

## **Impact of Nuclear and Renewable Energy on CO<sub>2</sub> Emissions in OECD countries Under the STIRPAT model: Evidence from the CS-ARDL Model**

**İbrahim Halil POLAT<sup>1</sup>**  
**Sevda YAPRAKLI<sup>2</sup>**  
**Serhat ÇAMKAYA<sup>3</sup>**

Received: 06.12.2023, Accepted: 26.06.2024

DOI Number: 10.5281/zenodo.14176539

### **Abstract**

In-depth evaluations of the short- and long-term effects of nuclear and renewable energy on emissions of carbon dioxide in 12 OECD countries are made in this study using the STIRPAT model. Using yearly data for the years 1980 to 2020, the CIPS unit root test, taking into account cross-sectional dependency (CD), Gengenbach et al. (2016) co-integration test, and Cross-Sectional Augmented Autoregressive Distributed Lag (CS-ARDL) technique are used. Additionally, the Dumitrescu-Hurlin (DH) panel causality tests are used for seeking the causal connections between variables. The empirical findings from the CS-ARDL approach demonstrate that CO<sub>2</sub> emissions are negatively impacted both in the short and long terms by nuclear and renewable energy. The CS-ARDL results also show that the long-run elasticity of economic growth is lower than the short-run elasticity, and that growing populations increases CO<sub>2</sub> emissions both in the short and long runs. According to the DH panel's findings on causality, there is only one way that economic development, CO<sub>2</sub> emissions, and nuclear energy output are related. These findings suggest that the OECD should concentrate on income-oriented policies, promote green economic growth, and subsidize greater nuclear and renewable energy consumption through

**Keywords:** Nuclear energy, Renewable energy, STIRPAT, CS-ARDL, OECD

**JEL Codes:** G15, F36, C58

### **1. Introduction**

Due to the tremendous industrialization and urbanization of the world in recent decades, economic growth has been unprecedented (Dong et al., 2018). The ecosystem has come under strain from human use of products and services, which has led to the contemporary dangers of environmental degradation, ecological imbalances, and climate change. As a result, environmentalists and economists have

---

<sup>1</sup> Assistant Professor Dr, Hakkari University, [ibrahimhalilpolat@hakkari.edu.tr](mailto:ibrahimhalilpolat@hakkari.edu.tr), 0000-0001-9785-160X

<sup>2</sup> Professor Dr., Ataturk University, Email: [sevda1@atauni.edu.tr](mailto:sevda1@atauni.edu.tr)

<sup>3</sup> Assistant Professor Dr., [serhatcamkaya36@gmail.com](mailto:serhatcamkaya36@gmail.com)

turned their attention to the global understanding and Sinitiative to achieve sustainable development, which can be defined as leaving at least the current economic, social, and environmental conditions to future generations, primarily to protect the ecological dimension/biological capacity. Since the 2000s, in an environment where humanitarian concerns have increased directly and indirectly (Bekun et al., 2019; A. Usman et al., 2022), much attention has been paid to environmental pollution caused by various economic factors such as population growth, energy supply and demand, and economic growth (Shahbaz and Sinha 2019; A. Usman et al., 2022).

According to data from the World Bank (2022), the world GDP, which was US\$ 22.73 trillion in 1990 (constant 2010 US\$), would increase by roughly 4 times to US\$ 86.86 trillion in 2022, assuming an average annual growth rate of 2.7%. Parallel to this, the global population has grown (about 1.5 times), from 5.3 billion in 1990 to 7.89 billion in 2022, growing at an average annual rate of 1.3% (WDI, 2022). Due to population and economic expansion, energy consumption has increased globally. According to BP (2022), the amount of energy consumed worldwide increased from 8133.3 million tons of oil equivalent (Mtoe) in 1990 to 88,528.4 Mtoe in 2021, an almost 10-fold increase. The fast rising energy demand has resulted in significant environmental problems, most notably the global climate change caused by an increase in carbon dioxide (CO<sub>2</sub>) emissions from the burning of fossil fuels (Dong et al., 2018; Jardón et al., 2017). From 22.7 billion tons in 1991 to 40.6 billion tons in 2022, the total CO<sub>2</sub> emissions from fossil fuels virtually doubled. The increase in CO<sub>2</sub> emissions is one of the primary causes of global climate change. The main problems caused by increased environmental pollution and global climate change include melting glaciers, the development of infectious diseases, the extinction of biological species, an increase in tropical storms, hurricanes, floods, and ecological footprints. In response to the escalating environmental issues and the holding of international climate change conferences, such as the 2015 Paris Climate Change Conference, a number of international conventions, including the United Nations Framework Convention on Climate Change (UNFCCC), have been signed (Çamkaya et al., 2022; Doğanlar et al., 2021; Dong et al., 2018).

In order to reduce CO<sub>2</sub> emissions and promote sustainable economic growth worldwide, the Sustainable Development Goals (SDGs) statement argues that expanded access to inexpensive, dependable, economical, and clean energy sources is essential (Dong et al., 2018; Murshed et al., 2022). World economies are looking into solutions to shift to clean energy within global energy networks in this environment (Murshed et al., 2022). The best ways to reduce CO<sub>2</sub> emissions and stop climate change often involve nuclear and renewable energy sources (Ahmed et al., 2020; Murshed et al., 2022; Zafar et al., 2022).

Electricity generation in the world is primarily obtained from fossil resources. Electric energy obtained from these sources causes significant CO<sub>2</sub> emissions. Nuclear energy (NE), which is shown as an alternative to this energy source, can be beneficial in both generating more electricity and mitigating climate change (Majeed et al., 2022; Rehman et al. 2022; Saidi and Ben Mbarek 2016; A. Usman et al., 2022). NE is one of the main substitutes for lowering the prices of fossil fuels and reducing dependence on foreign/imported energy. However, Ozgur

et al. (2022) argue that academics and policymakers are hesitant to use NE due to several issues ranging from safety concerns at NE production facilities, proliferation concerns, radioactive waste disposal, and related costs (Ozgur et al., 2022).

On the other hand, renewable energy sources, which generate essentially no environmental pollution during the production and consumption phases, become crucial in preventing environmental deterioration when the complete life cycle is taken into account. When compared to coal-fired power plants, renewable energy generation emits 90–99% fewer greenhouse gases (GHG) and 70–90% fewer pollutants. Renewable energy provides benefits, but it also has drawbacks, including expensive installation and maintenance costs, a low calorific value, and generation that is dependent on environmental conditions while renewable energy only makes up 12.6% of total energy consumption in 2020, it will generate roughly 28.3% of all electricity in 2021 (with hydropower at 15%, solar and wind at 10%, biofuel at 3%, and geothermal at 3%). The proportion of renewable energy in the generation of electricity rose by about 8% from 2011 to today (Zhang et al., 2023).

The Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model has been developed in accordance with studies on the topic and demonstrates how population, income level, and technology all effect the degradation of the environment. Technology is regarded as a broad variable in this model, and the impacts of technology on pollution may be assessed by employing a variety of variables that reflect technology (Dietz and Rosa, 1997). This study examines the short- and long-term impacts of NE and renewable energy on CO<sub>2</sub> emissions for 12 OECD member countries in the 1980–2020 timeframe within the framework of the STIRPAT model, and is motivated by discussions on the benefits and drawbacks of NE and renewable energy. The OECD countries have a combined population of almost 1.3 billion people. 53.6% of the global GDP is made up of their GDP. With a 41% use of fossil fuels, the OECD countries are among the energy consumers of the world (WDI, 2023). In this group of nations, at 4,130.81 kilograms per person, energy usage is higher than the global average (1,922.07 kg of oil equivalent). Despite the fact that the majority of the countries in the OECD are Kyoto Protocol signatories, their CO<sub>2</sub> emission rate (12,004,051.89 kt) is greater than the global average (35,998.94 kt) (Mujtaba et al., 2022; OECD 2023). To lessen or avoid environmental damage, it is therefore vital to show how resources like NE and renewable energy affect CO<sub>2</sub> (Mujtaba et al., 2022; Saidi and Omri, 2020). If the impact is negative/positive, it is crucial for countries in the OECD with NE and renewable energy potential to raise the proportion of these resources in overall energy production and to implement appropriate legislative measures. As a result, it is reasonable to state that the actions taken in the the OECD countries included by the study will help to mitigate climate change and environmental degradation in the concerned countries as well as globally.

