Journal of Cleaner Production 434 (2024) 139655

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

The relationship between renewable energy production and CO_2 emissions in 27 OECD countries: A panel cointegration and Granger non-causality approach

Gaetano Perone

Department of Economics and Management, University of Pisa (Pisa), Italy

ARTICLE INFO

Handling Editor: Panos Seferlis

Keywords:
CO_2 emissions
Renewable energy
Panel cointegration
PMG estimator
CCEMG estimator
Granger non-causality
OECD countries

ABSTRACT

Human-caused CO_2 emissions are the primary cause of global warming. In this regard, determining the most effective approach for lowering CO_2 emissions and the collateral risk of catastrophic natural disasters is crucial. This study examines the long-run relationship between disaggregated renewable energy production and carbon dioxide (CO_2) emissions per capita for a panel of 27 OECD countries from 1965 to 2020. The panel-autoregressive distributed lag (ARDL) models of the pooled mean group (PMG), mean group (MG), and dynamic fixed effect (DFE) were used to evaluate the relationship between CO_2 emissions and energy production from biofuel, aggregated geothermal and biomass (GEOB), hydropower, nuclear, solar, and wind. As robustness checks, fully modified ordinary least squares (FMOLS), dynamic ordinary least squares (DOLS), and common correlated effects mean group (CCEMG) estimators were used. Then, using a generalized method of moment (GMM) framework for panel vector autoregression (PVAR), the Granger non-causality between CO_2 emissions and renewable energy production was investigated. GEOB, hydropower, nuclear, solar, and wind were found to be negatively and significantly correlated with CO_2 emissions. GEOB, hydropower, and solar were the most effective renewable resources in reducing CO_2 emissions. Granger non-causality approach showed unidirectional causation from hydropower, solar, and wind to CO_2 emissions, bidirectional causation between CO_2, and biofuel and GEOB, and unidirectional causation from CO_2 emissions to nuclear. The findings were consistent across different model specifications and suggested a faster transition to GEOB, hydropower, and solar energy in OECD countries to reduce CO_2 emissions and enhance environmental sustainability.

1. Introduction

The need to balance economic growth and biodiversity preservation, as well as growing environmental concern about the impact of economic activities on carbon dioxide (CO_2) emissions, have pushed the international community to develop common agendas on eco-sustainability and global warming issues over the last three decades. The most noteworthy example is the Kyoto Protocol, enacted on December 11, 1997, which established legally binding and differentiated emission reduction objectives for greenhouse gas (GHG) emissions for 37 industrialized countries and the European Union (United Nations, 1997). However, multiple international awareness-raising campaigns have not always yielded the expected effects. In fact, the OECD countries' contribution to the total production of energy from fossil fuels (i.e., coal, gas, and oil) remained significant in 2021, accounting for 52% of the total (BP Statistical Review of World Energy, 2022). This is particularly worrying considering that 92% of global CO_2 emissions come from fossil fuels (World Resource Institute, 2022).

Moreover, the annual global average CO_2, methane (CH_4), and nitrous oxide (N_2O) concentrations reached record-breaking levels in 2021, hitting 414.7, 1895.7, and 334.3 parts per million (ppm), respectively (Blunden and Boyer, 2022). According to the most recent data, CO_2 emissions are the major global contributors to GHG emissions, accounting for 74.4% of total GHG emissions, followed by CH_4 and N_2O, which accounted for 17.3% and 6.2%, respectively, of total GHG emissions. Meanwhile, the Earth's temperature has significantly risen over the last decades. In particular, in 2020, the global average land-sea temperature was almost 1 °C greater than the 1961–1990 global land-sea average temperature (Ritchie et al., 2020a).

As a result, a substantial body of research has been devoted to the study of the link between CO_2 emissions and global warming, with the conclusion that an ongoing rise in CO_2 emissions, primarily caused by human activities, is the primary driver of global climate change

E-mail address: gaetano.perone@ec.unipi.it.

https://doi.org/10.1016/j.jclepro.2023.139655
Received 5 March 2023; Received in revised form 3 November 2023; Accepted 6 November 2023
Available online 17 November 2023
0959-6526/

Nomenclature

AGRI	agricultural land use
AMG	augmented mean group
ANS	American Nuclear Society
ARDL	panel-autoregressive distributed lag
BP SRWE	BP Statistical Review of World Energy
BRICTS	Brazil, Russian Federation, India, China, Turkey, and South Africa
CADF	cross-sectionally augmented Dickey-Fuller
CATT	cattle density
CCEMG	common correlated effects mean group
CCR	canonical cointegrating regression
CH4	methane
CIPS	cross-sectionally augmented IPS
CO2	carbon dioxide
CWE	combustible renewables and waste
DFE	dynamic fixed effect
DOLS	dynamic ordinary least squares
EC	energy consumption
ECB	European Central Bank
ECT	error correction term
EERE	Energy Efficiency & Renewable Energy
EF	ecological footprint
ECB	European Central Bank
FAO	Food and Agriculture Organization of the United Nations
FERT	fertilizers
FMOLS	fully modified ordinary least squares
GEOB	geothermal and biomass
GHG	greenhouse gas
GMM	generalized method of moment
HAC	heteroskedasticity and autocorrelation consistent
IAEA	International Atomic Energy Agency
IEA	International Energy Agency
IHA	International Hydropower Association
IPCC	Intergovernmental Panel on Climate Change
IRENA	International Renewable Energy Agency
KT	Karavias and Tzavalis
MENA	Middle East and North Africa
MG	mean group
N2O	nitrous oxide
NOOA	National Centers for Environmental Information
OECD	Organization for Economic Co-operation and Development
OLS	ordinary least squares
PD	population density
PMG	pooled mean group
ppm	parts per million
PVAR	panel vector autoregression
PVOUT	photovoltaic power potential
REP	renewable energy production
RMSE	root mean squared error
STIRPAT	stochastic impacts by regression on population, affluence, and technology
TWh	terawatt hours
USD	United States dollar
USEPA	United States Environmental Protection Agency
VAR	vector autoregression
VECM	vector error correction model
WRI	World Resource Institute
WTM	wavelet transform model

(Solomon et al., 2009; Stips et al., 2016; Al-Ghussain, 2019).

In this regard, the development and use of renewable energy derived from natural sources and processes is one of the most effective strategies for lowering energy-related carbon emissions and replacing fossil fuels (International Renewable Energy Agency, 2019). Their inclusion in the energy mix may have a dual benefit. On the one hand, renewable energy generation, such as wind and solar photovoltaic (PV), is already less expensive and more competitive than traditional fossil fuels (Ram et al., 2018). Renewable energy, on the other hand, is an ally in reducing human impact on the environment, with a 1% increase in aggregated renewable energy consumption/production resulting in a 0.1%–0.6% drop in CO_2 emissions (Cheng et al., 2019; Saidi and Omri, 2020; Jamil et al., 2022). Nonrenewable energy, typically derived from fossil fuels, on the other hand, has been shown to harm environmental ecosystems. For example, a 1% increase in aggregated nonrenewable energy production/consumption can result in a 0.68%–1% increase in CO_2 emissions (Chen et al., 2019; Dong et al., 2020; Saleem et al., 2022).

This study is noteworthy for the following reasons. Climate change is increasing the frequency of unexpected natural disasters, including heatwaves, hurricanes, drought, flooding, storms, and wildfires (Al-Ghussain, 2019). These natural calamities, which are mostly unforeseen, have major consequences for the environment and human society. They can, for example, affect ecosystems by changing habitats and the timing of natural processes, jeopardize human health by decreasing air and water quality, and hinder economic activity by inflicting damage to enterprises' assets, industrial processes, and transport infrastructure (European Central Bank, 2022; US Environmental Protection International Energy Agency, 2022). Moreover, extreme weather-related events resulted in a global GDP loss of roughly 0.17% each year between 1990 and 2020, affecting an average of 190 million people each year who were injured, required help, or were homeless (Ritchie et al., 2022a).[1]

In this regard, OECD countries play an essential role because they continue to contribute significantly to CO_2 emissions into the atmosphere, accounting for one-third of global CO_2 emissions in 2020 (Ritchie et al., 2020a). Furthermore, CO_2 emissions per capita in OECD countries were 8.1 metric tons in the same year, nearly double the global per capita average of 4.5 metric tons (World Bank, 2022). Identifying feasible ways to hasten the decarbonization process in such countries is critical to reducing the collateral risk of extreme weather and climate-related calamities. The purpose of this article is to provide advanced-country policymakers with recommendations for the optimal renewable energy mix to cut CO_2 emissions and pave the way to the ambitious goal of carbon neutrality by 2050 (Amoroso et al., 2021). As a result, from 1965 to 2020, this article investigates the long-term causal link between disaggregated renewable energy sources and CO_2 emissions in 27 OECD countries.

This paper contributes to the literature in the following ways. Although a growing number of studies have recently examined the impact of disaggregated renewable energy on CO_2 (Saidi and Omri, 2020; Yuaningsih et al., 2020; Busu and Nedelcu, 2021; Güney, 2022; Bashir et al., 2023; Umar et al., 2023; Waris et al., 2023), none have implemented all the major renewable energy sources. Biofuel, biomass, and geothermal energy, in particular, have received less attention than other forms of renewable energy. Furthermore, with a few exceptions (Al-Mulali et al., 2015; Yuaningsih et al., 2020; Busu and Nedelcu, 2021), the majority of the studies employed renewable energy consumption as an explanatory variable, with little attention paid to the

[1] Natural disasters assessed in this case include drought, extreme temperatures, floods, storms, and wildfires.

influence of renewable energy generation on CO_2 emissions. This is relevant because OECD countries accounted for 42.2% of global electricity generation in 2021 (Ritchie et al., 2022b). After that, except for some recent research (Destek and Aslan, 2020; Güney, 2022; Güney and Üstünda, 2022; Bashir et al., 2023), most researchers ignored the issue of cross-sectional dependence in panel data models, which is plausible in geographically adjacent and/or socioeconomically and culturally linked countries.

The main points of novelty in this work are stated below. To begin, it refreshes evidence on OECD countries and implements a comprehensive set of renewable energy sources (biofuel, GEOB,[2] hydropower, nuclear,[3] solar, and wind). Second, it considers renewable energy production rather than renewable energy consumption to better reflect each country's renewable energy production structure. Third, it incorporates relevant cofounders that may influence CO_2 emissions, such as energy usage, population density, and the agriculture and livestock sector, to minimize the omitted variable bias. Fourth, it employs a wide range of econometric approaches to examine the sensitivity of the results and to account for the issue of cross-country dependence. Specifically, this article investigates the long-term relationship between renewable energy and CO_2 emissions using panel cointegration methods. The benchmarks are the pooled mean group (PMG), mean group (MG), and dynamic fixed effect (DFE), and the robustness tests are the fully modified ordinary least squares (FMOLS), dynamic ordinary least squares (DOLS), and common correlated effects mean group (CCEMG) estimators. Then, as proposed by Abrigo and Love (2016), this study employs a generalized method of moment (GMM) framework for panel vector autoregression (PVAR) models to investigate the causal relationship between renewable energy sources and CO_2 emissions.

For the remainder, the structure of the paper is as follows. Section 2 highlights the historical CO_2 emissions and renewable energy production trends. Section 3 includes a thorough assessment of the literature. The data used for the empirical study are presented in Section 4. The empirical strategy and methodology are described in Section 5. Section 6 summarizes the findings. The policy implications are discussed in Section 7. Finally, Section 8 presents the conclusions of this work.

2. Historical CO_2 emissions and renewable energy trends

This section looks at the historical trajectory of CO_2 emissions and renewable energy output for the macro-regions and each nation investigated. On the one hand, this enables comprehension of differences between groupings of geographically and/or culturally related countries, while on the other, it enables comparison among individual countries. The sample has been divided into six groups as homogeneously as possible: Australasia (Australia and New Zealand), Central Europe (Austria, France, Germany, Ireland, the Netherlands, Poland, Switzerland, and the UK), Japan-South Korea, Mediterranean Europe (Cyprus,[4] Greece, Italy, Spain, and Portugal), North America (Canada and the USA), and Scandinavia (Denmark, Finland, Iceland, Norway, and Sweden). From 1965 to the early 2000s, CO_2 emissions increased significantly for all groups of countries (Fig. 1) (Ritchie et al., 2020a).[5] Since the 2007–2008 global financial crisis, CO_2 emissions have declined significantly in all groups, except for Japan and South Korea, where the reduction has been less pronounced. CO_2 emissions in Scandinavia fell by 32.2% between 2010 and 2020, 31.13% in Mediterranean Europe, 25.69% in Central Europe, 18.13% in North America, and 7.76% in Japan-South Korea. Fig. 2 (Ritchie et al., 2020a) depicts the trend of each country in each group, as well as a graphic representation of the countries excluded from Fig. 1: Chile, Israel, and Mexico.[6] It confirms that, except for Chile and South Korea, OECD countries exhibited a significant reduction in CO_2 emissions from 2007 to 2020.

In contrast, electricity generation from renewable sources increased steadily for all groups from 1965 to 2020 (Fig. 3) (Ritchie et al., 2020c; BP Statistical Review of World Energy, 2022). This is becoming more apparent in the period 2010–2020, particularly for solar and wind energy generation. North America and Japan-South Korea have seen the greatest increases in GEOB energy production. The best-increasing dynamic in hydropower energy generation occurred in Scandinavia and North America. In contrast, Mediterranean Europe and Central Europe experienced the greatest increases in wind and solar energy production, along with North America, which saw an exponential trend in both.

Figs. 4–9 show the historical data on electricity generation from biofuel, GEOB, hydropower, nuclear, solar, and wind in each country. From 1990 to 2020, the US, Germany, France, and the Netherlands observed the greatest growth in biofuel energy production, with absolute increases of 357.5 TWh, 40.7 TWh, 26.8 TWh, and 23.2 TWh, respectively (Fig. 4) (Ritchie et al., 2020c). While in Australia, biofuel energy production remained low throughout the period.

Between 1970 and 2020, the US, Germany, the UK, and Japan experienced the greatest growth in energy production from GEOB, with absolute increases of 58.1 TWh, 50.2 TWh, 39.3 TWh, and 34.6 TWh, respectively (Fig. 5) (BP Statistical Review of World Energy, 2022). GEOB energy production, on the other hand, was very low and stable in Cyprus, Greece, Ireland, Israel, and Norway during the same period. Between 1965 and 2020, Canada, Norway, the US, and Sweden reported the greatest growth in hydropower energy generation, with absolute increases of 264.9 TWh, 91.5 TWh, 81 TWh, and 26 TWh, respectively (Fig. 6) (Ritchie et al., 2020c). In contrast, no significant increases in hydropower energy production occurred in Cyprus, Denmark, Ireland, Israel, or the Netherlands, and their trend remained close to zero throughout the whole period considered. Between 1965 and 2020, the US, France, Canada, and Germany experienced the greatest growth in nuclear energy production, with absolute increases of 786 TWh, 352.9 TWh, 92.5 TWh, and 64.3 TWh, respectively (Fig. 7) (Ritchie et al., 2020b). Italy was the only country among nuclear power users to shut down nuclear reactors, which it did in 1987.

The US, Japan, Germany, and Italy experienced the greatest increases in solar energy production between 1965 and 2020, with absolute increases of 130.7 TWh, 78.6 TWh, 48.6 TWh, and 24.9 TWh, respectively (Fig. 8) (Ritchie et al., 2020c). In contrast, Cyprus, Finland, Iceland, Ireland, New Zealand, and Norway saw no significant increase in solar energy generation, which remained near zero from 1965 to 2020. Wind energy production increased the most in the US, Germany, the UK, and Spain, with absolute increases of 337.9 TWh, 132.1 TWh, 73.8 TWh, and 56.4 TWh, respectively (Fig. 9) (Ritchie et al., 2020c). While Cyprus, Iceland, Israel, and Switzerland have recorded very low values and a stable trend in solar energy production from 1965 to 2020.

