quality: The role of education and technology in Asia-Pacific Economic Cooperation countries. *Renewable and Sustainable Energy Reviews*, 142, 110868.

Zhen, Z., Ullah, S., Shaowen, Z., and Irfan, M. (2023). How do renewable energy consumption, financial development, and technical efficiency change cause ecological sustainability in European Union countries? *Energy & Environment*, 34(7), 2478–2496.