This study is expected to provide various contributions to the literature that are in line with the main goal mentioned above. First, in accordance with Dietz et al. (2007), this is the first research to incorporate NE and renewable energy consumption (TEC), a measure of technological advancement, into the STIRPAT

model and to examine at both the long-run and short-run simultaneous impacts. This is because, in the reviewed literature, it is observed that the impact of only a single energy source (NE or TEC) on the environment is intensively analyzed, or EKC-based studies are conducted (Bakhsh et al., 2017; Chopra et al., 2022; Magazzino et al., 2020). This allows for the simultaneous examination of the long- and short-term impacts of NE and TEC on CO<sub>2</sub> emissions, allowing for the determination of which source is more successful in preventing the degradation of the environment. The second is an estimation of the long- and short-term impacts using the new Cross-Sectional Augmented Autoregressive Distributive Lag (CS-ARDL) method. In contrast to methods that do not take into account these factors, this strategy allows for more precise predictions and eliminates the endogeneity issue by taking into account cross-sectional dependence (CD) and heterogeneity of the slope coefficients. Finally, to prevent the potential multicollinearity issue, the STIRPAT model is assessed using the Narayan and Narayan (2010) technique.

The rest of the paper is structured as follows. The empirical literature pertaining to the model under consideration is offered in the "*Literature Review*" section. The criteria for selecting data and models are provided in the "*Data and Model Selection*" section. The econometric technique is presented in the "*Methodology*" section. The part titled "*Empirical Findings and Discussion*" explores the empirical findings, and the section titled "*Conclusion*" offers insights and suggestions for policy development.

## 2. Literature review

The research generally agrees that elements including energy use, technology, population expansion, GDP, and industrialisation have a detrimental effect on the environment. To adopt more effective regulations, it is crucial to comprehend how these elements impact the environment given the complexity of environmental issues. Studies that are widely used in the literature demonstrate that CO<sub>2</sub> emissions increase when fossil energy usage increases. Recent studies have examined the potential of clean energy sources to prevent CO<sub>2</sub> emissions.

Using panel data from OECD and non-OECD nations, Richmond and Kaufmann (2006), examined the effect of NE on CO<sub>2</sub> emissions. According to the study, NE has a considerable impact on lowering CO<sub>2</sub> emissions in OECD countries. However, countries outside the OECD did not see this effect. Similarly, NE plays a significant impact in lowering CO<sub>2</sub> emissions, according to studies by Apergis et al. (2010) for 19 industrialized and developing countries, Menyah and Wolde-Rufael (2010), for the USA, and Iwata et al. (2010) for France. In addition, Iwata et al. (2011), examined the relationship between NE and CO<sub>2</sub> emissions for 11 OECD countries. As a result of the study, it is found that NE reduces CO<sub>2</sub> only in Finland, Spain, Korea, and Japan. Al-Mulali (2014), in his study on 30 major NE-consuming countries, found that NE has a minimal impact on the environment compared to other fossil fuels. Baek and Pride (2014), in their study of 6 major NE-producing countries, concluded that NE significantly impacts CO<sub>2</sub> reduction in all countries. Dong et al. (2018), Saidi and Omri (2020), Azam et al. (2021), Danish et al. (2022), Naimoğlu (2022), and Mahmood (2022) similarly found that NE has a significant impact on reducing CO<sub>2</sub> emissions. Wang et al. (2023), in their study of 24 NE-consuming countries, found that NE is important in reducing CO<sub>2</sub> emissions.

This effect was more significant, especially in Canada, Finland, Russia, Slovenia, Slovenia, South Korea, and the UK. Hassan et al. (2024), examined the impact of nuclear energy on CO<sub>2</sub> emissions in the United States over the period 1973-2021 using the ARDL method. The analysis results indicated that nuclear energy consumption has a negative effect on CO<sub>2</sub> emissions. Finally, Wang et al. (2024), investigated the relationship between nuclear energy and CO<sub>2</sub> emissions in BRIC countries over the period 1990-2018 using LM-Bootstrap Cointegration tests and Driscoll-Kraay regression models. The results indicated that nuclear energy significantly reduces CO<sub>2</sub> emissions. In contrast to these studies, some studies have found that NE does not significantly reduce CO<sub>2</sub> emissions (Jaforullah and King 2014; N. Mahmood et al. 2020; Saidi and Ben Mbarek, 2016). Summary information on the studies reviewed is given in Table 1.

**Table 1.** Applied Studies Examining the Effect of NE on CO<sub>2</sub>

Researcher(s)/Year	Period/Country	Method	Variable	Effect of NE on CO <sub>2</sub>	
				Positive	Negative
Richmond and Kaufmann (2006)	1973-1997/OECD (20) and Non-OECD (16) 36 Countries	Panel Data Analysis	GDP, CO <sub>2</sub> , NE, TE,	X	OECD: ✓
Apergis et al. (2010)	1984-2007/19 DC and EMC	Panel Data Analysis	GDP, CO <sub>2</sub> , NE, RE	X	✓
Menyah and Wolde-Rufael (2010)	1960-2007/USA	Granger Causality	GDP, CO <sub>2</sub> , NE, RE	X	✓
Iwata et al. (2010)	1960-2003/France	ARDL	GDP, CO <sub>2</sub> , NE	X	✓
Iwata et al. (2011)	1960-2003/ 28 Countries (11 OECD countries and 17 non-OECD countries)	Panel Data Analysis	GDP, CO <sub>2</sub> , NE	X	✓
Al-Mulali (2014)	1990-2010/ 30 major NE-consuming countries	Panel FMOLS	GDP, NE, CO <sub>2</sub> , TE, POP	X	Minimal ✓
Baek and Pride (2014)	1970-2010/ 6 major NE-consuming countries	CVAR	CO <sub>2</sub> , RE, NE, Income	X	✓
Jaforullah and King (2014)	1965-2012/US	Granger Causality	CO <sub>2</sub> , NE, RE, GDP	X	Minimal ✓
Saidi and Mübarek (2016)	1990-2013/	Panel Co-integration	NE, RE, GDP, CO <sub>2</sub>	X	Minimal ✓
Mahmood et al. (2020)	9 Developed Countries	FMOLS-DOLS	NE, GDP, CO <sub>2</sub>	X	Minimal ✓

Azam et al. (2021)	1990-2014/ Top 10 emitting countries	Panel Co-integration	CO <sub>2</sub> , NE, RE, NG, GDP, FDI,	X	✓
Danish et al. (2022)	2005-2016/ OECD	Regression Analysis	CO <sub>2</sub> , NE, RE, NG, GDP	X	✓
Naimoğlu (2022)	1990-2019/ 10 Major Energy Importing Countries	DOLS and FMOLS	GDP, NE, IMP, INF, CO <sub>2</sub>	X	✓
Mahmood (2022)	1996-2019/28 NE-Producing Country	Panel Data Analysis	CO <sub>2</sub> , NE, GDP	X	✓
Wang et al. (2023)	2001-2020/ 24 NE-Consuming Countries	FMOLS	NE, NG, OIL, GDP, COAL, CO <sub>2</sub>	X	✓
Hassan et al. (2024)	1973-2021 ABD	ARDL	NE, GDP, POP, CO <sub>2</sub> ,	X	✓
Wang et al. (2024)	BRIC 1990-2018	LM-Bootstrap Cointegration tests and Driscoll-Kraay	NE, GDP, EI, CO <sub>2</sub> , RE, FD	X	✓

Note: TE (Total Energy), RE(Renewable Energy), FD( Financial Development), FDI ( Foreign Direct Investment), NG (Natural Gas), TO (Trade Openness), GDP (Gross Domestic product), CO<sub>2</sub> (Carbon emissions), NE (Nuclear Energy), INF (Inflation), Pop (Population), (FMOLS): Fully modified ordinary least squares, (DOLS): Dynamic ordinary least squares, (CVAR),cointegrated vector autoregression

According to Table 1, which summarizes the studies, NE reduces environmental pollution in most analyzed studies. In four of the 17 studies, the effect is almost negligible.

On the other hand, Sulaiman et al. (2013), used the ARDL bounds test and VECM methodologies to analyze the connection between TEC and CO<sub>2</sub> emissions in Malaysia from 1980 to 2009. The study leads to the conclusion that TEC lowers CO<sub>2</sub> emissions. For 36 groups of industrialized and developing countries, Zbuday and Erbas (2015), evaluated the impact of GDP, TEC efficiency, POP, and energy efficiency index on CO<sub>2</sub>. The Panel data approach was used by the authors to study the years 1971 through 2009. The analysis's findings revealed that TEC and energy efficiency both helped the aforementioned country group lower their CO<sub>2</sub> emissions. The effects of TEC, natural gas, and GDP per capita on CO<sub>2</sub> for BRICS countries were examined by Dong et al. (2017), The authors used Panel Causality Analysis to examine the years 1985–2016. According to the results of the study, it was found that the use of natural gas and TEC significantly reduces CO<sub>2</sub> emissions. The effects of TEC, fossil fuels, GDP, GDP squared, and trade openness on CO<sub>2</sub> were examined by Inglesi-Lotz and Dogan (2018), in 10 Saharan African countries. Using a Panel Co-integration estimator, they examined the years 1980 to 2011. They concluded that TEC lowers CO<sub>2</sub> emissions based on the analysis's findings.