Table 1 shows the average electricity production from six renewable sources in terawatt-hours (TWh) per million inhabitants from 2010 to 2020. It allows for an objective comparison of production capacity and specialization level. According to the data, the US, the Netherlands, and Finland were the top three biofuel-producing countries, with average outputs of 1.16, 1.05, and 0.65 TWh per million inhabitants, respectively. Cyprus, Iceland, and Mexico, on the other hand, did not generate

[2] These are the only long-term geothermal and biomass electricity generation statistics available. The acronym GEOB will now be used to denote geothermal and biomass energy generation.

[3] Nuclear energy is included in the analysis because, while not technically a renewable energy source, it is widely regarded as a sustainable, zero-emission clean energy source (US Department of United States Department of Energy, 2021).

[4] Cyprus, while not officially an OECD member, is routinely featured in OECD documents and publications. It is included in the definition of OECD countries for the sake of simplicity.

[5] To avoid confusion, Chile, Israel, and Mexico are not represented in Fig. 1. The grouping of countries allows for a better understanding and clarity of the energy strategies of countries with cultural and socioeconomic commonalities.

[6] The latter are depicted in the chart alongside the Australasia region.

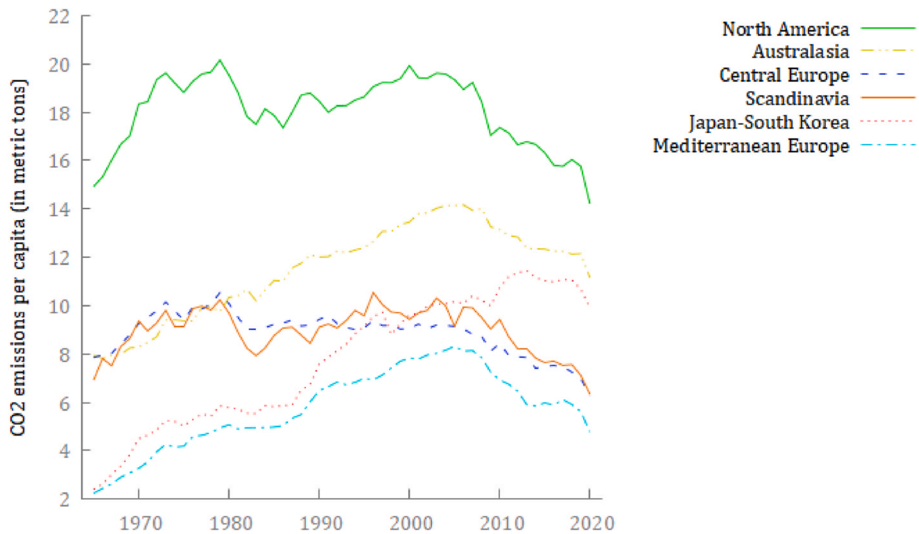

Fig. 1. CO_2 emissions per capita by country group from 1965 to 2020.
Sources: own elaborations on data from Ritchie et al. (2020a).

electricity from biofuel. For eight countries, there were no values available.

In terms of GEOB, Iceland ranked first, with an average production level of 15.71 TWh per million inhabitants, far exceeding Finland (2.15) and New Zealand (1.77), which were ranked second and third, respectively. Similarly, Iceland dominated hydroelectricity production, with an average of 39.18 TWh per million inhabitants, followed by Norway (25.87) and Canada (10.53).

Sweden, France, and Finland had the highest values for nuclear energy, with average electricity production of 6.31, 6.25, and 4.24 TWh per million inhabitants, respectively. In contrast, fourteen countries did not use nuclear energy. Germany, Italy, and Australia were the top three solar-producing countries, with 0.42, 0.33, and 0.29 TWh per million inhabitants, respectively.

Solar energy production was negligible in Finland, Iceland, Ireland, Norway, and Poland. Wind energy was mostly used in Denmark, Sweden, and Ireland, with average outputs of 2.24, 1.4, and 1.37 TWh per million inhabitants, respectively. In contrast, Israel, Switzerland, and Iceland had the lowest values, with average production of 0.01, 0.013, and 0.016 TWh per million inhabitants, respectively.

Finally, of the 27 OECD countries examined hydropower is by far the most extensively employed renewable energy source, while solar is the least. However, while hydropower increased considerably in only a few countries between 1965 and 2020, solar and wind increased significantly in the majority of countries, especially over the past decade.

Notably, Canada, Sweden, and the US have made the greatest investments in renewable energy generation, outpacing the OECD average in four of the six renewable energy sources examined. Cyprus, Mexico, and Poland, on the other hand, were the nations that bet lowest on renewable energy generation, with output constantly lower than the OECD average for all renewable energy sources.

3. Literature review

3.1. Aggregated renewable energy and CO_2 emissions

A large body of research has been conducted on the relationship between renewable energy consumption/production and CO_2 emissions. Most studies have focused on the likelihood of effectively substituting fossil fuels with renewable energy sources to reduce CO_2 emissions, employing both traditional methodologies, such as the ARDL cointegration technique, and novel empirical methodologies that account for cross-sectional dependence, such as the augmented mean group (AMG) and CCEMG.

The first line of research looked at aggregated renewable energy sources as explanatory factors for CO_2 emissions.

In this regard, Zoundi (2017) examined the link between renewable energy consumption and CO_2 emissions in 25 African countries from 1980 to 2012. The GMM, DOLS, DFE, MG, and PMG estimators were all used. The results revealed that a 1% increase in per capita renewable energy consumption was associated with a 0.1% and 0.13% reduction in CO_2 emissions in the short and long run, respectively. Waheed et al. (2018), Jamil et al. (2022), Mirziyoyeva and Salahodjaev (2022), and Sadiq et al. (2023) all found similar findings. Waheed et al. (2018) evaluated the relationship between renewable energy usage and CO_2 emissions in Pakistan from 1990 to 2014. Renewable energy consumption was negatively and significantly associated with CO_2 emissions in both the short and long run, according to ARDL bound estimates. Furthermore, the VECM Granger causality demonstrated a bidirectional correlation between renewable energy usage and CO_2 emissions. Jamil et al. (2022) employed FMOLS and DOLS estimators for a panel of seven selected G-20 countries (Argentina, Australia, Brazil, Canada, Japan, Russia, and Turkey) from 1990 to 2019. They found that a 1% increase in renewable energy consumption was correlated with a 0.2% reduction in CO_2 emissions. Mirziyoyeva and Salahodjaev (2022) investigated the relationship between renewable energy consumption and CO_2 emissions intensity of GDP using fixed effects regression and a two-step GMM estimator. The findings revealed that a 1% increase in renewable energy consumption was significantly associated with a 0.98% reduction in CO_2 emissions (kg per 2010 US$ of GDP). Sadiq et al. (2023) studied the relationship between renewable energy usage and CO_2 emissions in Brics-1 countries (Brazil, Russia, India, and China) between 1990 and 2020. They discovered that a 1% increase in renewable energy consumption resulted in a CO_2 decrease of 0.43% in the short run and a decrease ranging from 0.23% to 0.55% in the long run using AMG, CCMEG, cross-sectionally augmented ARDL (CS-ARDL), and cross-sectionally augmented distributed lag (CS-DL). Furthermore, the pairwise Dumitrescu-Hurlin panel causality demonstrated the presence of a one-way causation running from CO_2 to renewable energy.

As a result, these studies imply that using renewable energy can aid in the reduction of environmental deterioration, albeit more efforts need to be made to increase the effectiveness of renewable energy policies and technology, especially in developing countries (Zoundi, 2017).

Dong et al. (2020), Yurtkuran (2021), and Rehman et al. (2023) obtained a different outcome. From 1995 to 2015, Dong et al. (2020) found an insignificant association between renewable energy

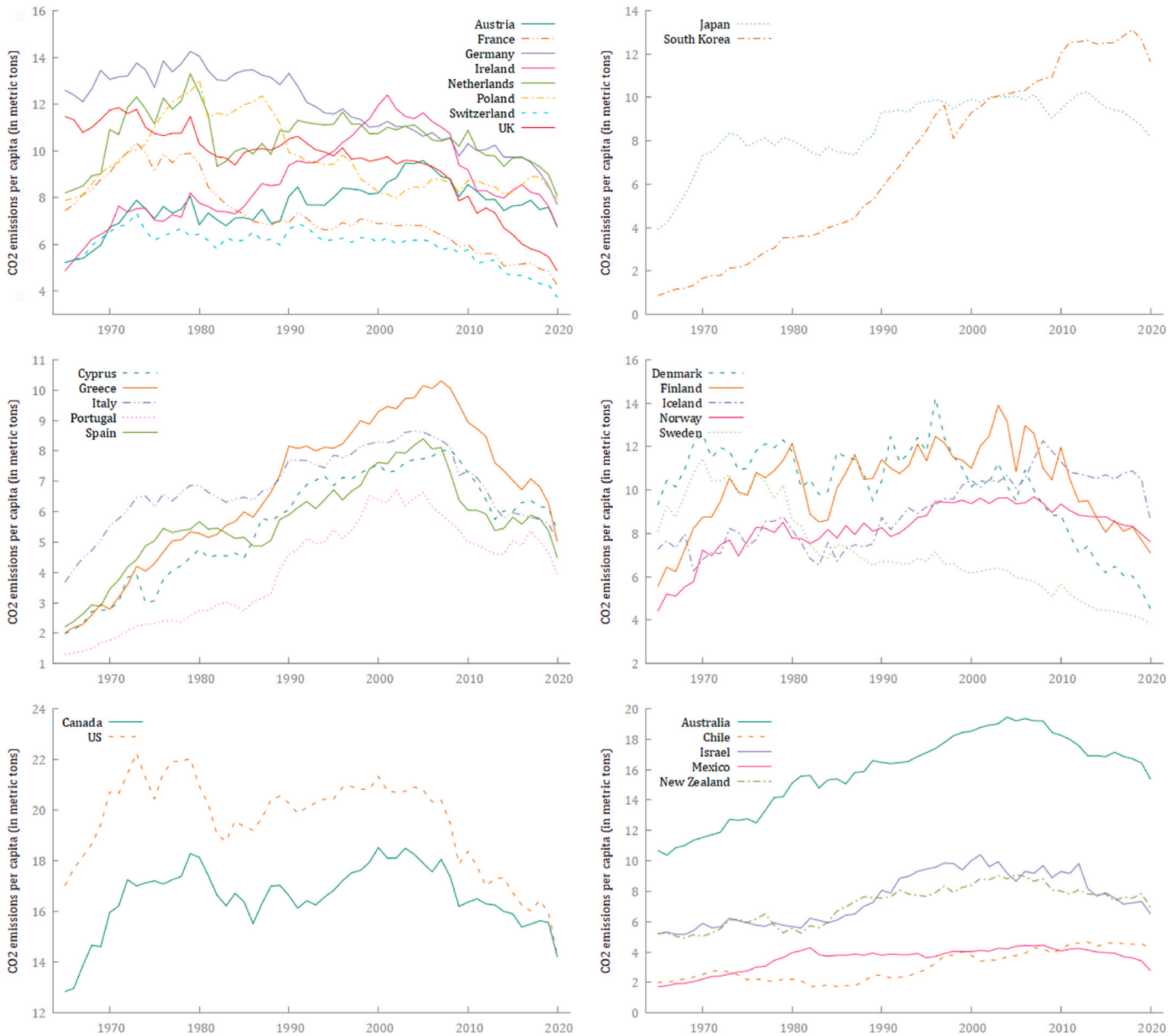

Fig. 2. CO_2 emissions per capita in 27 OECD countries from 1965 to 2020.
Sources: Own elaborations on data from Ritchie et al. (2020a).

consumption and CO_2 emissions for a sample of 120 countries, using the AMG, CCEMG, and MG estimators. Yurtkuran (2021) revealed a strong and positive long-run correlation between renewable energy production and CO_2 emissions in Turkey from 1970 to 2017 using a bootstrap ARDL technique, the FMOLS model, and the canonical cointegrating regression (CCR) model. Rehman et al. (2023) studied the impact of renewable energy consumption on CO_2 at the global level over the period 1985–2020. Using a nonlinear autoregressive distributed lag (NARDL) approach, they discovered that renewable energy consumption had no significant impact on CO_2 emissions.

3.2. *Disaggregated renewable energy and CO_2 emissions*

Other research looked at the association between CO_2 emissions and disaggregated renewable energy sources. For example, Saidi and Omri (2020) examined the link between nuclear energy use and CO_2 emissions in 15 OECD nations between 1990 and 2018. Using the FMOLS estimator, they discovered that a 1% increase in long-term nuclear energy usage was associated with a 0.03 reduction in CO_2 emissions. A one-way relationship between nuclear energy and CO2 emissions was also found by the VECM-Granger causality.

Hassan et al. (2020) discovered comparable findings for BRICS countries between 1993 and 2017, albeit the size of the nuclear energy consumption coefficient was significantly lower. They discovered that a 1% increase in nuclear energy consumption was associated with a 0.001% reduction in CO_2 emissions using the Continuously-Updated Bias-Corrected (CUP-BC) and Continuously-Updated Fully-Modified (CUP-FM) estimators.

For biomass and geothermal energy, Dogan and Inglesi-Lotz (2017) and Shahzad et al. (2021) reached similar conclusions. Dogan and Inglesi-Lotz (2017), in particular, used a group-mean FMOLS method to analyze a panel of 22 countries from 1985 to 2012, finding that a 1% increase in biomass energy consumption could effectively reduce CO_2 emissions, even if the long-run coefficient was low, ranging from 0.04% to 0.06%.

Collecting data from 1979 to 2016, Shahzad et al. (2021)

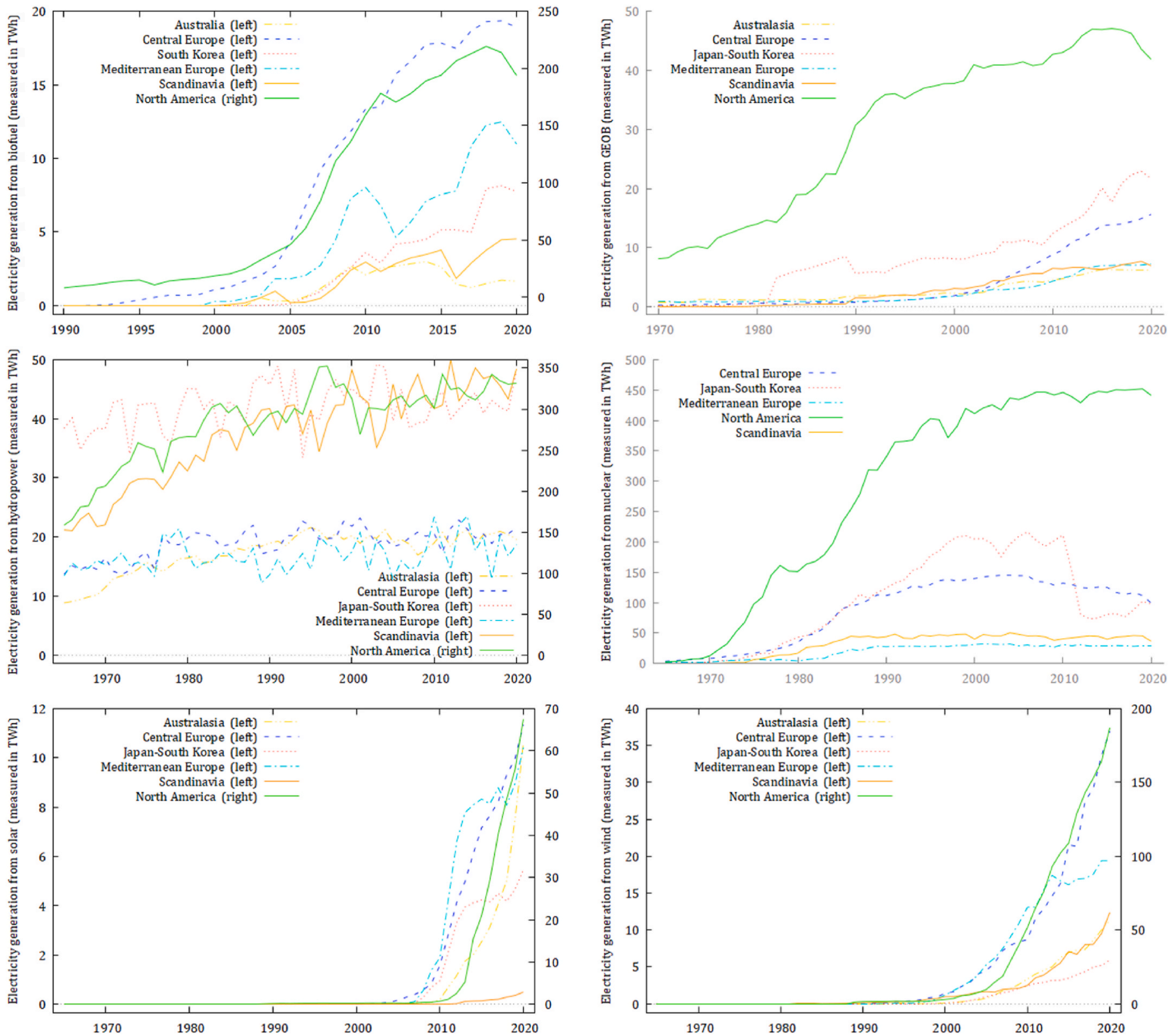

Fig. 3. Electricity generation from disaggregated renewable energy sources by country group, from 1965 to 2020.
Sources: Own elaborations on data from Ritchie et al. (2020c) and BP Statistical Review of World Energy Efficiency and Renewable Energy (2021).

investigated the long-run relationship between geothermal energy consumption and CO_2 emissions in the Philippines. They employed ARDL bound testing as well as the Granger non-causality technique. A 1% increase in geothermal energy consumption was found to be strongly associated with a 1.05% reduction in CO_2 emissions. A bidirectional causal relationship between geothermal energy use and CO_2 emissions was also identified.