The correlation between POP, TEC, financial development, GDP, and CO<sub>2</sub> emissions in Turkey was also examined by Pata and Yurtkuran (2018). The authors used the ARDL bounds test to evaluate the years 1981 to 2014. The analysis's findings indicate that increasing POP, economic growth, and GDP are also increasing CO<sub>2</sub> emissions. It is claimed that using TEC significantly lowers CO<sub>2</sub> emissions. Using the ARDL approach for 28 EU member states, Akadiri et al. (2019), investigated the long-term relationship between economic development, environmental sustainability, and TEC between 1995 and 2015. The study supports long-term connections between TEC, GDP, and ecological sustainability. According to the report, measures that increase TEC in particular EU countries successfully lessen environmental damage. For countries in the MENA area, Charfeddine and Kahia (2019), examined how TEC and financial development affected CO<sub>2</sub> emissions. They used the P-VAR approach to study the years 1980 through 2015. The studies' findings indicated that TEC and financial development in the MENA area are low effective at lowering CO<sub>2</sub> levels. For 104 countries at various stages of development, Ben Jebli et al. (2020), examined the effects of TEC, GDP, industrial value added, and service value added on CO<sub>2</sub>. Using GMM and Granger causality tests, they examined the 1990–2015 time frame. The analysis's findings showed that these nations' use of TEC greatly decreased CO<sub>2</sub> emissions. The authors recommended that these group of countries increase their investments in RE resources in the future as part of their policy recommendations. In Bangladesh, Rahman and Alam (2021), examined the relationships between green energy, POP, GDP, and CO<sub>2</sub> emissions. The data between 1973-2014 were analyzed using ARDL and Toda-Yamamoto tests. According to empirical data, using clean energy enhances environmental quality, whereas GDP harms the environment. Within the context of the STIRPAT model, Usman and Hammar (2021), examined the impacts of financial development, TEC, GDP, and POP growth on the ecological footprint of APEC member countries between 1990 and 2017. According to empirical studies, TEC and financial development contributed 0.09% and 0.43% to improving environmental quality. The impact of TEC use on CO<sub>2</sub> in China was examined by Jiang et al. (2022), within the context of the STIRPAT EKC hypothesis. Within the context of the STIRPAT model, Yasmeen et al. (2023), examined the effects of wind energy consumption on CO<sub>2</sub> in sixteen countries that produced the most wind energy globally between 1990 and 2020. The long-term relationship among the variables was investigated using the FMOLS approach by the researchers. The investigation concluded that using wind energy considerably lowers CO<sub>2</sub> emissions and is crucial for sustainable growth. The effect of TEC, tourism, foreign direct investment, and trade openness on CO<sub>2</sub> in the ASEAN countries was examined by Pata et al. (2023). The researchers analyzed the 1995-2018 period with the Panel ARDL method. According to the analysis results, tourism and foreign direct investment increased CO<sub>2</sub>, while TEC decreased CO<sub>2</sub> in the short run. Summary information on the analyzed studies is given in Table 2.

**Table 2.** Applied Studies Examining the Impact of TEC on CO<sub>2</sub>

Researcher(s)/Year	Period/Country	Method	Variable	Effect of TEC on CO <sub>2</sub>	
				Positive	Negative
Sulaiman et al. (2013)	1980-2009/Malaysia	ARDL-VECM	TEC, CO <sub>2</sub> , GDP, TO, RE	X	✓
Özbuğay and Erbas (2015)	1971-2009/ 36 Developed and Developing Countries	Panel data analysis	TEC, POP, GDP, Energy efficiency index, CO <sub>2</sub>	X	✓
Dong et al. (2017)	1985-2016/Brics Countries	Panel Granger Causality	TEC, NG, GDP, CO <sub>2</sub>	X	✓
Inglesi-Lotz and Dogan (2018)	1980-2011/ 10 Saharan African Countries	Panel Co-integration	TEC, Fossil Fuels, GDP, GDP2, CTR, CO <sub>2</sub>	X	✓
Pata and Yurtkuran (2018)	1981-2014/Turkey	APRIL	POP, TEC, FD, GDP, and CO <sub>2</sub> emissions	X	✓
Akadiri et al. (2019)	1995-2015/28 EU member states	APRIL	GDP, TEC, CO <sub>2</sub> ,	X	✓
Charfeddine and Kahia (2019)	1980-2015/ MENA Region 24 Countries	P-VAR	TEC, FD, GDP, CO <sub>2</sub>	X	Minimal ✓
Ben Jebli et al. (2020)	1990-2015/ 102 countries at different levels of development	GMM and Granger Causality	TEC, GDP, Industry Value Added, Service Value Added, CO <sub>2</sub>	X	✓
Rahman and Alam (2021)	1973-2014/Bangladesh	ARDL and Toda-Yamamoto tests	Green energy, POP, GDP, and CO <sub>2</sub> emissions	X	✓
Usman and Hammar (2021)	1990-2017/APEC member countries	Panel Co-integration Test	Ecological footprint, FD, TEC, GDP, POP increase	X	✓
Jiang et al. (2022)	1990-2020/ China	NARDL	TEC, POP, GDP, CO <sub>2</sub>	X	✓
Yasmeen et al. (2023)	1990-2020/16 Countries Producing Wind Energy	FMOLS	Wind energy consumption, CO <sub>2</sub>	X	✓
Pata et al. (2023)	1995-2018/ASEAN Countries	Panel ARDL	TEC, FDI, Tourism, TO, CO <sub>2</sub>	X	✓

Note: TE: (Total Energy), TEC:(Technology): RE:(Renewable Energy), FD:(Financial Development), FDI :( Foreign Direct Investment), NG: (Natural Gas), TO: (Trade Openness), GDP: (Gross Domestic product), CO<sub>2</sub> :(Carbon emissions), NE: (Nuclear Energy), INF: (Inflation), Pop: (Population), (FMOLS): Fully modified ordinary least squares, (DOLS): Dynamic ordinary least squares,



(ARDL): The autoregressive distributed lag, (NARDL): Nonlinear autoregressive distributed lag, GMM:(Generalized method of moment), ( P-VAR): Panel-Var

According to Table 2, which summarizes the studies, TEC affects reducing environmental pollution in most of the studies analyzed. In only 1 out of 14 studies, the effect is almost negligible.

Considering the studies in the above literature, to the best of the authors' knowledge, there is only one study that analyses the simultaneous effect of NE and TEC with the CS-ARDL procedure that takes into account horizontal cross-section dependence and heterogeneity of slope coefficients. This study is specific to EU countries. In this respect, this study investigates the simultaneous relationship between NE and TEC for OECD countries using the CS-ARDL approach. This study is expected to contribute to the existing literature in this context.

### 3. Data and model specification

This study uses balanced panel data from 1980-2020 for 12 OECD countries (presented in Annex Table 1A). The reason for choosing 1980-2020 as the study period is that the maximum data on nuclear energy consumption variable in OECD countries can be accessed between these dates. In the remaining 25 OECD countries, there is either no nuclear energy consumption for the analysed period (1980-2020 period) or there is a loss of observations in the data during the analysis period. Therefore, these countries could not be included in the scope of the analysis. Table 3 presents information on the data used in the study.

**Table 3. Variables**

Symbol	Variables description	Unit	Source
CO <sub>2</sub>	Carbon dioxide emission	Million tonnes	BP (2023)
POP	Population	Total	WDI (2023)
GDP	Gross domestic product	Constant 2015 US \$ (per capita)	WDI (2023)
NE	Nuclear energy consumption	Per capita (kWh equivalent)	OWD (2023)
TEC	Renewable energy consumption	Per capita (kWh equivalent)	OWD (2023)

The main objective of this study is to examine the impact of NE and TEC consumption on environmental pollution within the framework of the STIRPAT model. The STIRPAT model developed by Dietz and Rosa (1997) makes it possible to empirically test various hypotheses, unlike a classical accounting equation (York et al. 2003). The traditional STIRPAT can be written in panel data notation as follows:

$$I_{it} = \beta P_{it}^a A_{it}^b T_{it}^c e_{it} \quad (1)$$

Where I= environmental degradation,  $\beta$  = constant term, a, b, and c are the exponents of population, economic development, and technology, respectively, and  $e_{it}$  is the error term. The above STIRPAT model can be rewritten in logarithmic form as in equation 2 below:

$$\ln I_{it} = \beta_0 + a \ln P_{it} + b \ln A_{it} + c \ln T_{it} + e_{it} \quad (2)$$

Here a, b, and c represent P, A, and T elasticities, respectively. Dietz et al. (2007) showed that the STIRPAT model could be modified according to the variables used. Following this view, in this study, the STIRPAT model in equation 2 is extended and rewritten as in equation 3.

$$\ln CO_{2it} = \lambda_0 + \lambda_1 \ln POP_{it} + \lambda_2 \ln GDP_{it} + \lambda_3 \ln NE_{it} + \lambda_4 \ln TEC_{it} + e_{it} \quad (3)$$

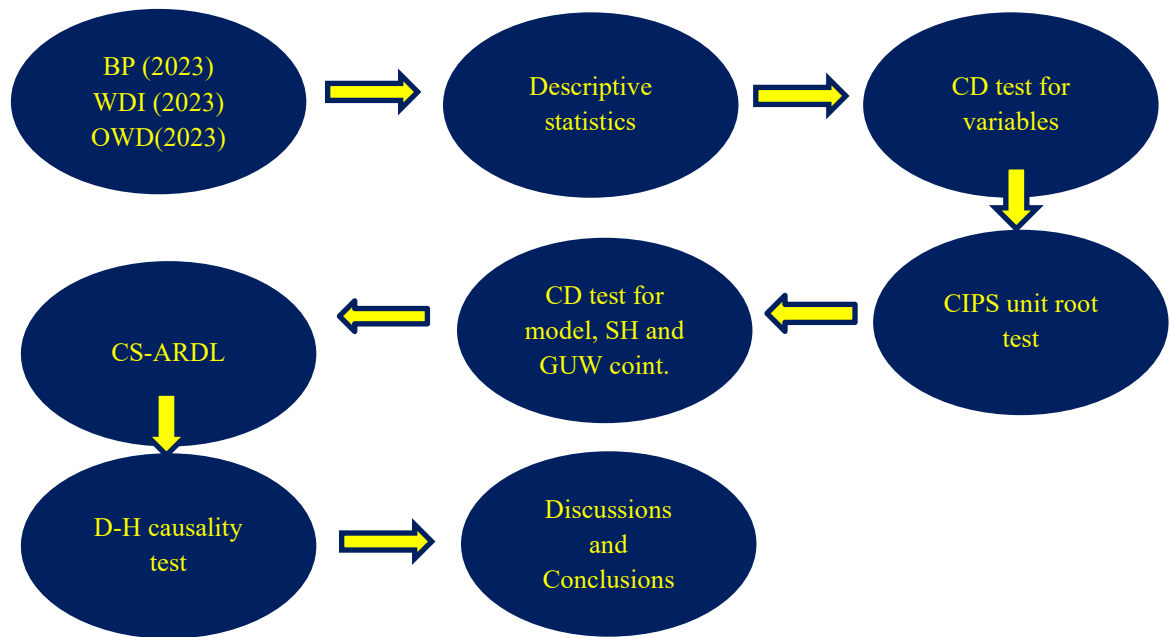
In Equation 3,  $\ln$  = natural logarithm,  $i$  = cross-sections,  $t$  = period,  $\lambda_0$  = constant term of the model,  $\lambda_i$  =  $i$ : 1, 2, ..., 4,  $CO_2$  = carbon dioxide emission,  $GDP$  = gross domestic product per capita,  $NE$  = nuclear energy consumption per capita, and  $TEC$  = renewable energy consumption per capita, which is used as an indicator of technological progress.

The increasing population may increase the consumption of fossil resource-using goods (e.g., automobiles, housing) and hence  $CO_2$ . In this case, the sign  $\lambda_1$  is expected to be positive. As Yilanci and Pata (2020) point out, countries with high economic growth rates also have high resource utilization rates. This increases the negative pressure on environmental pollution. Therefore, the expected sign is positive. Studies by Apergis et al. (2010), Iwata et al. (2011), Saidi and Omri (2020), Danish et al. (2022), and Wang et al. (2023) find that  $NE$  has a negative impact on  $CO_2$  emissions, while studies by Sulaiman et al. (2013), Pata and Yurtkuran (2018), Usman and Hammar (2021), and Karaaslan and Çamkaya (2022) find that  $TEC$  has a negative impact on  $CO_2$  emissions. In this context, the expected sign of  $\lambda_3$  and  $\lambda_4$  is negative.

## 4. Methodology

### 4.1. Methodology Framework

The empirical technique used in this investigation is shown in Figure 1. Data were originally gathered from relevant sources in this context. Second, the variables' descriptive statistics are obtained. Third, the variables' horizontal cross-section dependence is examined. Fourth, tests of the variables' unit roots are carried out. Fifth, the long-run coefficients (SH) of the model are assessed for heterogeneity, co-integration, and CD. Sixth, the model's short-run and long-run coefficients are calculated. The existence of a causal relationship between the variables is examined in step seven. Finally, based on the empirical findings, debates and conclusions are drawn, and the research is finished with future policy suggestions.



**Fig.1.** The methodology

#### 4.2. Cross-sectional dependency, unit root, and slope homogeneity

In panel data econometrics, the CD test is very important. Because a study without taking CD into account is likely to produce biased results in unit root and coefficient estimates (O’Connell 1998). Moreover, the CD test helps decide which tests (first and second generation) are appropriate for unit root, co-integration, and causality tests. Therefore, in this study, the CD test is performed using Breusch and Pagan's (1980) LM, Pesaran's (2004) CD, and Pesaran et al.'s (2008) LM<sub>adj</sub> tests.

After performing the CD test, the series are tested for unit root. This study performs the unit root test with the CIPS unit root test, a second-generation test that considers CD. The CIPS test statistic, introduced to the literature by Pesaran (2007), can be written as follows:

$$CIPS = \frac{\sum_{i=1}^N CADF_i}{N} \quad (4)$$

Here,  $CADF_i$  = the average of the extended ADF statistics for each cross-section. The critical values for this test are tabulated by Pesaran (2007).

After testing the stationarity of the series, before proceeding to the co-integration stage, the CD test for the errors obtained from the long-run equation is performed with Breusch and Pagan's (1980) LM, Pesaran's (2004) CD and Pesaran et al.'s (2008) LM<sub>adj</sub> tests.

Another important assumption of panel data models is the heterogeneity of slope coefficients. Most studies assume that slope coefficients do not vary from unit to unit, i.e., they are homogeneous. However, the effect of independent variables may differ from unit to unit. Therefore, estimators assuming that the coefficients are homogeneous will likely produce biased results (Guven et al. 2019). Therefore, before proceeding with the estimations, the slope heterogeneity test in this study is performed using delta tests developed by Pesaran and Yamagata (2008).

### 4.3. Panel co-integration test

In this study, the GUR panel co-integration test introduced by Gengenbach, Urbain, and Westerlund (2016) is used to investigate whether there is a co-integration relationship between the variables. This error correction-based panel co-integration test uses the common factor structure. The main features of this test are: i) It takes heterogeneity and CD into account, ii) It is allowed to investigate of the co-integration relationship in unbalanced panels. It allows the selection of different lag lengths for each panel unit. The GUR co-integration test can be written in vector notation as follows.

$$\Delta y_i = d\delta_{y.x_i} + \alpha_{y_i} y_{i,-1} + \omega_{i,-1} \gamma_i + \nu_i \pi_i + e_{y.x_i} = \alpha_{y_i} y_{i,-1} + g_i^d \lambda_i + e_{y.x_i} \quad (5)$$

The test statistic for this co-integration method can be written as follows:

$$\bar{T}_c = \frac{1}{N} \sum_{i=1}^N T_{c_i} \quad (6)$$

The hypotheses of this test are as follows:

$$H_0 : \alpha_{y_1} = \dots = \alpha_{y_N} = 0 \quad \text{versus} \quad (7)$$

$$H_1 : \alpha_{y_i} < 0 \quad \text{for at least some } i.$$

The test statistic in equation 6 above is compared with the critical values obtained from Gengenbach et al. (2016) in order to test whether there is co-integration.

### 4.4. Long-run elasticities

After obtaining a long-run relationship between the series, the coefficients of this long-run relationship need to be estimated. In this context, the CS-ARDL model developed by Chudik and Pesaran (2015) was used to estimate the long-term coefficients in the study. Certain advantages make this method superior to other methods. These are: i) The CS-ARDL Approach allows for the simultaneous derivation of long-run and short-run parameters and the error correction term. ii) It allows for the investigation of a long-run relationship even when the series are integrated of different orders (I(0) or I(1), but not I(2)). iii) It makes it possible to consider CD in long and short-term forecasts (Chudik and Pesaran 2015). iv) It considers the heterogeneity of slope parameters (Chudik et al. 2017). In the CS-

ARDL model, the endogeneity problem is avoided by adding lagged cross-sectional averages (A. Usman et al. 2022). The basic CS-ARDL model can be written as follows:

$$\Delta CO_{2it} = C_i + \gamma_i \left( CO_{2it-1} - \beta_i X_{it-1} - \partial_{1i} \overline{CO}_{t-1} - \partial_{2i} \overline{X}_{t-1} \right) \sum_{j=1}^{p-1} \mathcal{G}_{ij} \Delta CO_{2it-j} + \sum_{j=0}^{q-1} \zeta_{ij} \Delta X_{it-j} + \psi_{1i} \Delta \overline{CO}_{2i} + \psi_{2i} \Delta \overline{X}_t + \varepsilon_{it} \quad (8)$$

Here,  $CO_{2it}$  = dependent variable,  $X_{it-1}$  = independent variables, in the long run,  $\overline{CO}_{t-1}$  = average of the dependent variable in the long run,  $\overline{X}_{t-1}$  = average of independent variables in the long run,  $\Delta CO_{2it-j}$  = dependent variable in the short run,  $\Delta X_{it-j}$  = independent variables in the short run,  $\Delta \overline{CO}_{2i}$  = average of the dependent variable in the short run,  $\Delta \overline{X}_t$  = average of independent variables in the short run,  $\varepsilon_{it}$  = error term,  $t$  = time,  $j$  = units,  $\beta_i$  = coefficients of the long-run independent variables,  $\mathcal{G}_{ij}$  = coefficient of the short-run dependent variable,  $\zeta_{ij}$  = coefficient of the short-run independent variables,  $\psi_{1i}$  = coefficient of the mean of the short-run dependent variable and  $\psi_{2i}$  = coefficient of the mean of the short-run independent variables.