Bilgili et al. (2021) used a novel wavelet transform model (WTM) to examine the significance of the relationship between hydroelectric energy consumption and CO_2 emissions in the US from January 1980 to August 2019. Their analysis showed that hydropower produced more CO_2 emissions in the short run (at higher frequencies). In contrast, hydroelectric energy consumption reduced CO_2 emissions significantly in the long run (at lower frequencies). Mohsin et al. (2023) used a Quantile-on-Quantile technique to corroborate this finding for ten European nations from 1991 to 2019. In nine of the ten countries studied, hydropower energy production was identified as a key factor in reducing CO_2 emissions.

Güney and Üstündağ (2022) studied the long-term relationship between wind energy consumption and CO_2 emissions for 37 countries from 2000 to 2019. They found that a 1% increase in wind energy consumption was significantly correlated with a 0.019%–0.075% decrease in CO_2 emissions using the AMG estimation model, the FMOLS estimator, and ordinary least squares (OLS) regression.

Al-Mulali et al. (2015) investigated the long-run relationship between five disaggregated renewable energy sources and CO_2 emissions in 23 EU nations from 1990 to 2013 using the FMOLS estimator and VECM-Granger causality approach. According to the FMOLS technique, a 1% increase in the production of energy from hydropower and combustible renewables and waste (CWE) was associated with a 0.2% and 0.1% reduction in CO_2 emissions, respectively. While nuclear, solar, and wind energy generation were not statistically significant. Furthermore, the VECM-Granger causality showed a one-way causation from CWE and nuclear to CO_2 emissions, a bidirectional causality between hydropower and CO_2 emissions, and no causality between solar, wind, and CO_2 emissions.

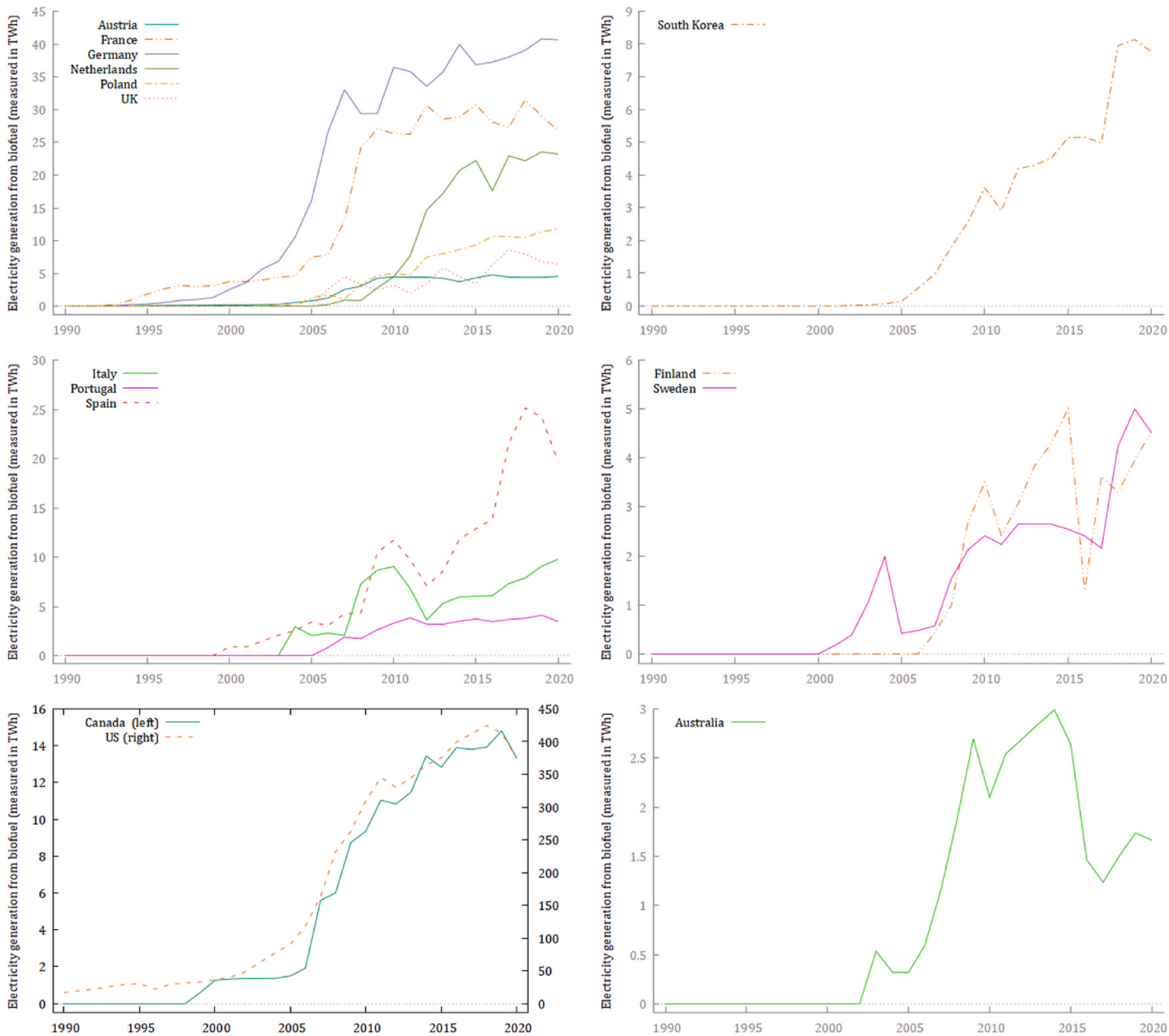

Fig. 4. Biofuel electricity generation in 15 OECD countries from 1965 to 2020. Sources: Own elaborations on data from Ritchie et al. (2020c).

Destek and Aslan (2020) examined the relationship between biomass, hydroelectric, solar, and wind energy, and environmental degradation in G-7 countries from 1991 to 2014. Using the AMG estimator, they found that biomass energy was the most effective renewable energy source in lowering CO_2 emissions for France, Germany, and Japan, hydropower energy was the most effective for Italy and the UK, and wind energy was the most effective for Canada. Solar energy, on the contrary, was the least successful in decreasing environmental degradation for the majority of countries. Using a panel bootstrap causality test, they discovered predominantly unidirectional causation from hydropower and wind to CO_2 emissions, as well as bidirectional causation between biomass, solar, and CO_2 emissions. Thus, most of these studies suggest that renewable energy, especially geothermal and hydropower energy, can help to reduce CO_2 emissions.

Yuaningsih et al. (2020) and Waris et al. (2023) discovered a partially contradictory result compared to this research. Yuaningsih et al. (2020) studied the impact of biogas, solar, and wind energy generation on CO_2 emissions in Indonesia from 1990 to 2018. Using the GMM, they found that a 1% increase in biogas, solar, and wind energy production was associated with an increase in CO_2 emissions of 21.3%, 22.8%, and 28.5%, respectively.

Waris et al. (2023) conducted a study in 19 G-20 member countries to examine the relationship between CO_2 emissions and biofuel, hydropower, solar, and wind energy consumption. Using the DFE, FE, and GMM, they demonstrated that from 2000 to 2019, biofuel and solar energy were negatively and significantly associated with CO_2 emissions, whereas wind energy was positively and significantly correlated with CO_2 emissions. Hydropower had no statistically significant association with CO_2 emissions. As a whole, the literature revealed that the relationship between CO_2 emissions and biofuel (Busu and Nedelcu, 2021; Waris et al., 2023), biomass (Dogan and Inglesi-Lotz, 2017; Destek and Aslan, 2020; Bibi et al., 2021), hydropower (Al-Mulali et al., 2015; Sinaga et al., 2019; Destek and Aslan, 2020; Mohsin et al., 2023), and nuclear (Apergis et al., 2010; Saidi and Omri, 2020) was prevalently negative. The results for the remaining renewable energy sources are mixed.

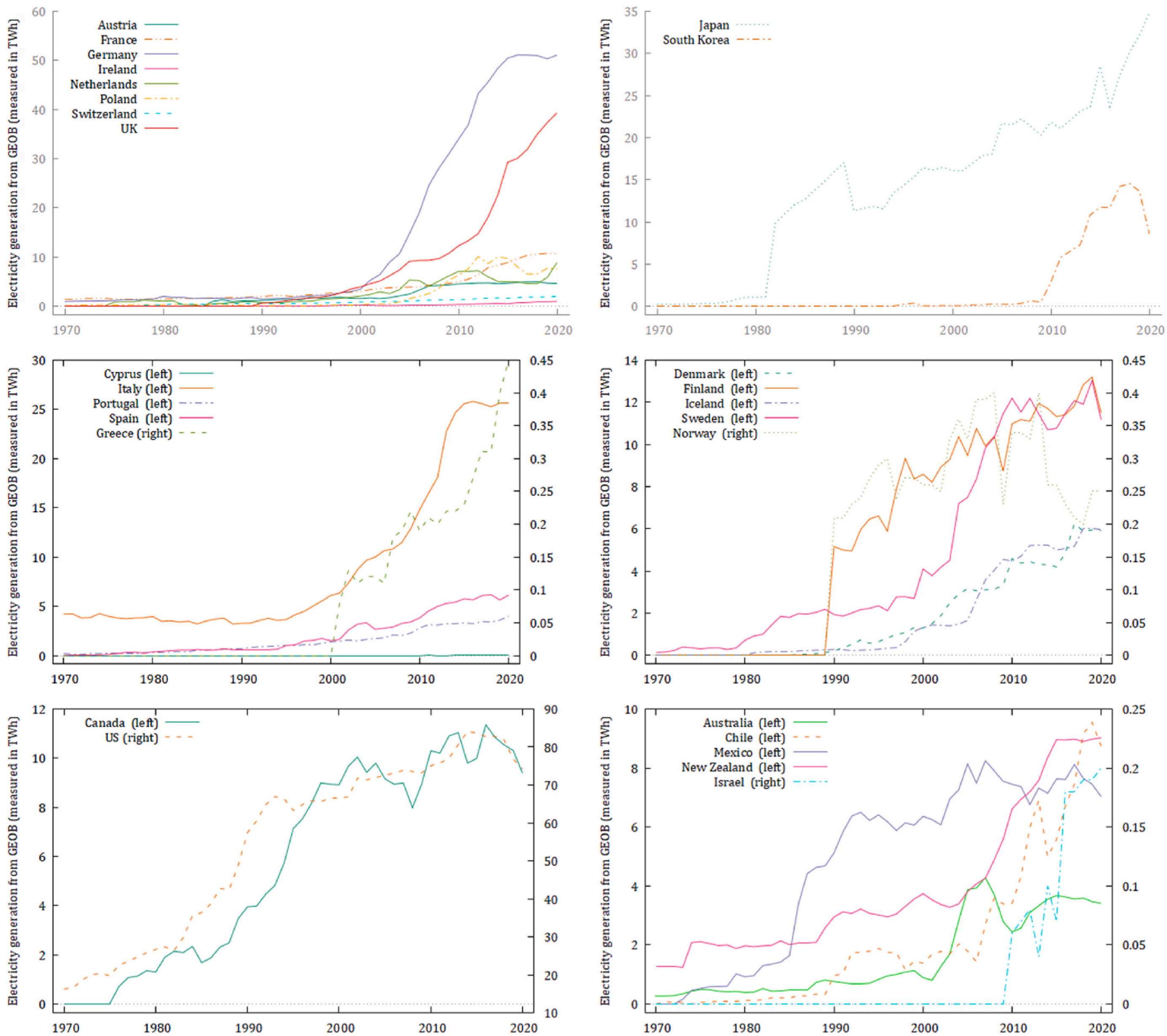

Fig. 5. GEOB electricity generation in 27 OECD countries from 1965 to 2020.
Sources: Own elaborations on data from BP Statistical Review of World Energy (2022).

3.3. Research gap

This paper seeks to fill the following gaps in the literature. First, looking at the literature as a whole, most research on this topic uses aggregated renewable energy sources and/or one disaggregated renewable energy source at a time as explanatory variables. In particular, biofuel, biomass, and geothermal energy received less attention than other forms of renewable energy. Second, the studies on the relationship between renewable energy and CO_2 emissions in OECD countries are outdated and consider only aggregated renewable sources (see Table 2).

Third, the majority of the literature focuses on the influence of renewable energy consumption on CO_2 emissions while neglecting the role of renewable energy generation. Four, they frequently overlook the issue of cross-sectional dependence of the errors in their empirical analyses, which can significantly bias the policy implications. In fact, it is plausible that advanced and spatially adjacent countries, such as OECD countries, share some socioeconomic and cultural features (Hanusch and Hara, 2018). Ignoring cross-sectional dependence can have serious consequences, by potentially leading to misleading inference and inefficient estimation results (De Hoyos and Sarafidis, 2006; Chudik and Pesaran, 2013). Five, some important confounders, such as agriculture and livestock, have typically been skipped over in the literature, while having a significant impact on global CO_2 emissions, amounting to roughly 15% of total global CO_2 emissions (Climate Watch, 2023).

As a result, this study aims to bridge these gaps (i) by comparing all the major renewable energy sources, (ii) by updating the evidence on OECD countries, (iii) using disaggregated renewable energy production as a metric, (iv) considering the potential impact of cross-sectional dependence on the results, and (v) including relevant control variables into the empirical models. Table 2 provides a summary of empirical studies on the causal relationship between renewable energy consumption/production and CO_2 emissions.