#### 4.5. Panel causality test

In the last stage of the analysis part of the study, whether there is a causality relationship between the variables is tested. The causality relationship is analyzed with the panel causality test (DH Test) introduced to the literature by Dumitrescu and Hurlin (2012). This test can be used for both homogeneous and heterogeneous panels. Moreover, since the critical values of the test can be obtained through bootstrap simulations, CD is also considered. The basic equation of the DH Test can be written as follows:

$$Y_{it} = \alpha_i + \sum_{k=1}^K \lambda_i^{(k)} Y_{it-k} + \sum_{k=1}^K \beta_i^{(k)} X_{it-k} + \varepsilon_{it} \quad (9)$$

Where  $k$  = lag length,  $\lambda_i^{(k)}$  and  $\beta_i^{(k)}$  = autoregressive and slope parameters that vary depending on the units (I), while the lag length is fixed. The null hypothesis of no causality is tested by calculating the following test statistic.

$$\overline{W}_{N,T} = \frac{1}{N} \sum_{i=1}^N W_{i,T} \quad (10)$$

Here,  $W_{i,T}$  = denotes the unit-specific Wald test statistic, and  $\overline{W}_{N,T}$  = denotes the average of Wald test statistics.

In addition, Eviews and Stata programs and appropriate codes were used for the analyses.

## 5. Empirical results and discussion

The descriptive statistics for the data set are shown in Table 4. The results show that lnPOP has the greatest mean value (17.279) and lnCO<sub>2</sub> has the lowest mean value (5.665). The variables with the highest and lowest standard deviations are, respectively, lnTEC with 1.546 and lnGDP with 0.451. More specifically, lnTEC deviates from the mean more than lnGDP does. Among all variables, the value of lnPOP is the maximum while the value of lnTEC is the minimum.

**Table 4. Descriptive statistics**

Variables	lnCO <sub>2</sub>	lnPOP	lnGDP	lnNE	lnTEC
Mean	5.665	17.279	10.421	8.581	7.844
Std. Dev.	1.357	1.204	0.451	1.028	1.546
Maximum	8.680	19.619	11.375	10.140	10.324
Minimum	3.487	15.380	8.308	4.521	1.324
Observations	492	492	492	492	492

CD analysis is crucial in studies of panel data. This is because a shock's effects—crisis, flood, fire, etc.—are likely to spread to neighboring countries. In this situation, research without accounting for CD might result in biased findings. This investigation examined CD using the LM, CD, and LM<sub>adj</sub> tests; the outcomes are shown in Table 5. At a 1% significance level, all three statistics strongly reject the null hypothesis that there is no CD. In other words, the data examined in this study contain a CD.

**Table 5. CD test results**

Variables	LM	p-value	CD	p-value	LM <sub>adj</sub>	p-value
lnCO <sub>2</sub>	977.711*	0.000	15.481*	0.000	79.204*	0.000
lnPOP	2256.381*	0.000	47.208*	0.000	190.498*	0.000
lnGDP	2559.682*	0.000	50.581*	0.000	216.897*	0.000
lnNE	1091.803*	0.000	27.145*	0.000	89.135*	0.000
lnTEC	1332.949*	0.000	26.002*	0.000	110.123*	0.000

Note: \* denote the rejection of the null of cross-section dependence at 1% level.

The unit root test for the variables using the CIPS unit root test was performed after confirming the existence of CD. The results of the CIPS unit root test are shown in Table 6 below. At the first difference, I(1), all variables become

stationary. The second difference, I(2), does not cause any of the variables to become fixed.

**Table 6. CIPS test results**

Variables	Test statistic	Variables	Test statistic
lnCO <sub>2</sub>	-1.888	ΔlnCO <sub>2</sub>	-4.649***
lnPOP	-1.969	ΔlnPOP	-2.373**
lnGDP	-1.950	ΔlnGDP	-3.439***
lnNE	-2.038	ΔlnNE	-4.231***
lnTEC	-1.999	ΔlnTEC	-4.086***

Note: \*, \*\*, and \*\*\* denote the rejection of the null of unit root at 1%, 5%, and 10% levels, respectively. Critical values of 1%, 5%, and 10% of CIPS are -2.51, -2.30, and -2.18, respectively.

**Table 7. CD, GUW co-integration, and slope heterogeneity test results**

<i>Panel A: CD test results</i>			
Test	Test statistic	p-value	
LM	296.5***	0.000	
CD	64.17***	0.000	
LM <sub>adj</sub>	13.57***	0.000	
<i>Panel B: GUW co-integration test results</i>			
y(t-1)	Coefficient	T-bar	p-value
	-0.816***	-4.194	≤ 0.01
<i>Panel C: Slope heterogeneity test results</i>			
Delta test	p-value	Delta <sub>adj</sub> test	p-value
28.684***	0.000	21.046***	0.000

Note: \*\*\* indicates that the coefficients are significant at the 1% significance level.

The CD test for the errors obtained from the long-run equation was carried out using LM, CD, and LM<sub>adj</sub> tests right after the unit root test of the variables and before moving on to the co-integration stage. The findings in Table 7 clearly support the presence of CD for errors at a 1% level of significance. The GUW co-integration test was used to determine whether there was a long-term relationship between the variables after the CD test. At a 1% significance level, the GUW co-integration test findings in Table 5 show a long-term relationship between the variables. The long-term relationship between the variables must be calculated if any exists. The homogeneity of the long-run parameters should be checked prior to estimating the

relationship and the right estimator should be used. The long-run coefficients in this study are shown to be heterogeneous at a 1% significance level when the homogeneity of the long-run coefficients is examined using delta tests, as shown in Table 7.

Following the determination of co-integration, the long and short-run parameters are estimated using the CS-ARDL procedure. According to the CS-ARDL estimation results presented in Table 8, a 1% increase in lnPOP in both the long and short run increases lnCO<sub>2</sub> by 0.671% and 1.262%, respectively. In other words, an increase in lnPOP significantly increases environmental pollution in OECD countries in the long and short run. This result can be interpreted as a sign that the population in OECD countries remains insensitive to environmental issues. Pata and Yurtkuran (2018) obtained similar results in their study for Turkey. When the long and short-run effects of lnGDP on lnCO<sub>2</sub> are analyzed, it is observed that lnGDP has a positive effect of 0.341% and 0.674%, respectively. However, this effect is more minor in the long run compared to the short run. With an increase in income, it will be possible for environmental quality to improve. This result is supported by Richmond and Kaufmann (2006), Iwata et al. (2010), Baek and Pride (2014), Pata and Yurtkuran (2018), and Yasmeeen et al. (2023).

**Table 8. CS-ARDL test results**

Variables	Coefficient	z-statistic	p-value
Long-run			
lnPOP	0.671**	2.15	0.031
lnGDP	0.341***	3.19	0.001
lnNE	-0.027**	-2.33	0.020
lnTEC	-0.029**	-2.22	0.027
Short-run			
ΔECM (-1)	-1.912***	-34.35	0.000
ΔlnPOP	1.262**	2.09	0.037
ΔlnGDP	0.674***	3.30	0.001
ΔlnNE	-0.054**	-2.49	0.013
ΔlnTEC	-0.057**	-2.12	0.034

Note: \*\*\*, \*\*, and \* indicate that the coefficients are significant at the 1%, 5%, and 10% significance levels, respectively.

The effect of lnNE on lnCO<sub>2</sub> is -0.054% in the short run and (-0.027%) in the long run. This finding indicates that lnNE reduces lnCO<sub>2</sub> both in the short and long run. This result is consistent with the results of Apergis et al. (2010), Iwata et al. (2011), Al-Mulali (2014), Saidi and Omri (2020), Danish et al. (2022), Naimoğlu (2022) and Wang et al. (2023), unlike Jaforullah and King (2014), Saidi and Mbarek



(2016) and Mahmood et al. (2020). With the Kyoto Protocol, the share of nuclear energy use is increasing. Ultimately, fewer resources are used in the production phase of nuclear energy. Therefore, less waste is released into the environment, resulting in fewer GHG emissions (A. Usman et al. 2022). Thus, nuclear energy can be an important tool for OECD countries to reduce CO<sub>2</sub> emissions and improve environmental quality.

**Table 9. DH test results**

H <sub>0</sub>	Z-bar	p-value
lnPOP → lnCO <sub>2</sub>	5.218	0.436
lnCO <sub>2</sub> → lnPOP	10.116**	0.040
lnGDP → lnCO <sub>2</sub>	1.593	0.620
lnCO <sub>2</sub> → lnGDP	0.424	0.690
lnNE → lnCO <sub>2</sub>	-0.048	0.985
lnCO <sub>2</sub> → lnNE	0.123	0.970
lnTEC → lnCO <sub>2</sub>	2.288*	0.080
lnCO <sub>2</sub> → lnTEC	3.381	0.420
lnPOP → lnGDP	5.333	0.480
lnGDP → lnPOP	14.456**	0.040
lnPOP → lnNE	21.128***	0.000
lnNE → lnPOP	1.518	0.810
lnPOP → lnTEC	0.421	0.970
lnTEC → lnPOP	1.523	0.740
lnGDP → lnNE	0.069	0.970
lnNE → lnGDP	2.871	0.430
lnGDP → lnTEC	1.118	0.280
lnTEC → lnGDP	1.681	0.620
lnNE → lnTEC	0.500	0.890
lnTEC → lnNE	4.875	0.260

Note: \*, \*\*, and \*\*\* denote the rejection of the null of non-causality at 1%, 5%, and 10% levels, respectively. P-values computed using bootstrap replications.

Similarly, as expected, the impact of TEC on CO<sub>2</sub> emissions is negative. CO<sub>2</sub> emissions are decreased by 0.029% over the long run with a 1% rise in TEC, whereas they are reduced by 0.057% over the short term. The findings of Sulaiman et al. (2013), Pata and Yurtkuran (2018), and Usman and Hammar (2021) are all in agreement with this conclusion. This negative impact of TEC on CO<sub>2</sub> emission

levels is a significant indication that OECD nations may use renewable energy sources like nuclear energy to lower environmental pollution. The impacts of nuclear and renewable energy on CO<sub>2</sub> emissions, both in the short and long terms, are deemed to be quite little when compared to other factors. By creating a slowdown in emission levels, progressively expanding the usage of these two energy in this context can assist to greatly reduce environmental pollution.

The DH causality test was then used to see whether there could be a causal relationship between the variables. The results of the DH causality analysis are presented in Table 9, and they show that there is a unidirectional causality link between lnCO<sub>2</sub> and lnGDP and lnPOP, as well as between lnPOP and lnNE. The findings show that lnNE and lnTEC have only a little influence on emission levels since there is no causal relationship between them and lnCO<sub>2</sub>. From this perspective, this result is consistent with the CS-ARDL findings and suggests that the CS-ARDL coefficients are reliable.

## **6. Conclusions**

The recent increase in industrialization and globalization worldwide has increased the energy demand. The rise in fossil fuel consumption has caused significant damage to the environment. Global warming, which is brought on by an increase in CO<sub>2</sub> emissions as a result of the increased use of fossil fuels for energy, has been one of the main problems for a number of countries. Due to this adverse perspective, environmental awareness has grown, and countries are now turning to renewable energy sources to satisfy their energy needs. Nuclear and renewable energy are currently in the forefront as a result of the challenge of global warming. Given this fact, discussions over the importance of alternative energy sources (such as nuclear and renewable energy) in lowering CO<sub>2</sub> emissions have gained prominence in existing literature.

This study's main goal is to experimentally investigate the long- and short-term impacts of POP, GDP, NE, and TEC on CO<sub>2</sub> emissions within the STIRPAT model for 12 countries in the OECD from 1990 to 2020. CD is examined at the initial stage of the empirical analysis. The CIPS unit root test is then used to assess the varied integration levels. Following the unit root test of the variables, before moving on to the co-integration stage, the CD test for the errors obtained from the long-run equation was carried out with LM, CD, and LM<sub>adj</sub> tests. After the CD test, the GUR co-integration test was used to determine whether the variables had a long-run relationship. As a result of the GUR test, it is determined that there is a long-run relationship between the variables at a 1% significance level. The CS-ARDL approach was used to estimate the long-run and short-run parameters once co-integration had been established. The research reveals that a growth in lnPOP causes CO<sub>2</sub> emissions to rise in several OECD member countries, both in the long and short term. The results also demonstrate that lnNE and lnTEC reduce lnCO<sub>2</sub> in the long and short terms. The research' findings highlight the fact that using lnNE and lnTEC concurrently is the best way to lower CO<sub>2</sub> emissions in a few OECD nations. Accordingly, several significant policy recommendations for relevant stakeholders are provided below based on the study's results.

First, selected OECD countries should use clean technologies to pursue income-enhancing economic growth with less environmental damage. In doing so,

incentives should be provided for the increased use of renewable and nuclear energy in production processes.

Second, it is crucial for the OECD countries to set stringent rules and inspections for the safe use of nuclear energy. In order to promote investment in and usage of renewable energy sources, different financial incentives and subsidies should be offered. Additionally, incentives should be developed to help academics working in nuclear and renewable energy collaborate with worldwide stakeholders. Additionally, it is important to grow and develop infrastructure investments for the use of nuclear and renewable energy sources, notably those for the distribution and storage of clean energy from renewable energy sources. Finally, awareness-raising activities should be carried out by stakeholders and relevant institutions to increase the acceptability of nuclear and renewable energy use in society.

This study is restricted to countries in the OECD and uses the STIRPAT model to analyze how nuclear and renewable energy affect CO<sub>2</sub> emissions. Future research on the effects of these two energy sources on broader metrics—instead of CO<sub>2</sub> emissions for different countries and country groups—such as the ecological footprint or load capacity factor, would be interesting.

**Authors' contribution** SC: conceptualization, methodology, data curation, writing—original draft, formal analysis, visualization. SY: investigation, methodology, supervision. İHP: writing—original draft, conceptualization, writing—review and editing.

**Funding** This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

**Data availability** Data will be made available on request.

#### **Declarations**

**Ethical approval** This article does not contain any studies with human participants performed by any of the authors.

**Consent to participate** Not applicable.

**Consent for publication** Not applicable.

**Competing interests** The authors declare no competing interests.

#### **Appendix**

**Table 1A. Countries**

Belgium	Germany	Netherlands	Switzerland
Finland	Japan	Spain	United Kingdom
France	South Korea	Sweden	United States

## References

- Ahmed, Z., Zafar, M. W., Ali, S., & Danish. (2020). Linking urbanization, human capital, and the ecological footprint in G7 countries: An empirical analysis. *Sustainable Cities and Society*, 55, 102064. <https://doi.org/10.1016/j.scs.2020.102064>
- Al-Mulali, U. (2014). Investigating the impact of nuclear energy consumption on GDP growth and CO2 emission: A panel data analysis. *Progress in Nuclear Energy*, 73, 172–178. <https://doi.org/10.1016/j.pnucene.2014.02.002>
- Apergis, N., Payne, J. E., Menyah, K., & Wolde-Rufael, Y. (2010). On the causal dynamics between emissions, nuclear energy, renewable energy, and economic growth. *Ecological Economics*, 69(11), 2255–2260. <https://doi.org/10.1016/j.ecolecon.2010.06.014>
- Azam, A., Rafiq, M., Shafique, M., Zhang, H., & Yuan, J. (2021). Analyzing the effect of natural gas, nuclear energy and renewable energy on GDP and carbon emissions: A multi-variate panel data analysis. *Energy*, 219, 119592. <https://doi.org/10.1016/j.energy.2020.119592>
- Baek, J., & Pride, D. (2014). On the income-nuclear energy-CO2 emissions nexus revisited. *Energy Economics*, 43, 6–10. <https://doi.org/10.1016/j.eneco.2014.01.015>
- Bakhsh, K., Rose, S., Ali, M. F., Ahmad, N., & Shahbaz, M. (2017). Economic growth, CO2 emissions, renewable waste and FDI relation in Pakistan: New evidences from 3SLS. *Journal of Environmental Management*, 196, 627–632. <https://doi.org/10.1016/j.jenvman.2017.03.029>
- Bekun, F. V., Alola, A. A., & Sarkodie, S. A. (2019). Toward a sustainable environment: Nexus between CO2 emissions, resource rent, renewable and nonrenewable energy in 16-EU countries. *Science of the Total Environment*, 657, 1023–1029. <https://doi.org/10.1016/j.scitotenv.2018.12.104>
- Ben Jebli, M., Farhani, S., & Guesmi, K. (2020). Renewable energy, CO2 emissions and value added: Empirical evidence from countries with different income levels. *Structural Change and Economic Dynamics*, 53, 402–410. <https://doi.org/10.1016/j.strueco.2019.12.009>
- BP. (2022). British Petroleum. <https://www.bp.com/en/global/corporate/energy-economics/statistical-review-of-world-energy.html>
- BP. (2023). British Petroleum. <https://www.bp.com/en/global/corporate/energy-economics/statistical-review-of-world-energy.html>
- Breusch, T. S., & Pagan, A. R. (1980). The Lagrange Multiplier Test and its Applications to Model Specification in Econometrics. *The Review of Economic Studies*, 47(1), 239. <https://doi.org/10.2307/2297111>
- Çamkaya, S., Polat, İ. H., & Polat, Ü. (2022). Are Foreign Direct Investments Effective on Environmental Quality in Turkey? an Approach With Non-Linear Ardl Method. *İktisadi İdari ve Siyasal Araştırmalar Dergisi*, 30–46.