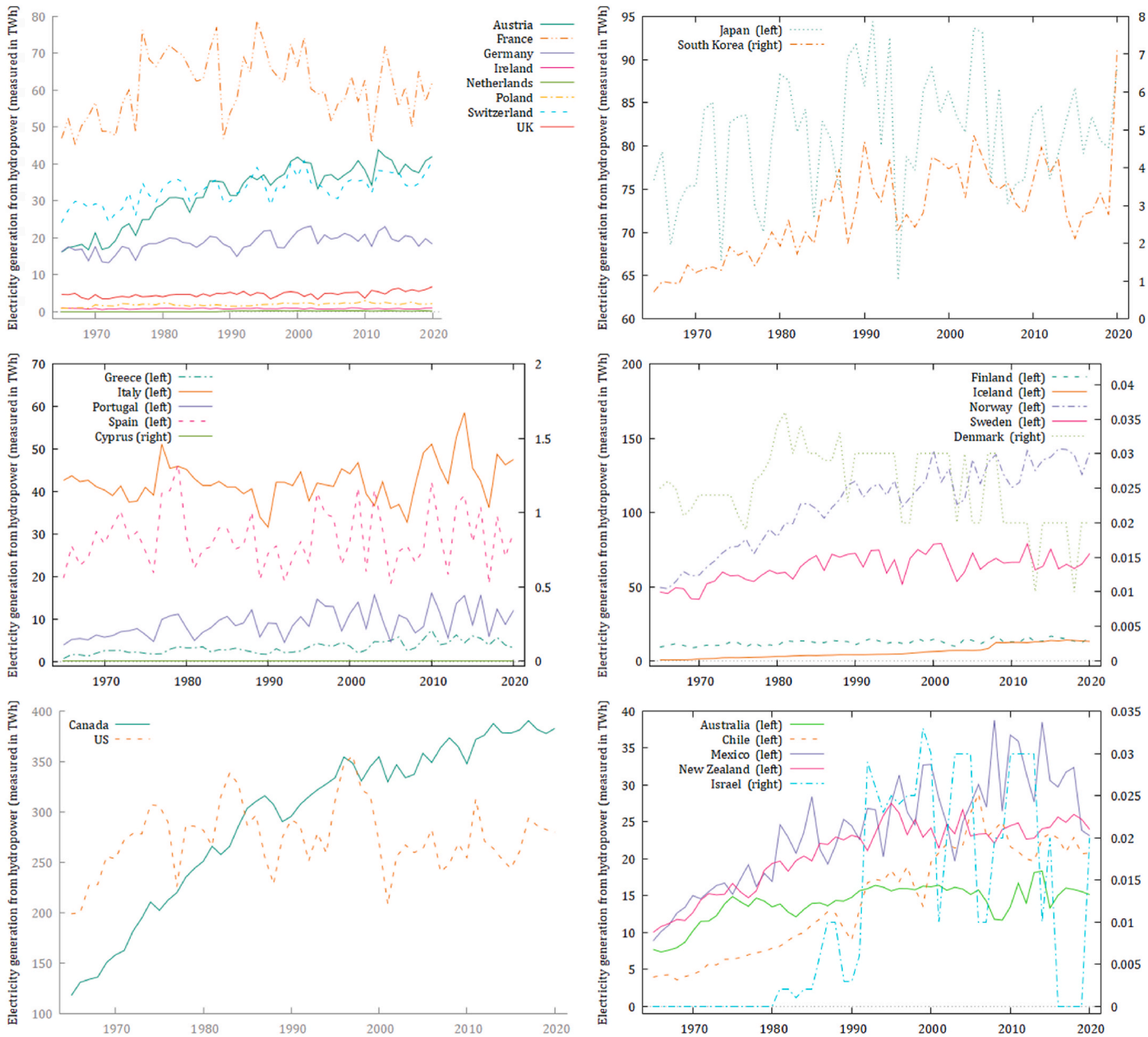

Fig. 6. Hydropower electricity generation in 27 OECD countries from 1965 to 2020.
Sources: Own elaborations on data from Ritchie et al. (2020c).

4. Data sources

4.1. Control variables

This paper examines panel data for the following 27 OECD countries from 1965 to 2020: Australia, Austria, Canada, Chile, Cyprus, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Israel, Italy, Japan, Mexico, the Netherlands, New Zealand, Norway, Poland, Portugal, South Korea, Spain, Sweden, Switzerland, the UK, and the US. The sample has been chosen because these countries contribute considerably to the release of CO_2 emissions into the atmosphere, accounting for approximately one-third of total global CO_2 emissions (Ritchie et al., 2020a).

All the variables included in the empirical investigation, as well as the logic behind their selection, are explained in depth in this section. The variables are divided into three groups for clarity: control factors, explanatory variables, and the dependent variable.

First, a set of control variables is implemented to mitigate omitted variable bias and lower the risk of inconsistent estimates. In OECD countries the energy use (in buildings, industry, and transport) and agricultural and livestock sectors were the largest contributors to CO_2 emissions in 2020, accounting for 75.95%, and 14.31% of total CO_2 emissions, respectively (Fig. 10). As a result, energy usage, agricultural and livestock activities, and population density are all considered (Table A1, Appendix A).

The investigation of the pairwise correlations between control variables justifies the inclusion of all of them in the analysis. Pearson's correlation coefficients for each pair of variables are lower or slightly higher than the conservative threshold of 0.5 (Donath et al., 2012), ranging from 0.07 to 0.54 in absolute value (Table B1, Appendix B). Moreover, they have the potential to impact CO_2 emissions. In particular, a large portion of global electricity is generated by burning fossil fuels (BP Statistical Review of World Energy, 2022), which results in significant emissions of pollutants such as CO_2, nitrogen oxides (NO_x),

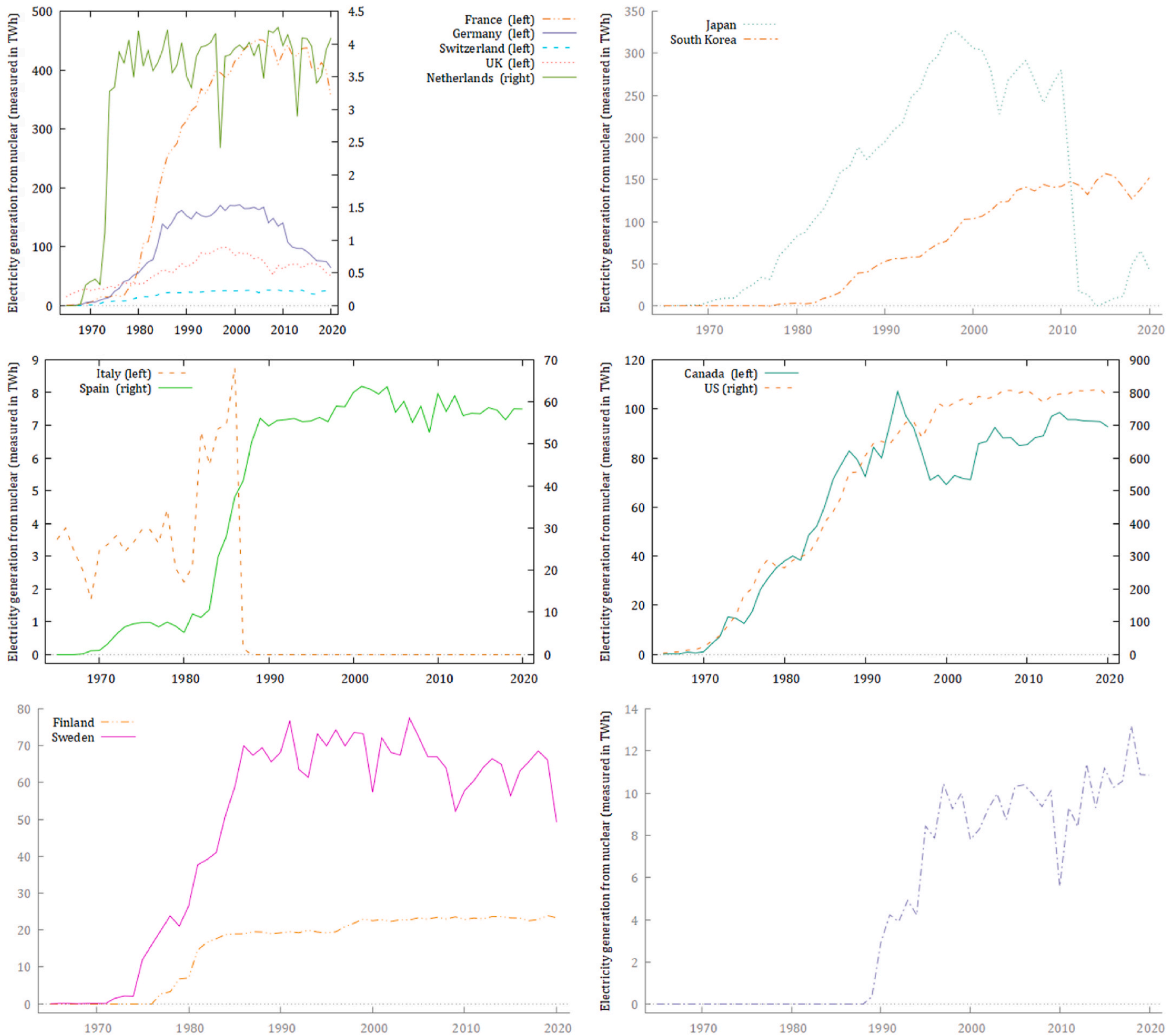

Fig. 7. Nuclear electricity generation in 14 OECD countries from 1965 to 2020.
Sources: Own elaborations on data from Ritchie et al. (2020b).

sulfur dioxide (SO_2), and particulate matter (PM) (Paraschiv S. and Paraschiv L. S., 2020).[7] For instance, from 1990 to 2009, Al-Mulali et al. (2013) found that a 1% increase in energy consumption was associated with a 0.83% rise in CO_2 emissions in the Middle East and North Africa (MENA). Wang et al. (2016) and Khan et al. (2019) confirmed the negative impact of energy use on CO_2 emissions, finding that a 1% increase in energy consumption was associated with a 0.69% and 0.5% increase in CO_2 emissions in China and Pakistan, respectively, in the long-run. The population density may have two opposing effects on CO_2. On the one hand, high urban population density may favor agglomeration effects and economies of scale, increasing urban productivity and lowering CO_2 emissions. According to this hypothesis, Abdouli et al. (2018) and Wang and Li (2021) found an inverted U-shaped relationship between population density and CO_2 emissions in BRICTS[8] countries, and a large panel of 154 countries, respectively.

High urban population density, on the other hand, may result in adverse agglomeration effects such as traffic congestion and higher construction and maintenance costs due to an overwhelming infrastructure demand, which increases CO_2 emissions (Wang et al., 2019). In this regard, Ohlan (2015) found that a 1% increase in population density is significantly associated with a 5.5% increase in CO_2 emissions in India. The adverse impact of population density is also confirmed by

[7] Notably, Canada, Finland, Iceland, Norway, Sweden, the US, and particularly Iceland, have much higher per capita energy usage than other countries. This is mainly due to lower industry and end-user electricity prices in those countries, as well as lower average temperatures in Canada and Scandinavia, which increase residential and industrial heat demand. For example, the lower cost of electricity generation in Scandinavia is mostly owing to the massive hydropower supply, whereas in the US, it is due to cheap fuel costs (International Energy Agency, 2020b).

[8] The acronym BRICTS stands for Brazil, Russian Federation, India, China, Turkey, and South Africa.

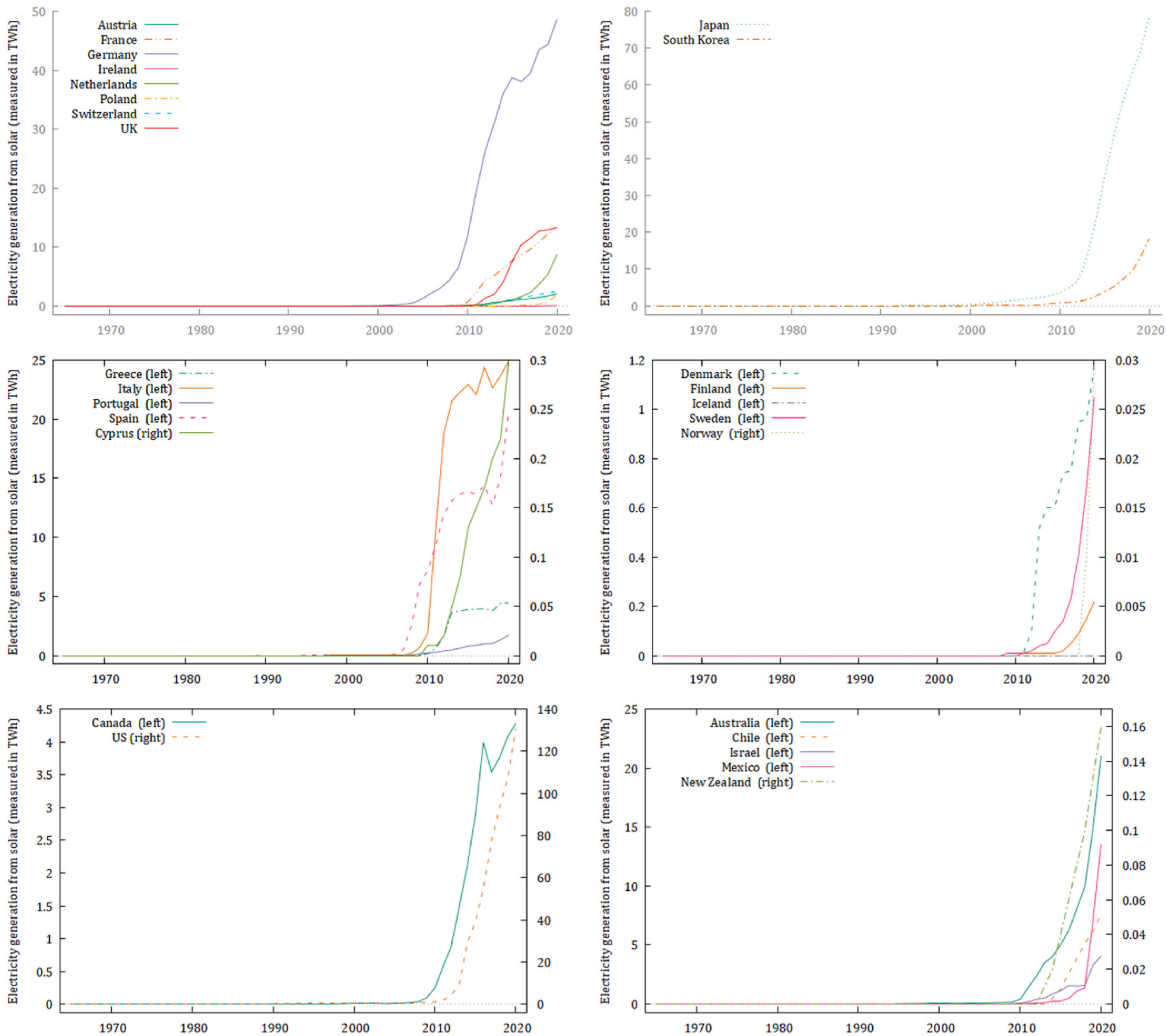

Fig. 8. Solar electricity generation in 27 OECD countries, from 1965 to 2020. Sources: Own elaborations on data from Ritchie et al. (2020c).

other studies (Nasreen et al., 2017; Rahman and Alam, 2021). Agriculture and related land use emissions generated 9.3 billion tons of CO_2 equivalent in 2018, accounting for 17% of the global anthropogenic emissions of GHG emissions (Food and Agriculture Organization of the United Nations, 2020). The majority of those emissions were caused by deforestation, the livestock industry, and fertilization. Deforestation was primarily caused by increased agricultural activity and accounted for 4 billion tons of CO_2 equivalent. The livestock sector accounted for about 3.5 billion tons of CO_2 equivalent and contributed to GHG emissions in two ways: i) through the enteric fermentation in ruminant animals (primarily cattle), which is a natural part of their digestive process, and ii) through direct gas emissions from livestock manure. Synthetic nitrogen fertilizer use in agriculture is a key factor in increasing crop yield (Ritchie et al., 2022d) and produced approximately 0.7 billion tons of CO_2 equivalent in 2018 (Food and Agriculture Organization of the United Nations, 2020). Some research investigated the effect of these variables on CO_2 emissions. For instance, in a panel of 86 heterogeneous nations, Parajuli et al. (2019) found that a 1% increase in agricultural land area expansion is positively and significantly associated with a 0.15% increase in CO_2 emissions from 1990 to 2014. Raihan and Tuspekova (2022) and Raihan et al. (2022) confirmed these findings for Peru and Malaysia, respectively. According to Rehman et al. (2022), fertilizer consumption had a positive and significant association with CO_2 emissions in Nepal from 1965 to 2018. Furthermore, cattle contribute the most to CO_2 emissions among livestock animals (Food and Agriculture Organization of the United Nations, 2019, p. 23). Buffalo meat, in particular, is responsible for 404 kg of CO_2 equivalent per kilogram of protein, followed by beef, small ruminant, and cattle milk, which are responsible for 295 kg, 201 kg, and 87 kg of CO_2 equivalent per kg of protein, respectively. This emphasizes the need to include agricultural activities in the explanation of CO_2 emissions.