<https://doi.org/10.25204/iktisad.1023839>

- Charfeddine, L., & Kahia, M. (2019). Impact of renewable energy consumption and financial development on CO2 emissions and economic growth in the MENA region: A panel vector autoregressive (PVAR) analysis. *Renewable Energy*, 139, 198–213. <https://doi.org/10.1016/j.renene.2019.01.010>
- Chopra, R., Magazzino, C., Shah, M. I., Sharma, G. D., Rao, A., & Shahzad, U. (2022). The role of renewable energy and natural resources for sustainable agriculture in ASEAN countries: Do carbon emissions and deforestation affect agriculture productivity? *Resources Policy*, 76, 102578. <https://doi.org/10.1016/j.resourpol.2022.102578>
- Chudik, A., Mohaddes, K., Pesaran, M. H., & Raissi, M. (2017). Is there a debt-threshold effect on output growth? *Review of Economics and Statistics*, 99(1), 135–150. [https://doi.org/10.1162/REST\\_a\\_00593](https://doi.org/10.1162/REST_a_00593)
- Chudik, A., & 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. <https://doi.org/10.1016/j.jeconom.2015.03.007>
- Danish, Ulucak, R., & Erdogan, S. (2022). The effect of nuclear energy on the environment in the context of globalization: Consumption vs production-based CO2 emissions. *Nuclear Engineering and Technology*, 54(4), 1312–1320. <https://doi.org/10.1016/j.net.2021.10.030>
- Dietz, T., & Rosa, E. A. (1997). Effects of population and affluence on CO2 emissions. *Proceedings of the National Academy of Sciences of the United States of America*, 94(1), 175–179. <https://doi.org/10.1073/pnas.94.1.175>
- Dietz, T., Rosa, E. A., & York, R. (2007). Driving the human ecological footprint. *Frontiers in Ecology and the Environment*, 5(1), 13–18. [https://doi.org/10.1890/1540-9295\(2007\)5\[13:DTHEF\]2.0.CO;2](https://doi.org/10.1890/1540-9295(2007)5[13:DTHEF]2.0.CO;2)
- Doğanlar, M., Mike, F., Kızılkaya, O., & Karlılar, S. (2021). Testing the long-run effects of economic growth, financial development and energy consumption on CO2 emissions in Turkey: new evidence from RALS cointegration test. *Environmental Science and Pollution Research*, 28(25), 32554–32563. <https://doi.org/10.1007/s11356-021-12661-y>
- Dong, K., Sun, R., & Hochman, G. (2017). Do natural gas and renewable energy consumption lead to less CO2 emission? Empirical evidence from a panel of BRICS countries. *Energy*, 141, 1466–1478. <https://doi.org/10.1016/j.energy.2017.11.092>
- Dong, K., Sun, R., Jiang, H., & Zeng, X. (2018). CO2 emissions, economic growth, and the environmental Kuznets curve in China: What roles can nuclear energy and renewable energy play? *Journal of Cleaner Production*, 196, 51–63. <https://doi.org/10.1016/j.jclepro.2018.05.271>
- Dumitrescu, E. I., & Hurlin, C. (2012). Testing for Granger non-causality in heterogeneous panels. *Economic Modelling*, 29(4), 1450–1460.

<https://doi.org/10.1016/j.econmod.2012.02.014>

- Gengenbach, C., Urbain, J.-P., & Westerlund, J. (2016). Errors Correction Testing in Panels with Common Stochastic Trends. *Journal of Applied Econometrics*, 21, 982–1004. <https://doi.org/10.1002/jae>
- Güven, M., Calik, E., Cetinguc, B., Guloglu, B., & Calisir, F. (2019). Assessing the effects of flight delays, distance, number of passengers and seasonality on revenue. *Kybernetes*, 48(9), 2138–2149. <https://doi.org/10.1108/K-01-2018-0022>
- Hashem Pesaran, M., & Yamagata, T. (2008). Testing slope homogeneity in large panels. *Journal of Econometrics*, 142(1), 50–93. <https://doi.org/10.1016/j.jeconom.2007.05.010>
- Hassan, A., Haseeb, M., Bekun, F. V., Yazdi, A. H., Ullah, E., & Hossain, M. E. (2024). Does nuclear energy mitigate CO2 emissions in the USA? Testing IPAT and EKC hypotheses using dynamic ARDL simulations approach. *Progress in Nuclear Energy*, 169, 105059.
- Inglesi-Lotz, R., & Dogan, E. (2018). The role of renewable versus non-renewable energy to the level of CO2 emissions a panel analysis of sub-Saharan Africa's Big 10 electricity generators. *Renewable Energy*, 123, 36–43. <https://doi.org/10.1016/j.renene.2018.02.041>
- Iwata, H., Okada, K., & Samreth, S. (2010). Empirical study on the environmental Kuznets curve for CO2 in France: The role of nuclear energy. *Energy Policy*, 38(8), 4057–4063. <https://doi.org/10.1016/j.enpol.2010.03.031>
- Iwata, H., Okada, K., & Samreth, S. (2011). A note on the environmental Kuznets curve for CO2: A pooled mean group approach. *Applied Energy*, 88(5), 1986–1996. <https://doi.org/10.1016/j.apenergy.2010.11.005>
- Jaforullah, M., & King, A. (2014). Does the use of renewable energy sources mitigate CO2 emissions? A reassessment of the US evidence. *Energy Economics*, 49, 711–717. <https://doi.org/10.1016/j.eneco.2015.04.006>
- Jardón, A., Kuik, O., & Tol, R. S. J. (2017). Economic growth and carbon dioxide emissions: An analysis of Latin America and the Caribbean. *Atmosfera*, 30(2), 87–100. <https://doi.org/10.20937/ATM.2017.30.02.02>
- Jiang, Y., Batool, Z., Raza, S. M. F., Haseeb, M., Ali, S., & Zain Ul Abidin, S. (2022). Analyzing the Asymmetric Effect of Renewable Energy Consumption on Environment in STIRPAT-Kaya-EKC Framework: A NARDL Approach for China. *International Journal of Environmental Research and Public Health*, 19(12). <https://doi.org/10.3390/ijerph19127100>
- Karaaslan, A., & Çamkaya, S. (2022). The relationship between CO2 emissions, economic growth, health expenditure, and renewable and non-renewable energy consumption: Empirical evidence from Turkey. *Renewable Energy*, 190, 457–466. <https://doi.org/10.1016/j.renene.2022.03.139>
- Magazzino, C., Mele, M., Schneider, N., & Vallet, G. (2020). The relationship between nuclear energy consumption and economic growth: Evidence from Switzerland. *Environmental Research Letters*, 15(9), 0940a5.

<https://doi.org/10.1088/1748-9326/abaded>

- Mahmood, H. (2022). Nuclear energy transition and CO2 emissions nexus in 28 nuclear electricity-producing countries with different income levels. *PeerJ*, 10, e13780. <https://doi.org/10.7717/peerj.13780>
- Mahmood, N., Danish, Wang, Z., & Zhang, B. (2020). The role of nuclear energy in the correction of environmental pollution: Evidence from Pakistan. *Nuclear Engineering and Technology*, 52(6), 1327–1333. <https://doi.org/10.1016/j.net.2019.11.027>
- Majeed, M. T., Ozturk, I., Samreen, I., & Luni, T. (2022). Evaluating the asymmetric effects of nuclear energy on carbon emissions in Pakistan. *Nuclear Engineering and Technology*, 54(5), 1664–1673. <https://doi.org/10.1016/j.net.2021.11.021>
- Menyah, K., & Wolde-Rufael, Y. (2010). CO2 emissions, nuclear energy, renewable energy and economic growth in the US. *Energy Policy*, 38(6), 2911–2915. <https://doi.org/10.1016/j.enpol.2010.01.024>
- Mujtaba, A., Jena, P. K., Bekun, F. V., & Sahu, P. K. (2022). Symmetric and asymmetric impact of economic growth, capital formation, renewable and non-renewable energy consumption on environment in OECD countries. *Renewable and Sustainable Energy Reviews*, 160, 112300. <https://doi.org/10.1016/j.rser.2022.112300>
- Murshed, M., Saboori, B., Madaleno, M., Wang, H., & Doğan, B. (2022). Exploring the nexuses between nuclear energy, renewable energy, and carbon dioxide emissions: The role of economic complexity in the G7 countries. *Renewable Energy*, 190, 664–674. <https://doi.org/10.1016/j.renene.2022.03.121>
- Naimoğlu, M. (2022). The impact of nuclear energy use, energy prices and energy imports on CO2 emissions: Evidence from energy importer emerging economies which use nuclear energy. *Journal of Cleaner Production*, 373, 133937. <https://doi.org/10.1016/j.jclepro.2022.133937>
- Narayan, P. K., & Narayan, S. (2010). Carbon dioxide emissions and economic growth: Panel data evidence from developing countries. *Energy Policy*, 38(1), 661–666. <https://doi.org/10.1016/j.enpol.2009.09.005>
- O’Connell, P. G. J. (1998). The overvaluation of purchasing power parity. *Journal of International Economics*, 44(1), 1–19. [https://doi.org/10.1016/S0022-1996\(97\)00017-2](https://doi.org/10.1016/S0022-1996(97)00017-2)
- OECD. (2023). Organisation for Economic Co-Operation and Development. <https://data.oecd.org/>
- OWD. (2023). Our World in Data. <https://ourworldindata.org/>
- Özbuğday, F. C., & Erbas, B. C. (2015). How effective are energy efficiency and renewable energy in curbing CO2 emissions in the long run? A heterogeneous panel data analysis. *Energy*, 82, 734–745. <https://doi.org/10.1016/j.energy.2015.01.084>

- Ozgur, O., Yilanci, V., & Kongkuah, M. (2022). Nuclear energy consumption and CO<sub>2</sub> emissions in India: Evidence from Fourier ARDL bounds test approach. *Nuclear Engineering and Technology*, 54(5), 1657–1663. <https://doi.org/10.1016/j.net.2021.11.001>
- Pata, Ugur Korkut, Dam, M. M., & Kaya, F. (2023). How effective are renewable energy, tourism, trade openness, and foreign direct investment on CO<sub>2</sub> emissions? An EKC analysis for ASEAN countries. *Environmental Science and Pollution Research*, 30(6), 14821–14837. <https://doi.org/10.1007/s11356-022-23160-z>
- Pata, Uğur Korkut, & Yurtkuran, S. (2018). Yenilenebilir Enerji Tüketimi, Nüfus Yoğunluğu ve Finansal Gelişmenin Co2 Salımın Etkisi:Türkiye Örneği. *Uluslararası İktisadi ve İdari İncelemeler Dergisi*, 303–318. <https://doi.org/10.18092/ulikidince.441173>
- Pesaran, M. H. (2004). *General diagnostic tests for cross-sectional dependence in panels*. CESifo Working Paper Series No. 1229; IZA Discussion Paper No. 1240. <https://doi.org/10.1007/s00181-020-01875-7>
- Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross-section dependence. *Journal of Applied Econometrics*, 22, 265–312.
- Pesaran, M. H., Ullah, A., & Yamagata, T. (2008). A bias-adjusted LM test of error cross-section independence. *Econometrics Journal*, 11, 105–127.
- Rahman, M. M., & Alam, K. (2021). Clean energy, population density, urbanization and environmental pollution nexus: Evidence from Bangladesh. *Renewable Energy*, 172, 1063–1072. <https://doi.org/10.1016/j.renene.2021.03.103>
- Rehman, A., Ma, H., Ozturk, I., & Radulescu, M. (2022). Revealing the dynamic effects of fossil fuel energy, nuclear energy, renewable energy, and carbon emissions on Pakistan's economic growth. *Environmental Science and Pollution Research*, 29(32), 48784–48794. <https://doi.org/10.1007/s11356-022-19317-5>
- Richmond, A. K., & Kaufmann, R. K. (2006). Is there a turning point in the relationship between income and energy use and/or carbon emissions? *Ecological Economics*, 56(2), 176–189. <https://doi.org/10.1016/j.ecolecon.2005.01.011>
- Saidi, K., & Ben Mbarek, M. (2016). Nuclear energy, renewable energy, CO<sub>2</sub> emissions, and economic growth for nine developed countries: Evidence from panel Granger causality tests. *Progress in Nuclear Energy*, 88, 364–374. <https://doi.org/10.1016/j.pnucene.2016.01.018>
- Saidi, K., & Omri, A. (2020). Reducing CO<sub>2</sub> emissions in OECD countries: Do renewable and nuclear energy matter? *Progress in Nuclear Energy*, 126, 103425. <https://doi.org/10.1016/j.pnucene.2020.103425>
- Saint Akadiri, S., Alola, A. A., Akadiri, A. C., & Alola, U. V. (2019). Renewable energy consumption in EU-28 countries: Policy toward pollution mitigation and economic sustainability. *Energy Policy*, 132, 803–810. <https://doi.org/10.1016/j.enpol.2019.06.040>



- Shahbaz, M., & Sinha, A. (2019). Munich Personal RePEc Archive Environmental Kuznets Curve for CO2 Emission : A Literature Survey. *Journal of Economic Studies*, (86281).
- Sulaiman, J., Azman, A., & Saboori, B. (2013). The potential of renewable energy: Using the environmental kuznets curve model. *American Journal of Environmental Sciences*, 9(2), 103–112. <https://doi.org/10.3844/ajessp.2013.103.112>
- Usman, A., Ozturk, I., Naqvi, S. M. M. A., Ullah, S., & Javed, M. I. (2022). Revealing the nexus between nuclear energy and ecological footprint in STIRPAT model of advanced economies: Fresh evidence from novel CS-ARDL model. *Progress in Nuclear Energy*, 148, 104220. <https://doi.org/10.1016/j.pnucene.2022.104220>
- Usman, M., & Hammar, N. (2021). Dynamic relationship between technological innovations, financial development, renewable energy, and ecological footprint: fresh insights based on the STIRPAT model for Asia Pacific Economic Cooperation countries. *Environmental Science and Pollution Research*, 28(12), 15519–15536. <https://doi.org/10.1007/s11356-020-11640-z>
- Wang, Q., Guo, J., Li, R., & Jiang, X. ting. (2023). Exploring the role of nuclear energy in the energy transition: A comparative perspective of the effects of coal, oil, natural gas, renewable energy, and nuclear power on economic growth and carbon emissions. *Environmental Research*, 221, 115290. <https://doi.org/10.1016/j.envres.2023.115290>
- Wang, S., Zafar, M. W., Vasbieva, D. G., & 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.
- WDI. (2022). World Bank. <https://databank.worldbank.org/source/world-development-indicators>
- WDI. (2023). World Bank. <https://databank.worldbank.org/source/world-development-indicators>
- Yasmeen, R., Zhang, X., Sharif, A., Shah, W. U. H., & Sorin Dincă, M. (2023). The role of wind energy towards sustainable development in top-16 wind energy consumer countries: Evidence from STIRPAT model. *Gondwana Research*, 121, 56–71. <https://doi.org/10.1016/j.gr.2023.02.024>
- Yilanci, V., & Pata, U. K. (2020). Investigating the EKC hypothesis for China: the role of economic complexity on ecological footprint. *Environmental Science and Pollution Research*, 27(26), 32683–32694. <https://doi.org/10.1007/s11356-020-09434-4>
- York, R., Rosa, E. A., & Dietz, T. (2003). STIRPAT, IPAT and ImPACT: Analytic tools for unpacking the driving forces of environmental impacts. *Ecological Economics*, 46(3), 351–365. [https://doi.org/10.1016/S0921-8009\(03\)00188-5](https://doi.org/10.1016/S0921-8009(03)00188-5)
- Zafar, M. W., Saleem, M. M., Destek, M. A., & Caglar, A. E. (2022). The dynamic

linkage between remittances, export diversification, education, renewable energy consumption, economic growth, and CO2 emissions in top remittance-receiving countries. *Sustainable Development*, 30(1), 165–175. <https://doi.org/10.1002/sd.2236>

Zhang, S., Liu, J., & Liu, X. (2023). Comparing the environmental impacts of nuclear and renewable energy in top 10 nuclear-generating countries: evidence from STIRPAT model. *Environmental Science and Pollution Research*, 30(11), 31791–31805. <https://doi.org/10.1007/s11356-022-24438-y>