4.2. Explanatory variables

Explanatory variables include renewable energy generation from the following sources: biofuel, GEOB, hydropower, nuclear, solar, and wind.

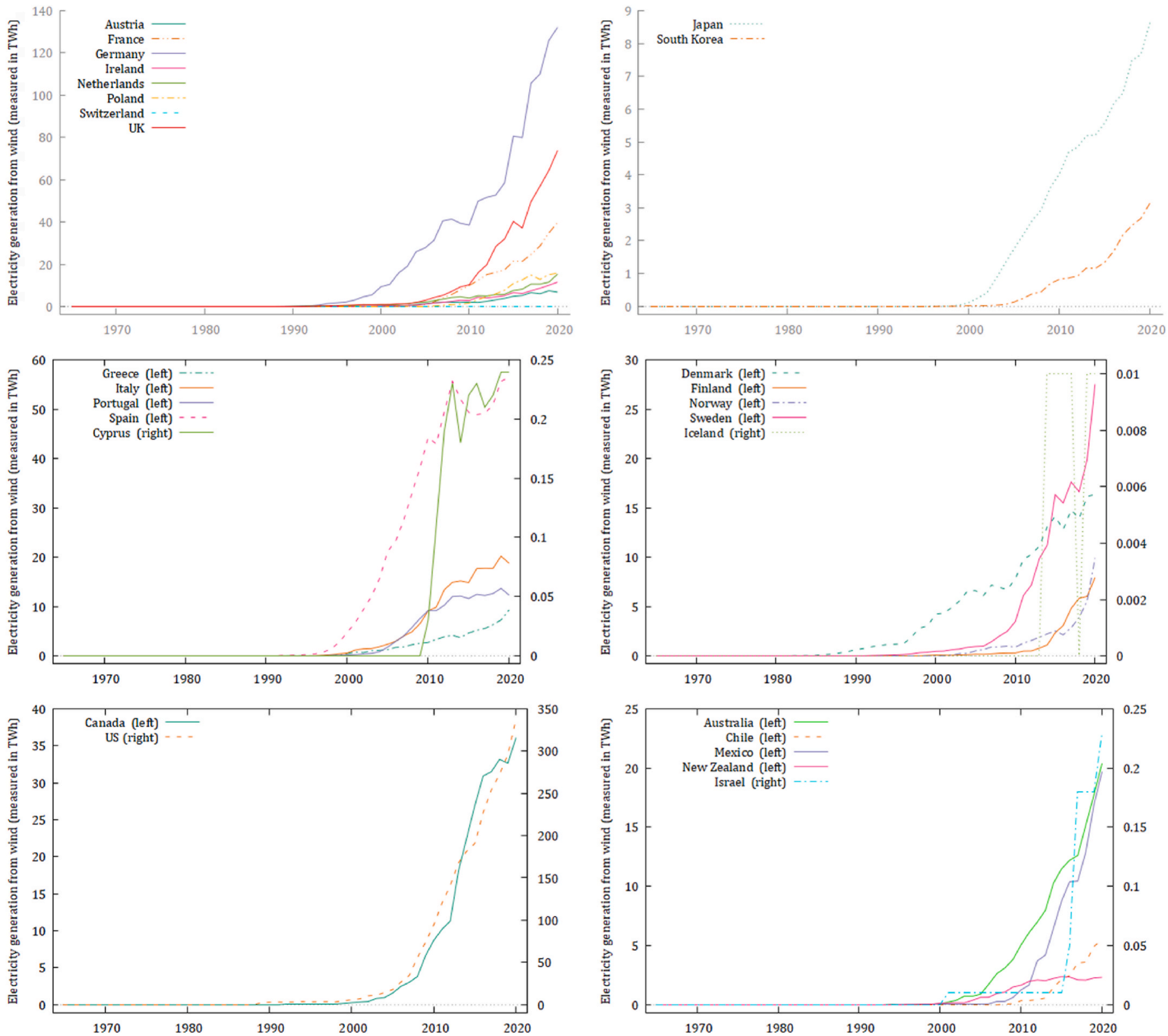

Fig. 9. Wind electricity generation from wind in 27 OECD countries from 1965 to 2020.
Sources: Own elaborations on data from Ritchie et al. (2020c).

Explanatory variables are included in the empirical models separately since they correspond to different periods and have high pairwise correlations.[9] They are chosen for this study because they are the most popular and widely used renewable energy sources (see, for example, Al-Mulali et al., 2015; Destek and Aslan, 2020; Umar et al., 2023). Specifically, nuclear accounted for 32.4% of renewable energy production in OECD countries in 2021, followed by hydropower (24.42%), wind (16.56%), biofuel (10.81%), solar (8.87%), and GEOB (6.95%) (International Energy Agency, 2021; Ritchie et al., 2022c). Including all of them in the empirical study allows for comparison and identification of the optimal combination of renewable sources to reduce CO_2 emissions.

4.3. Dependent variable

Finally, as a dependent variable, this paper uses the CO_2 emissions expressed in metric tons per capita. This choice is justified by the fact that CO_2 is the most significant GHG that contributes significantly to climate change by warming the planet. The warming process has an impact on both human health and economic activities, as it increases the likelihood of sudden natural disasters such as burdensome drought, flooding, and storms (Intergovernmental Panel on Climate Change, 2023). As a result, finding solutions to reduce CO_2 emissions is critical to ensure sustainable development in the long-term.

All the dependent and independent variables used in the empirical analysis are described in detail in Table A1 (Appendix A). The main descriptive statistics of all the variables used in the empirical analysis are reported in Table C1 (Appendix C). In particular, energy consumption has the greatest mean, whereas solar energy has the lowest. Energy consumption also has the highest standard deviation, while CO_2 emissions have the lowest. The data on the extreme values of renewable

[9] Solar and wind energy production, for example, have a correlation coefficient of 0.78 (1512 observations); biofuel and wind energy production have a correlation coefficient of 0.87 (462 observations); and GEOB and nuclear energy production have a correlation coefficient of 0.79 (1377 observations).

Table 1
The average annual electricity generation from 2010 to 2020.

Country	Biofuel	GEOB	Hydropower	Nuclear	Solar	Wind
Australia	0.0893	0.1385	0.6538	0	0.2924	0.4797
Austria	0.5103	0.5433	4.5816	0	0.1108	0.5301
Canada	0.3515	0.2906	10.532	2.6034	0.0704	0.6644
Chile	N/a	0.3667	1.1916	0	0.1362	0.1268
Cyprus	0	0.0329	0	0	0.1103	0.1644
Denmark	N/a	0.8803	0.0032	0	0.1026	2.2389
Finland	0.6462	2.146	2.6184	4.2427	0.0096	0.5513
France	0.4301	0.1282	0.8962	6.2461	0.1116	0.3307
Germany	0.4601	0.5701	0.2427	1.1229	0.4195	0.9839
Greece	N/a	0.0252	0.4624	0	0.2875	0.4673
Iceland	0	15.707	39.183	0	0	0.0164
Ireland	N/a	0.1277	0.1557	0	0.0027	1.3683
Israel	N/a	0.0147	0.0018	0	0.163	0.0095
Italy	0.1165	0.3788	0.7824	0	0.3272	0.2564
Japan	N/a	0.2062	0.647	0.4651	0.2835	0.0472
Mexico	0	0.0609	0.2554	0.0829	0.0181	0.0719
Netherlands	1.0524	0.353	0.0049	0.2245	0.13	0.4773
N. Zealand	N/a	1.7667	5.255	0	0.0117	0.4552
Norway	N/a	0.054	25.874	0	0.0007	0.6095
Poland	0.2353	0.2118	0.0586	0	0.008	0.2521
Portugal	0.3437	0.3193	1.1034	0	0.0763	1.1162
South Korea	0.1047	0.1931	0.0712	2.8337	0.1133	0.0328
Spain	0.3234	0.1157	0.665	1.2481	0.2835	1.0791
Sweden	0.3091	1.1877	6.831	6.3079	0.0253	1.3974
Switzerland	N/a	0.2012	4.4092	2.8809	0.1396	0.0127
UK	0.0822	0.3967	0.0849	1.0066	0.1063	0.5989
US	1.1608	0.2482	0.8523	2.4872	0.1553	0.6479
Mean	0.3453	0.9876	3.9784	1.176	0.1295	0.555

Notes: N/a, not available. The values are expressed in TWh per million inhabitants. Own elaborations on data from Ritchie et al. (2020b, 2020c), and BP Statistical Review of World Energy Efficiency and Renewable Energy (2021).

energy sources reveal that nuclear has the highest value, while GEOB has the lowest value. The variables with the fewest observations are biofuel and nuclear, with 465 and 784 observations, respectively. Moreover, the weighted coefficient of variation for the independent variables, obtained by dividing the standard deviation by the mean of each country and averaging them, is greater than zero. This is especially true for renewable energy sources. As a result, the regressors exhibit enough variability to justify their inclusion in the empirical analysis.

5. Study methodology

5.1. Cross-sectional dependence tests

The primary goal of this paper is to look at the long-term relationship between six renewable energy sources and CO_2 emissions in 27 OECD countries from 1965 to 2020. The panel cointegration framework and the Granger non-causality test approach are employed to achieve this goal.

First, a large body of literature has demonstrated that large panel data models are prone to cross-sectional dependence of errors (De Hoyos and Sarafidis, 2006; Chudik and Hashem Pesaran, 2015). Ignoring this factor is rarely a reasonable guess because it may result in skewed statistical results (Hoes et al., 2017). Pesaran's (Pesaran, 2004) CD test is used to assess the presence of cross-sectional dependence across units. This test has a strong power in the presence of weak cross-sectional dependence and can handle data with non-normally distributed random errors. Pesaran's CD test statistic is as follows (Pesaran, 2004) [1]:

$$CD(N,T)=\sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\widehat{\rho}_{ij}\right) \quad [1]$$

where N represents the cross-sectional units, T identifies the time series dimension, i and j are the connection matrix elements (w_{ij}), and $\widehat{\rho}_{ij}$ is the sample estimate of the pairwise correlation of the residuals.

5.2. Unit root tests

First, to choose the most appropriate panel cointegration technique, this study checks the stationarity of each independent and dependent variable's time series using the second-generation Pesaran's (2007) cross-sectionally augmented Dickey-Fuller (CADF) panel unit root test. It is particularly helpful in this case since it takes into consideration cross-sectional dependence across units. The CADF regression is calculated by augmenting the standard Dickey-Fuller regression with the cross-section average of lagged levels and first differences of the individual series (Pesaran, 2007) [2]:

$$\Delta y_{i,t}=a_i+b_i y_{i,t-1}+c_i\overline{y}_{t-1}+d_i\Delta\overline{y}_t+\varepsilon_{it} \quad [2]$$

where $\overline{y}_t = N^{-1}\sum_{i=1}^{N} y_{i,t}$, and ε_{it} is the error term. The CADF statistics are given by the OLS t-ratio of b_i in Equation [2].

It should also be noted that the study spanned nearly six decades. As a sensitivity check, the panel unit root test developed by Karavias and Tzavalis (KT) (2014) is employed to account for structural breaks that are likely to occur in such a long time series. The KT test against a common structural break in the intercepts of the series at the time T_0 is based on the two nonlinear AR(1) panel models [3 and 4], denoted by $m=\{M1,M2\}$ (Karavias and Tzavalis, 2014):

$$M1: y_i=\varphi y_{i-1}+(1-\varphi)\left(a_i^{(\lambda)}e^{(\lambda)}+a_i^{(1-\lambda)}e^{(1-\lambda)}\right)+u_i, i=1,2,\ldots N \quad [3]$$

$$\begin{aligned}M_2: y_i=\varphi y_{i-1}+\varphi\beta_i e+(1-\varphi)\left(a_i^{(\lambda)}e^{(\lambda)}+a_i^{(1-\lambda)}e^{(1-\lambda)}\right)\\ +(1-\varphi)\left(\beta_i^{(\lambda)}\tau^{(\lambda)}+\beta_i^{(1-\lambda)}\tau^{(1-\lambda)}\right)+u_i\end{aligned} \quad [4]$$

where $y_i=(y_{i1},\ldots,y_{iT})'$ is a vector containing the cross-sectional units (i) and the time series dimension (T), $y_{i-1}=(y_{i0},\ldots,y_{iT-1})'$ is the vector y_i lagged by one period, φ is the autoregressive parameter, and a_i identifies the common break in the individual effects.

Table 2
Summary of studies on the interaction between renewable energy and CO_2 emissions.

Authors	Cointegration	Causality	Period	Methodology	Investigated area
Menyah and Wolde-Rufael (2010)	NUEC (−), REC (Ns)	NUEC ⇒ CO_2 REC ≠ CO_2	1960–2007	VAR causality, GFEVD	US
Apergis et al. (2010)	NUEC (−), REC (+)	NUEC ⇔ CO_2 REC ⇔ CO_2	1984–2007	VECM-Granger causality	19 developed and developing countries
Alam (2013)	N/a	NUEC ⇒ CO_2	1993–2010	VECM-Granger causality	25 developed and developing countries
Shafiei and Salim (2014)	REC (−)	CO_2 ⇒ REC	1980–2011	STIRPAT framework (AMG, GMM)	29 OECD countries
Al-Mulali et al. (2015)	HEP (−), NUEP (Ns), CWEP (−), SEP (Ns), WEP (Ns)	HEP ⇔ CO_2 NUEP ⇒ CO_2 CWEP ⇒ CO_2 SEP ≠ CO_2 WEP ≠ CO_2	1990–2013	FMOLS, VECM-Granger causality	23 European countries
Özbuğday and Erbas (2015)	REC (−)	N/a	1971–2009	CCEMG, MG	36 developed and non-developed countries
Dogan and Seker (2016)	NREP (+), REP (−)	CO_2 ⇒ NREP REP ⇔ CO_2	1980–2012	DOLS, Granger causality	15 EU countries
Bilgili et al. (2016)	REC (−)	N/a	1977–2010	DOLS, FMOLS	17 OECD countries
Saidi and Mbarek (2016)	NUEC (Ns), REC (−)	NUEC ≠ CO_2 REC ≠ CO_2	1990–2013	DOLS, FMOLS, VECM-Granger causality	nine developed countries
Dogan and Inglesi-Lotz (2017)	BMEC (−)	N/a	1985–2012	group-mean FMOLS	22 countries
Zoundi (2017)	REC (−)	N/a	1980–2012	DOLS, DFE, GMM, MG, PMG	25 African countries
Waheed et al. (2018)	REC (−)	N/a	1990–2014	ARDL, DOLS, FMOLS, VECM-Granger causality	Pakistan
Chen et al. (2019)	NREP (+), REP (−)	NREP ⇔ CO_2 (LR) REP ⇒ CO_2 (LR) CO_2 ⇒ REP (SR)	1980–2014	ARDL, VECM-Granger causality	China
Cheng et al. (2019)	REP (−)	N/a	2000–2013	OLS, QR	BRIICS countries
Sinaga et al. (2019)	HEC (−)	N/a	1978–2016	ARDL	Malaysia
Destek and Aslan (2020)	BMEC (−), HEC (−), SEC (Ns), WEC (−)	BMEC ⇔ CO_2 HEC ⇒ CO_2 SEC ⇔ CO_2 WEC ⇔ CO_2	1991–2014	AMG, bootstrap Granger causality	G-7 countries
Dong et al. (2020)	NREC (+), REC (Ns)	NREC ⇔ CO_2 REC ⇔ CO_2	1995–2015	AMG, CCEMG, Granger causality, MG	120 countries
Eyuboglu and Uzar (2020)	REC (−)	REC ⇒ CO_2	1995–2014	DOLS, FMOLS, VECM-Granger causality	Seven countries
Hassan et al. (2020)	NUEC (−)	N/a	1993–2017	CUP-BC, CUP-FM	BRICS countries
Koengkan and Fuinhas (2020)	REC (−)	N/a	1990–2014	ARDL-UECM	Latin American & Caribbean countries
Saidi and Omri (2020)	NUEC (−), REC (−)	NUEC ⇒ CO_2 REC ⇒ CO_2	1990–2018	FMOLS, VECM-Granger causality	15 OECD countries
Yuaningsih et al. (2020)	BIOEP (+), SEP (+), WEP (+)	N/a	1990–2018	GMM	Indonesia
Bibi et al. (2021)	BMEC (−)	BMEC ⇒ CO_2	1981–2019	Bootstrap Granger RW causality	US
Bilgili et al. (2021)	HEC (SR +; LR -)	N/a	1980–2019	WTM	US
Busu and Nedelcu (2021)	REC (−), BEP (−), BP (−)	N/a	2000–2019	RE	EU Countries
Shahzad et al. (2021)	GEC (+)	GEC ⇔ CO_2	1979–2016	ARDL bounds testing, Granger causality	The Philippines
Yurtkuran (2021)	REP (+)	N/a	1970–2017	Bootstrap ARDL, CCR, FMOLS	Turkey
Jamil et al. (2022)	REC (−)	N/a	1990–2019	DOLS, FMOLS	G-20 countries
Güney (2022)	SEC (−)	N/a	2005–2018	AMG, CCEMG, FMOLS	35 countries
Güney and Üstündağ (2022)	WEC (−)	N/a	2000–2019	AMG, FMOLS, OLS	37 countries
Mirziyoyeva and Salahodjaev (2022)	REC (−)	N/a	2000–2015	FE, Two-Step GMM	50 top carbon-emitting countries
Saleem et al. (2022)	NREP (−)	NREP ⇒ CO_2	2008–2018	GMM-PVAR	38 OECD countries
Bashir et al. (2023)	GEC (−)	N/a	1990–2019	AMG, CCEMG, MMQR	10 NICs
Sadiq et al. (2023)	REC (−)	CO_2 ⇒ REC	1990–2020	AMG, CCEMG, CS-ARDL, CS-DL, Granger causality	BRICS-1
Mohsin et al. (2023)	HEC (−)	N/a	1991–2019	QQ	ten European countries
Rehman et al. (2023)	REC (Ns)	N/a	1985–2020	NARDL	Global level
Umar et al. (2023)	GEC (mixed)	GEC ⇒ CO_2	1990–2019	QQ, NPCQ	Top seven consuming countries
Waris et al. (2023)	BEC (−), HEC (Ns), SEC (−), WEC (+)	N/a	2000–2019	DFE, FE, GMM	19 G-20 member countries

Notes: N/a, not available; ⇒ indicates unidirectional causality; ⇔ indicated bidirectional causality; ≠ indicates no causality. Methods: AMG, augmented mean group; ARDL, autoregressive distributed lag; BRICS, Brazil, Russia, India, China, and South Africa; BRICS-1, Brazil, Russia, India, and China; CCEMG, common correlated effects mean group; CCR, canonical cointegrating regression; CUP-BC Continuously-Updated Bias-Corrected; CUP-FM, Continuously-Updated Fully-Modified; DFE, dynamic fixed effects; DOLS, dynamic ordinary least squares; FE, fixed effects; FMOLS, fully modified ordinary least squares; GFEVD, Generalized forecast error variance decomposition; GMM, generalized method of moments; GMM-PVAR, generalized method of moments estimator for panel vector autoregression model; MG, mean group; MMQR, method of moments quantile regression; NARDL, nonlinear autoregressive distributed lag; NCIs, newly industrialized countries; NPCQ, nonparametric causality-in-quantiles; OLS, ordinary least squares; PMG, pooled mean group; QQ, quantile-on-quantile; QR, quantile regression; RE, random effects; STIRPAT, stochastic impacts by regression on population, affluence, and technology; SVAR, structural vector autoregressive; UECM, unrestricted error-correction model; VECM, and vector error correction model; WTM, wavelet transform model.

Variables: BIOEP, biogas energy production; BEC, biofuel energy consumption; BEP, biofuel energy production; BMEC, biomass energy consumption; CWEP, combustible renewables and waste energy production; BP, bioenergy productivity; GEC, geothermal energy consumption; HEC, hydroelectric energy consumption; HEP, hydroelectric energy production; LR, long run; NREC, non-renewable energy consumption; NREP; non-renewable energy production; NUEC, nuclear energy consumption; NUEP, nuclear energy production; Ns, not significant; REC, renewable energy consumption; REP, renewable energy production; RW, rolling window; SEC, solar energy consumption; SEP, solar energy production; SR, short run; WEC, wind energy consumption; WEP, wind energy production.

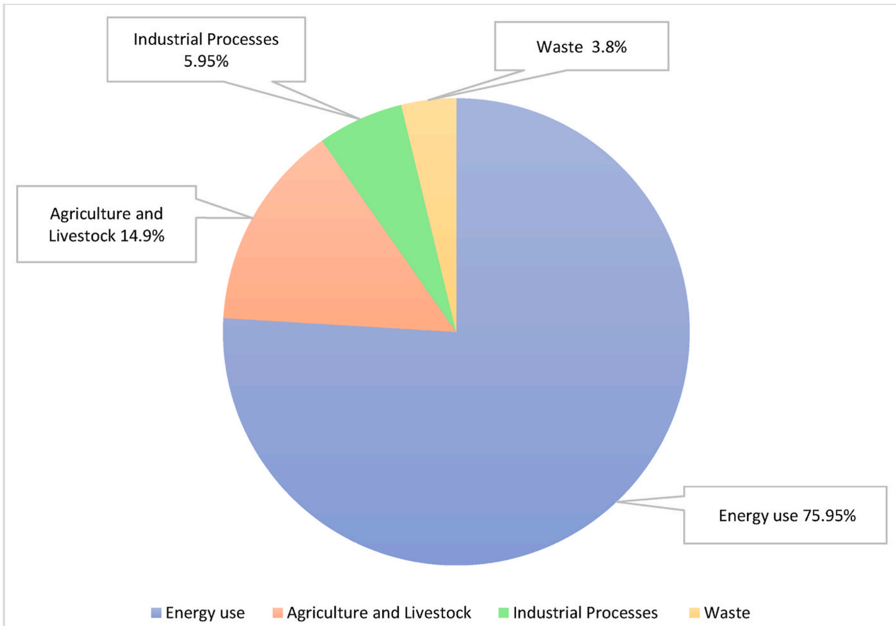

Fig. 10. OECD countries' average GHG emissions (in CO_2 equivalent) by sector in 2020.
Sources: Own elaboration on data from Climate Watch (2023).

5.3. Slope homogeneity test

Another factor that can lead to biased results, according to Pesaran and Smith (1995), is ignoring the presence of slope heterogeneity. Thus, this study employs the heteroskedasticity and autocorrelation consistent (HAC) robust version of the Delta test (denoted with Δ) for panels with large cross-sectional (N) and time series (T) dimensions, which was originally proposed by Pesaran and Yamagata (2008). Blomquist and Westerlund's (2013) robust version allows for the safe handling of residual homoscedasticity and serial independence violations. The HAC robust version of Δ is defined as follows [5]:

$$\Delta_{HAC} = \sqrt{N}\left(\frac{N^{-1}S_{HAC} - k}{\sqrt{2k}}\right) \qquad [5]$$

$$\text{with} S_{HAC} = \sum_{i=1}^{N} T\left(\widehat{\beta}_i - \widehat{\beta}\right)^{'}\left(\widehat{Q}_{i,T}\widehat{V}_{i,T}^{-1}\widehat{Q}_{i,T}\right), \widehat{V}_{i,T} = \widehat{\Gamma}_i(0) + \sum_{j=1}^{T-1}\kappa\left(j / M_{i,T}\right)\left[\widehat{\Gamma}_i(j) + \widehat{\Gamma}_i(j)^{'}\right] \qquad [6]$$

where i denotes the cross-sectional units, T identifies the time series dimension, $\widehat{\beta}_i$ is the OLS estimator for each i, $\widehat{Q}_{i,T} = T^{-1}(X_i^{'}M_\tau X_i)$, $\widehat{V}_{i,T}$ is the estimator used to compute the HAC correction, $\widehat{\Gamma}_i(j) = T^{-1}\sum_{t=j+1}^{T}\widehat{u}_{i,t}\widehat{u}_{i,t-j}^{'}$, κ is the kernel function, and $M_{i,T}$ identifies the bandwidth parameter.

5.4. Panel ARDL models

The relationship between CO_2 emissions and renewable energy production in 27 OECD countries is assessed using a panel ARDL approach.

The following three estimators are used in the basic long-run ARDL models: the MG estimator (Pesaran and Smith, 1995), the PMG estimator (Pesaran et al., 1999), and the DFE estimator (Weinhold, 1999). The PMG estimator constrains the long-run coefficients to be the same but allows slope coefficients, error variances, and short-run coefficients to vary across groups. As a result, it is appropriate when there is slope heterogeneity in data (Pesaran et al., 1999).[10] The MG estimator imposes no constraints (Pesaran and Smith, 1995), whereas the DFE estimator assumes that all slope coefficients and error variances are equal, allowing the intercepts to differ across groups (Weinhold, 1999). Furthermore, they can all be used regardless of whether the variables are $I(0)$ or $I(1)$. The general ARDL (p, q) model is reparametrized in the error correction (EC) form, allowing consideration of the short-run and long-run dynamics (Loayza and Rancière, 2006) separately:

$$\Delta COE_{i,t} = ECT_{i,t} + \sum_{j=1}^{p-1}\vartheta_j^i \Delta COE_{i,t-j} + \sum_{j=0}^{q-1}\theta_j^i \Delta X_{i,t-j} + \varepsilon_{i,t} \qquad [7]$$

where $ECT_{i,t} = \varphi^i[(y_{i,t-1} - \{\beta_0^i + \beta_1^i(X_{i,t-1}\}]$ [8]

i and t identify the countries and time series dimension (with $t = 1965, 1966, \ldots n$), Δ is the first difference operator, $ECT_{i,t}$ represents the error correction term, i.e., the speed of adjustment coefficient towards equilibrium,[11] φ^i is the coefficient of the speed of adjustment term, β represents the long-run coefficients, $X_{i,t}$ is a vector of the independent variable $(EC, PD, AGRI, FERT, CATT, REP)$, $\vartheta_j^{'}$ and θ_j^i are the dependent and independent variable short-run coefficients, respectively, p and q are the

[10] Furthermore, as in this case, it can be used safely with high dimensional panel data (Pesaran et al., 1999).

[11] A long-run relationship between variables exists if $-1 < ECT_{i,t} < 0$, and Student's t-distribution is statistically significant.

optimal lag orders for the dependent and independent variables, respectively, and $\varepsilon_{i,t}$ is the error term. $COE_{i,t}$ represents CO_2 emissions, *EC* represents total energy consumption, *PD* represents population density, *AGRI* represents agricultural land use, *FERT* represents fertilizers, *CATT* represents cattle density, and *REP* represents energy production from six renewable energy sources (biofuel, GEOB, hydropower, nuclear, solar, and wind) added one by one to the model.[12] Furthermore, the ARDL approach has recently been widely used in the literature to investigate the long-run relationship between CO_2 and renewable energy (Waheed et al., 2018; Sinaga et al., 2019; Koengkan and Fuinhas, 2020; Shahzad et al., 2021).

However, using a single class of panel estimators is rarely a safe bet, and may result in biased and inconsistent results (Özbuğday and Erbas, 2015; Zoundi, 2017; Dong et al., 2020; Yurtkuran, 2021; Güney, 2022). Thus, to improve the robustness of the panel cointegration analysis, this study employs the FMOLS, DOLS, and CCEMG estimators, proposed by Phillips and Hansen (1990), Kao and Chiang (1999), and Pesaran (2006), respectively. These methodologies differ from the panel ARDL approach in several ways. FMOLS is a non-parametric estimator that can handle cross-sectional heterogeneity, endogeneity, and serial correlation (Pedroni, 2001a). The group-mean panel FMOLS estimator of Pedroni (2001, p. 728–729) for the coefficient β of the basic OLS regression model $CO2_{i,t} = a_i + \beta X_{i,t} + u_{i,t}$, is constructed as follows [9]:

$$\widehat{\beta}^*_{GFM} = N^{-1}\sum_{i=1}^{N}\left(\sum_{t=1}^{T}(x_{i,t}-\overline{x}_i)^2\right)^{-1}\left(\sum_{t=1}^{T}(x_{i,t}-\overline{x}_i)\mu^*_{i,t} - T\widehat{\gamma}_i\right) \quad [9]$$

$$\text{where}\mu^*_{i,t} = (\mu_{i,t}-\overline{\mu}_i) - \frac{\widehat{\Omega}_{21i}}{\widehat{\Omega}_{22i}}\Delta x_{i,t}. \quad [10]$$

i represents the individual cross-sections, *t* represents the time series, $\widehat{\beta}^*_{GFM}$ identifies the transformed form of the standard OLS estimator $\widehat{\beta}_{GFM}$, $\mu^*_{i,t}$ is the transformed form of the true residuals $\mu_{i,t}$, and Ω_i is the long-run covariance matrix. Thus, the between-dimension FMOLS estimator is given by $\widehat{\beta}^*_{GFM} = N^{-1}\sum_{i=1}^{N}\widehat{\beta}^*_{FM,i}$, where $\widehat{\beta}^*_{FM,i}$ represents the conventional FMOLS estimator for the *i* th country.

DOLS is an alternative (parametric) estimator that uses first differenced regressor leads and lags to estimate the long-run correlation between variables, as proposed by Kao and Chiang (1999). Using Monte Carlo simulations, Kao and Chiang (1999) demonstrated that DOLS has better finite-sample properties than FMOLS, with less bias. The basic DOLS regression is defined as follows [11] (Dong et al., 2017):

$$\begin{aligned} COE_{i,t} = a_i + \beta_{i,t}X_{i,t} &+ \sum_{k=-K_i}^{K_i} p1_{i,k}\Delta EC_{i,t-k} + \sum_{k=-K_i}^{K_i} p2_{i,k}\Delta PD_{i,t-k} \\ &+ \sum_{k=-K_i}^{K_i} p3_{i,k}\Delta AGRI_{i,t-k} + \sum_{k=-K_i}^{K_i} p4_{i,k}\Delta FERT_{i,t-k} \\ &+ \sum_{k=-K_i}^{K_i} p5_{i,k}\Delta CATTLE_{i,t-k} + \sum_{k=-K_i}^{K_i} p6_{i,k}\Delta REP_{i,t-k} + \mu^*_{i,t} \end{aligned} \quad [11]$$

where K_i and $-K_i$ identify the lags and the leads, respectively. The group-mean panel DOLS estimator can be constructed in the same way as the FMOLS estimator (Pedroni, 2001b, p. 729) [12]:

$$\widehat{\beta}^*_{GD} = \left[N^{-1}\sum_{i=1}^{N}\left(\sum_{t=1}^{T} z_{i,t}z'_{i,t}\right)^{-1}\left(\sum_{t=1}^{T} z_{i,t}\widetilde{\mu}_{i,t}\right)\right]_1 \quad [12]$$

where $z_{i,t}$ is the $2(K+1)\times 1$ vector of independent variables $z_{i,t} = (p_{i,t} - \overline{p}_i, \Delta p_{i,t-K}, \ldots \Delta p_{i,t+K})$, and $\widetilde{\mu}_{i,t} = (\mu_{i,t} - \overline{\mu}_i)$. Thus, the between-dimension DOLS estimator is given by $\widehat{\beta}^*_{GD} = N^{-1}\sum_{i=1}^{N}\widehat{\beta}^*_{D,i}$, where $\widehat{\beta}^*_{D,i}$ represents the conventional DOLS estimator for the *i* th country.[13]

Finally, the CCEMG estimator allows for the unobservable common factors to be controlled by taking the cross-sectional averages of the dependent and independent variables and including them as additional regressors in the regression equation (Pesaran, 2006).[14] Chudik et al. (2011) showed, in particular, that it is robust to the presence of a few strong common factors and an infinite number of weak factors. It can also account for slope heterogeneity, unit roots in unobserved common factors, and structural breaks in the mean of those unobserved factors (Kapetanios et al., 2011; Chudik and Hashem Pesaran, 2015). The CCEMG estimator can be defined as a simple average of the individual slope coefficient estimators [13] (Pesaran, 2006):

$$\widehat{\beta}_{CCEMG} = N^{-1}\sum_{i=1}^{N}\widehat{\beta}_{CCE,i} \quad [13]$$

$$\text{where}\widehat{\beta}_{CCE,i} = \left(X'_i\overline{M}_wX_i\right)^{-1}X'_i\overline{M}_wy_i \quad [14]$$

$X_i = (x_{i1}, x_{i2}, \ldots, x_{iT})'$, $y_i = (y_{i1}, y_{i2}, \ldots, y_{iT})'$, and $\overline{M}_w$ can be defined as $\overline{M}_w = I_T - \overline{H}_w(\overline{H}'_w\overline{H}_w)^{-1}\overline{H}'_w$.

5.5. Granger non-causality

Finally, the Granger non-causality between CO_2 emissions and renewable energy production is investigated using a GMM-style PVAR estimator and the Dumitrescu and Hurlin (2012) panel causality test. PVAR combines the traditional vector autoregression (VAR) model, in which all variables are considered endogenous, with a panel data approach. The PVAR has two main features: i) first, it accounts for individual heterogeneity in all variables by including fixed effects in the model; and ii) second, it includes country-specific time dummies in the model to account for macro-shocks that can impact the dependent variables in the same way (Love and Zicchino, 2006). The model begins with the first-order VAR model [15]:

$$z_{i,t} = \Gamma_0 + \Gamma_1 z_{i,t-1} + f_i + d_{c,t} + \varepsilon_t \quad [15]$$

where $z_{i,t}$ is a vector of six variables $(EC, PD, AGRI, FERT, CATT, REP)$, Γ_1 is the lag operator, f_i denotes the fixed effects, $d_{c,t}$ denotes the country-specific time dummies, and ε_t identifies the vector of residuals. Because the inclusion of the dependent variable's lags makes fixed effects and the independent variables correlated, Love and Zicchino (2006) proposed using the Helmert forward mean-differencing transformation procedure (Arellano and Bover, 1995), which allows controlling for fixed effects while maintaining orthogonality between transformed variables and lagged independent variables. As a result, the lags in the independent variables are used as instruments in the GMM estimations. Furthermore, because several variables have a unit root, the GMM estimator is more prone to weak instrument issues. To overcome this issue, Abrigo and Love (2016, pp. 780–781) proposed using the variables in the first differences.

Given the possibility of cross-sectional dependence and heterogeneity in the series, Dumitrescu and Hurlin (2012) developed a bivariate causality test for heterogeneous panels based on Granger's (1969) original non-causality test. The panel causality test developed by Dumitrescu and Hurlin (2012) for two variables, given and observed, can be expressed using the following linear model [16]:

[12] Because the primary goal of the article is to figure out the best long-term strategies for environmental sustainability, this research is solely focused on the long-term relationship between renewable energy production and CO_2 emissions, ignoring short-term estimates.

[13] For comparison, both the group-mean panel FMOLS and the DOLS estimators are used.

[14] Another popular method for dealing with cross-sectional dependence is the AMG estimator developed by Eberhardt and Bond (2009). The CCEMG estimator, on the other hands, outperforms the AMG estimator on the root mean squared error (RMSE) and yields better results in Pesaran's (Pesaran, 2004; Pesaran, 2015) CD test on residuals (Table D1, Appendix D).

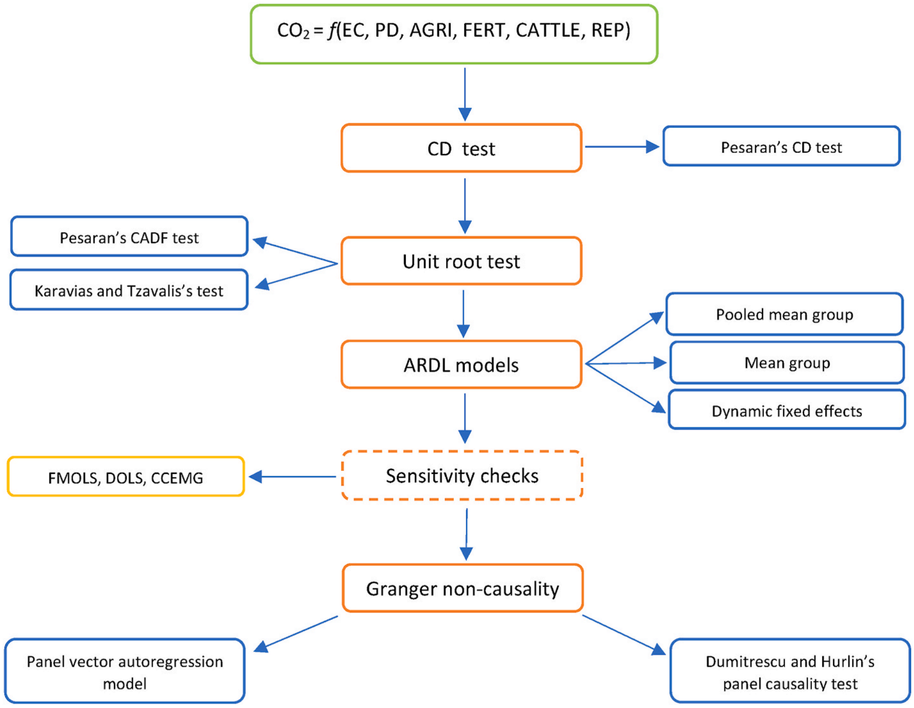

Fig. 11. The flowchart of the paper's empirical methodology.

Table 3
Results from Pesaran's (Pesaran, 2004; Pesaran, 2015) CD-test for cross-sectional dependence.

Variables	CD-test	mean (ρ)	mean (ρ_{abs})
CO_2	42.655***	0.3	0.5
EC	121.842***	0.88	0.88
PD	129.324***	0.92	0.92
AGRI	73.537***	0.52	0.67
FERT	51.794***	0.37	0.62
CATT	4.029***	0.03	0.59
Biofuel	51.11***	0.9	0.9
GEOB	111.082***	0.83	0.83
Hydropower	49.062***	0.35	0.38
Nuclear	42.955***	0.6	0.77
Solar	114.222***	0.81	0.81
Wind	128.475***	0.92	0.92

Notes: p-value <0.01***.

$$y_{i,t} = a_i + \sum_{k=1}^{K} \gamma_i^{(k)} y_{i,t-k} + \sum_{k=1}^{K} \beta_i^{(k)} x_{i,t-k} + \varepsilon_{i,t} \quad [16]$$

where i and t represent each individual and time series dimension, respectively, $y_{i,t}$ and $x_{i,t}$ are the (given and observable) variables supposed to be causally interrelated,[15] a_i represents the fixed individual effects, $\gamma_i^{(k)}$ is the autoregressive parameter, $\beta_i^{(k)}$ is the regression coefficients slope, K identifies the optimal lag order,[16] and $\varepsilon_{i,t}$ depicts the residuals. The null hypothesis of homogenous non-causality is based on β_i and is associated with the Granger non-causality test's average Wald statistics [17]:

$$W_{N,T}^{Hnc} = \frac{1}{N} \sum_{i=1}^{N} W_{i,T} \quad [17]$$

where $W_{i,T}$ denotes the individual Wald statistics of the Granger non-causality test that correspond to the individual test $H_0 : \beta_i = 0$. The issue of cross-sectional dependence is addressed by using a bootstrap procedure to compute p-values and critical values (Dumitrescu and Hurlin, 2012; Section 6.2). Fig. 11 depicts the flowchart of the paper's empirical methodology.

6. Results

6.1. Cross-sectional dependence test

Table 3 displays the results of Pesaran's (Pesaran, 2004; Pesaran, 2015) CD test for all dependent and independent variables,[17] as performed with Wursten's (Wursten, 2017) STATA command "xtcdf". The test shows that the null hypothesis of strict cross-sectional independence (or weak cross-sectional dependence) is always rejected at the 1% level of statistical significance for all variables investigated. Moreover, the average absolute correlation coefficient (ρ_{abs}) is high for nearly all of them, ranging from 0.38 for hydropower to 0.92 for population density and wind energy. As a result, units in the same cross-section are correlated, indicating that cross-sectional dependency exists in the panel data. To avoid erroneous statistical inferences, this issue must be addressed when doing the empirical study.

6.2. Unit root tests

Table 4 reports the results of second generation Pesaran's (2007) CADF panel unit root test, which is computed using Lewandowski's (2007) STATA command "pescadf". According to the findings, energy consumption per capita, population density, agricultural land, GEOB, and nuclear energy production all have a unit root process at the level but become stationary at the first difference. This implies that they are integrated of order 1, i.e., an I(1) process. Biofuel, hydropower, and solar energy production, on the other hand, are stationary at level,

[15] The given and observable variables are both used in the first differences.
[16] It should be noted that the lag order is the same for all cross-sectional units.

[17] Because data on renewable energy production per capita, in a number of cases, ranges between 0 and 1, the log transformation is not applied to the variables.

Table 4
Results from Pesaran's (2007) CADF panel unit root test.

Variables	Level		First Difference		Order of integration
	Constant	Constant + trend	Constant	Constant + trend	
CO_2	−2.096**	−2.548	–	−5.03***	I(0) or I(1)
EC	−1.319	−1.416	−3.994***	−4.452***	I(1)
PD	−1.933	−2.482	−2.867***	−3.541***	I(1)
AGRI	−1.952	−2.35	−4.653***	−4.877***	I(1)
FERT	−2.008*	−2.53	–	−5.154***	I(0) or I(1)
CATT	−1.763	−2.704**	−4.432***	–	I(0) or I(1)
Biofuel	−2.777***	−2.879***	–	–	I(0)
GEOB	−1.487	−2.167	−4.037***	−4.234***	I(1)
Hydropower	−3.613***	−4.007***	–	–	I(0)
Nuclear	−1.997	−2.379	−4.969***	−5.067***	I(1)
Solar	−2.285***	−2.66**	–	–	I(0)
Wind	−2.153**	−2.304	–	−4.379***	I(0) or I(1)

Notes: p-value <0.01***; p-value <0.05**; p-value <0.1*. The unit root test is performed using Lewandowski's (2007) STATA command "pescadf" (with 1 lag).

indicating an I(0) process. The test produces inconclusive results for the remaining variables.

The KT (Karavias and Tzavalis, 2014) test is employed as a sensitivity check using the STATA command "xtbunitroot" developed by Chen et al. (2022). The latter enables the computing of a statistical test robust to non-normality and cross-sectional heteroskedasticity and dependence (Table 5).[18] The results are generally comparable to those obtained with the CADF test, confirming that the panel data was a mix of I(0) and I(1) variables.[19]

6.3. Slope homogeneity test

The slope homogeneity hypothesis is tested using the STATA command "xthst" developed by Bersvendsen and Ditzen (2021), which is suitable for large panels and is robust to cross-sectional dependence across units. Table 6 shows each model with all control variables and renewable energy sources introduced one at a time. In all models, the standard and HAC robust delta tests show that the null hypothesis of slope homogeneity is always rejected at the 1% level of statistical significance (Table 6). As a result, the slope coefficients vary across cross-sectional units, highlighting the need for estimators that allow for heterogeneous slopes for fitting the panel cointegration models.

6.4. Panel cointegration models

6.4.1. Panel ARDL models

The panel ARDL approach (DFE, MG, and PMG) appears to be more appropriate than traditional cointegration techniques because the dependent and independent variables are a mixture of I(0) and I(1) (Pesaran et al., 2001). Moreover, in the presence of heterogeneous slopes, such as in this situation, the use of MG and PMG estimators is strongly recommended (Bersvendsen and Ditzen, 2021). The STATA command "xtpmg" developed by Blackburne and Frank (2007) is used to fit the panel's basic ARDL models.[21] Hausman's (1978) general specification test is used to select the preferred models. Table 7 displays the results, which have been divided into three parts (A, B, and C). DFE estimator outperforms PMG and MG estimators for biofuel (Table 7, A), GEOB (Table 7, A), and nuclear (Table 9, B). PMG outperforms MG and DFE estimators for wind (Table 7, C). While PMG and DFE are the efficient estimators for hydropower (Table 7, B) and solar (Table 7, C).[22] The existence of a stable long-run relationship between CO_2 emissions and the explanatory variables is confirmed because the ECT is highly significant and ranges always between −1 and 0. The findings reveal that biofuel, GEOB, hydropower, solar, and wind are negatively and strongly correlated with CO_2 emissions, with a statistical significance level of 1% (Table 7). Hydropower, GEOB, and solar are the most effective renewable resources in reducing CO_2 emissions; biofuel and wind are the least effective. Nuclear energy does not have a significant coefficient. Specifically, a 10 TWh increase in GEOB, hydropower, and solar energy generation is associated with an average reduction of 1.17, 0.87, and 0.77 metric tons of CO_2 emissions per capita, respectively.[23] While a 10 TWh increase in wind and biofuel energy production is associated with an average reduction of only 0.21 and 0.19 metric tons of CO_2 emissions per capita.[24]

The results are consistent with some recent studies that looked at electricity production or consumption from disaggregated renewable sources. Specifically, the negative association between biofuel energy and CO_2 emissions is consistent with (Busu and Nedelcu, 2021) and Waris et al. (2023), the negative relationship between GEOB and CO_2 emissions is consistent with Dogan and Inglesi-Lotz (2017), Destek and Aslan (2020) and Bibi et al. (2021) for biomass and with Bashir et al. (2023) for geothermal, the negative association between hydropower and CO_2 emissions is consistent with Al-Mulali et al. (2015), Sinaga et al. (2019), Destek and Aslan (2020), Bilgili et al. (2021), and Mohsin et al. (2023), the insignificant relationship between nuclear and CO_2 emissions is consistent with Al-Mulali et al. (2015) and Saidi and Mbarek (2016), the negative association between solar and CO_2 emissions is

[18] Moreover, it can be used safely when the time-series dimension is large, as in this case (Chen et al., 2022).

[19] It should be noted that in KT test population density is neither I(0) nor I(1). This condition may invalidate the ARDL models' results. Thus, the STATA command "xtcips" (Sangiacomo, 2014) has been implemented to perform Pesaran's (Pesaran, 2007, p. 275–279) cross-sectionally augmented IPS (CIPS) test for unit root. The results show that the null hypothesis of non-stationarity is rejected at a 1% level of significance (test statistics: −2.519 and −3.362) when the first difference of population density is taken. As a result, it is integrated of order one.

[20] The structural breaks for each variable are reported in Table E1 (Appendix E).

[21] The optimal lag order is identified by maximizing the log-likelihood function while minimizing the RMSE. The findings are summarized in Table F1 (Appendix F).

[22] Overall, PMG and DFE are the best models. According to Pesaran et al. (1999), this is not surprising given that PMG and DFE have much smaller standard errors than MG. Furthermore, unlike MG, PMG is less susceptible to outliers.

[23] Because no estimator is dominant, the hydropower and solar values are calculated by averaging the coefficients from the two preferred models (PMG and DFE).

[24] Only the coefficients of the preferred models are examined. The coefficients for solar and hydropower are computed by averaging the values obtained from PMG and DFE.

Table 5
Results from Karavias and Tzavalis's (2014) panel unit root test.

Variables	Level		First difference		Order of integration
	Constant	Constant + Trend	constant	Constant + Trend	
CO_2	−0.3923	−0.6073	−32.0639***	−18.7235***	I(1)
EC	0.3021	−2.1224**	−40.5232***	–	I(0) or I(1)
PD	1.4159	1.7723	−0.8552	−0.6003	–
AGRI	−0.1738	−1.2485	−19.6117***	−12.5255***	I(1)
FERT	−3.9317***	−2.869***	–	–	I(0)
CATT	0.384	1.9522	−27.437***	−15.5659***	I(1)
Biofuel	0.9097	2.645	−9.0972***	−7.5717***	I(1)
GEOB	−1.4655	−1.3938	−9.1066***	−5.7444***	I(1)
Hydropower	−13.717***	−12.702***	–	–	I(0)
Nuclear	0.8229	1.2633	−27.8934***	−15.5699***	I(1)
Solar	4.895	−3.0041***	−3.3624***	–	I(0) or I(1)
Wind	9.1395	−6.2175***	−27.8319***	–	I(0) or I(1)

Notes: p-value <0.01***; p-value <0.05**; p-value <0.1*. The unit root test is performed using STATA command "xtbunitroot" developed by Chen et al. (2022). The structural breaks are identified using the STATA command "xtbreak" developed by Ditzen et al. (2021).[20].

Table 6
Results from Blomquist and Westerlund's (2013) slope homogeneity test.

	Biofuel	GEOB	Hydro	Nuclear	Solar	Wind
Delta	7.399*** [0.000]	6.72*** [0.000]	7.062*** [0.000]	9.308*** [0.000]	23.738*** [0.000]	15.766*** [0.000]
Adj. Delta	9.626*** [0.000]	7.581*** [0.000]	7.869*** [0.000]	10.367*** [0.000]	26.45*** [0.000]	17.567*** [0.000]

Notes: p-value <0.01. Null hypothesis: slope coefficients are homogenous. Each model contains a constant as wells as five control variables (energy consumption, population density, agricultural land, fertilizer, and cattle density). The estimations are performed using the STATA command "xthst", developed by Bersvendsen and Ditzen (2021). The Bartlett kernel heteroskedasticity and autocorrelation consistent (HAC) standard errors with bandwidths are automatically determined.

Table 7
(part A). Panel ARDL estimations (biofuel and GEOB).

Variables	PMG	MG	DFE	PMG	MG	DFE
ECT	−0.1739*** [0.0514]	−0.7318*** [0.0911]	−0.0998*** [0.0141]	−0.1176*** [0.0187]	−0.3901*** [0.0475]	−0.0561*** [0.0126]
EC	0.0008*** [0.0001]	0.0008*** [0.0002]	0.0007** [0.0003]	0.0009*** [0.0001]	0.0015*** [0.0004]	0.0001 [0.0001]
PD	−0.0139 [0.009]	−1.3434** [0.6852]	−0.0316 [0.0262]	−0.0472*** [0.007]	−1.2522** [0.6365]	−0.0027 [0.0132]
AGRI	0.1137*** [0.0293]	0.5066 [0.5491]	0.1826*** [0.067]	0.0322 [0.0199]	0.3539 [0.8567]	0.1327 [0.1005]
FERT	0.0466*** [0.0059]	0.0338 [0.0311]	0.0311 [0.0229]	0.0093** [0.0044]	−0.0421 [0.0321]	0.0627*** [0.0181]
CATT	0.0168 [0.0133]	1.0658 [0.7826]	0.0795*** [0.028]	−0.0502*** [0.0167]	−0.2453 [0.394]	−0.0029 [0.0416]
Biofuel	0.0054 [0.0079]	−0.0974 [0.1222]	−0.0194*** [0.0019]			
GEOB				−0.056*** [0.0156]	−1.8247* [1.0877]	−0.1165*** [0.0334]
MG_a vs PMG_b	Chi-sq. 0.87 [0.99] = PMG is preferred			Chi-sq. 8.36 [0.2132] = PMG is preferred		
MG_a vs DFE_b	Chi-sq. 0.01 [1] = DFE is preferred			Chi-sq. 0.59 [0.9966] = DFE is preferred		
PMG_a vs DFE_b	Chi-sq. 4.2 [0.6492] = DFE is preferred			Chi-sq. 1.73 [0.9426] = DFE is preferred		
N. of groups	15	15	15	27	27	27
Observations	449	449	449	1339	1332	1332

Notes: p-value <0.01***; p-value <0.05**; p-value <0.1*. Under the null hypothesis of Hausman's test, the "b" estimator is efficient. Hausman's test is carried out using the option "sigmamore". Estimates for the PMG, MG, and DFE models are generated using the STATA command "xtpmg" (Blackburne and Frank, 2007).

Table 7
(part B). Panel ARDL estimations (hydropower and nuclear).

Variables	PMG	MG	DFE	PMG	MG	DFE
ECT	−0.0735*** [0.0155]	−0.3082*** [0.0317]	−0.0416*** [0.0119]	−0.0842*** [0.0329]	−0.5094*** [0.1152]	−0.0532*** [0.0197]
EC	0.0004*** [0.0001]	0.0012*** [0.0003]	0.0001 [0.0000]	0.0009*** [0.0001]	0.0017* [0.0009]	0.0004* [0.0002]
PD	−0.0551*** [0.0083]	−1.0596* [0.6261]	−0.0236 [0.0173]	−0.0389*** [0.0101]	0.5576 [0.6276]	−0.0155 [0.0305]
AGRI	0.04296 [0.03]	1.0724 [1.0328]	0.25* [0.1431]	0.2494*** [0.0448]	1.7653 [1.4551]	0.351* [0.1893]
FERT	−0.001 [0.0105]	−0.0417 [0.0722]	0.0819*** [0.025]	−0.094*** [0.0203]	0.0036 [0.0373]	−0.0065 [0.0359]
CATT	−0.0816** [0.0338]	−0.1375 [0.6603]	0.0168 [0.0824]	0.0303 [0.0204]	1.2139 [0.808]	0.0126 [0.0706]
Hydropower	−0.1112*** [0.0245]	−2.6379 [4.0848]	−0.0632*** [0.0208]			
Nuclear				0.0027** [0.0012]	0.0081 [0.052]	−0.0039 [0.0037]
MG_a vs PMG_b	Chi-sq. 2.63 [0.7572] = PMG is preferred			Chi-sq. 29.59 [0.0000] = MG is preferred		
MG_a vs DFE_b	Chi-sq. 0.07 [0.9999] = DFE is preferred			Chi-sq. 0.02 [1] = DFE is preferred		
PMG_a vs DFE_b	Chi-sq. −58.16 = Inconclusive			Chi-sq. 1.38 [0.9669] = DFE is preferred		
N. of groups	27	27	27	14	14	14
Observations	1448	1448	1448	749	749	749

Notes: p-value <0.01***; p-value <0.05**; p-value <0.1*. Under the null hypothesis of Hausman's test, the "b" estimator is efficient. Hausman's test is carried out using the option "sigmamore". Estimates for the PMG, MG, and DFE models are generated using the STATA command "xtpmg" (Blackburne and Frank, 2007).

Table 7
(part C). Panel ARDL estimations (solar and wind).

Variables	PMG	MG	DFE	PMG	MG	DFE
ECT	−0.1196*** [0.0182]	−0.3549*** [0.0322]	−0.0528*** [0.0117]	−0.1364*** [0.0229]	−0.492*** [0.0374]	−0.063*** [0.0138]
EC	0.0002*** [0.0000]	0.0008*** [0.0003]	0.0000 [0.0001]	0.0008*** [0.0001]	0.0006** [0.0003]	0.0000 [0.0000]
PD	0.0003 [0.0056]	−0.9487** [0.409]	−0.0106 [0.0134]	−0.0188*** [0.0065]	−0.7158 [0.7811]	−0.0065 [0.0117]
AGRI	−0.0254 [0.0167]	0.1792 [0.9418]	0.1544* [0.0907]	0.0489*** [0.0186]	−0.1779 [0.3831]	0.1016 [0.0743]
FERT	−0.0151 [0.0073]	0.0012 [0.0227]	0.0531*** [0.0204]	0.0087** [0.0039]	0.008 [0.01]	0.0494*** [0.0163]
CATT	−0.0186 [0.0202]	0.166 [0.8392]	0.029 [0.0684]	0.0029 [0.0125]	0.9141 [0.8208]	0.0225 [0.0513]
Solar	−0.058*** [0.0176]	62.6236 [64.3049]	−0.0963*** [0.0231]			
Wind				−0.0205*** [0.0056]	−8.5366 [7.4865]	−0.0227 [0.0211]
MG_a vs PMG_b	Chi-sq. 3.95 [0.5567] = PMG is preferred			Chi-sq. 0.78 [0.9782] = PMG is preferred		
MG_a vs DFE_b	Chi-sq. 0.18 [0.9993] = DFE is preferred			Chi-sq. 0.25 [0.9984] = DFE is preferred		
PMG_a vs DFE_b	Chi-sq. −54.2 = Inconclusive			Chi-sq. 43.7 [0.0000] = PMG is preferred		
N. of groups	27	27	27	27	27	27
Observations	1448	1448	1448	1447	1447	1447

Notes: p-value <0.01***; p-value <0.05**; p-value <0.1*. Under the null hypothesis of Hausman's test, the "b" estimator is efficient. Hausman's test is carried out using the option "sigmamore". Estimates for the PMG, MG, and DFE models are generated using the STATA command "xtpmg" (Blackburne and Frank, 2007).

consistent with Güney (2022) and Waris et al. (2023), and finally, the negative relationship between wind and CO_2 emissions is consistent Destek and Aslan (2020) and Güney and Üstündağ (2022).

While they differ significantly from Al-Mulali et al. (2015), who found an insignificant relationship between CO_2 emissions and solar and wind energy production, Yuaningsih et al. (2020), who figured out a positive relationship between CO_2 and biofuel, solar, and wind energy production, Shahzad et al. (2021), who observed a positive relationship between CO_2 emissions and geothermal energy consumption, and Waris et al. (2023), who discovered a positive association between wind energy consumption and CO_2 emissions, but not between hydropower energy consumption and CO_2 emissions.

Regarding the control variables, the results show that energy consumption, agricultural land, and fertilizer are positively and significantly correlated with CO_2 emissions, whereas population density is negatively and significantly associated with CO_2 emissions.[25] Instead, the relationship between cattle density and CO_2 emissions is ambiguous.

6.4.2. Robustness checks: CCEMG, DOLS, and FMOLS

Table 9 summarizes the FMOLS and DOLS estimators' results, while Table 8 displays the CCEMG estimator's results. For FMOLS and DOLS, I calculate Pedroni's (2001) panel group mean (β) by averaging the individual β generated for each panel unit. Specifically, I used the STATA command "xtcointreg" (Khodzhimatov, 2018). The FMOLS and DOLS estimators reveal that all renewable energy sources have a negative and significant relationship with CO_2 emissions at the 1% level of statistical significance (Table 8). The only exception is biofuel, which shows a negative association with CO_2 in FMOLS models but a positive association in DOLS models.

Pesaran's (2006) CCEMG estimator is calculated using the STATA command "xtmg" (Eberhardt, 2011). Pesaran's (2004) CD test shows that no residual cross-section dependence remains (Table 9). The null hypothesis of strict cross-sectional independence (or weak cross-sectional dependence) in residuals is rejected at the conventional level of 5%, with the model that included biofuel being the only exception. The findings reveal that electricity generation by hydropower, nuclear power, solar power, and wind power is negatively and significantly correlated with CO_2 emissions, at a statistical level ranging from 1% to 5% (Table 9). The relationship between CO_2 emissions, and biofuel, and GEOB, on the other hand, is not significant, albeit negative for GEOB. Furthermore, the nuclear coefficient, while negative and highly significant for all sensitivity models (FMOLS, DOLS, and CCEMG), is very low. Overall, the robustness tests confirmed that GEOB, hydropower, and solar are the most effective CO_2 reduction strategies. Finally, the results appear to be consistent and robust to changes in specifications.

6.5. Panel granger non-causality

6.5.1. PVAR models

The STATA "pvar" package proposed by Abrigo and Love (2016) is used to perform GMM-style PVAR Granger estimations.[26] The five control variables are considered by all six fitted models (Table 10). According to Hamilton (1994) and Lütkepohl (2005), PVAR satisfies the stability condition because the moduli of each eigenvalue of the estimated models are strictly less than 1, i.e., they lay within the unit circle. Furthermore, Hansen's (1982) J test shows that at the conventional level of significance (5%), the null hypothesis of valid overidentifying restrictions is never rejected, confirming that there are no misspecification issues (Table 11).

The Granger non-causality test results based on PVAR models reveal unidirectional causality from hydropower and solar to CO_2 emissions at the 5% level of significance, from wind to CO_2 emissions at the 1% level of significance, and from CO_2 emissions to nuclear at the 5% level of significance. Thus, the null hypothesis that hydropower, solar, and wind do not Granger-cause CO_2 emissions is rejected at a statistical significance level ranging from 1% to 5%. A bidirectional causal relationship is found between biofuel and CO_2 emissions, as well as between GEOB and CO_2 emissions (Table 10).

Thus, hydropower, solar, and wind energy production are found to be predictors of CO_2 emissions, while the latter is a predictor of nuclear energy production. The bidirectional causality between biofuel, GEOB, and CO_2 emissions may imply that when CO_2 emissions increase, GEOB and biofuel energy generation decrease, exacerbating environmental issues. The results are similar to those of Destek and Aslan (2020) for biomass and hydropower in G-7 countries, and those of Shahzad et al. (2021) for geothermal energy in the Philippines. While they diverge, for instance, from Menyah and Wolde-Rufael (2010) for nuclear in the US, Al-Mulali et al. (2015) for hydropower, nuclear, solar, and wind in 23 European countries, and Umar et al. (2023) for geothermal in the top seven geothermal consuming countries.

6.5.2. Robustness checks: Dumitrescu-Hurlin causality

Dumitrescu and Hurlin's (2012) bivariate Granger non-causality test

[25] The findings for energy consumption are consistent with Al-Mulali et al. (2013) and Khan et al. (2019), the results for agricultural land agree with Parajuli et al. (2019) and Raihan and Tuspekova (2022), the outcomes for fertilizer are in line with Rehman et al. (2022), and the inferences for population density align with Abdouli et al. (2018) and Wang and Li (2021).

[26] The panel VAR model selection is carried on using the STATA command pvarsoc (Abrigo and Love, 2016). The results on optimal lag order are reported in Table G1 (Appendix G).

Table 8
Results from FMOLS and DOLS estimators.

Variable	FMOLS-β	FMOLS-β	FMOLS-β	FMOLS-β	FMOLS-β	FMOLS-β
	(1)	(2)	(3)	(4)	(5)	(6)
EC	0.00***[63.41]	0.00***[58.18]	0.00***[53.69]	0.00***[26.3]	0.00***[38.07]	0.00***[40.51]
PD	−0.53***[-14.95]	−0.34***[-22.69]	−0.4***[-33.84]	−0.4***[-20.11]	−0.41***[-22.65]	−0.24***[-11.31]
AGRI	0.07***[8.46]	0.08***[8.74]	−0.27***[3.79]	−0.51***[-2.09]	−0.26***[-1.50]	−0.2***[-2.97]
FERT	0.00***[-0.87]	−0.00***[-3.54]	0.02***[6.43]	0.02***[2.47]	0.02***[7.63]	0.01***[3.25]
CATT	0.59***[31.31]	−0.05***[6.66]	0.03***[6.56]	0.46***[5.57]	0.22***[11.09]	0.01***[11.61]
Biofuel	−0.11***[-21.35]					
GEOB		−2.37***[-19.16]				
Hydropower			−1.53***[-5.54]			
Nuclear				−0.03***[-14.7]		
Solar					−2.51***[-21.33]	
Wind						−1.78***[-33.45]
	DOLS-β	DOLS-β	DOLS-β	DOLS-β	DOLS-β	DOLS-β
	(1)	(2)	(3)	(4)	(5)	(6)
EC	0.00***[36.55]	0.00***[48.15]	0.00***[78.41]	0.00***[32.42]	0.00***[45.85]	0.00***[29.38]
PD	−1.05***[-6.38]	−0.53***[-25.82]	0.1***[-32.91]	−0.33***[-25.81]	−0.48***[-23.07]	0.38***[-7.71]
AGRI	0.53***[-6.95]	−0.04***[8.30]	−0.52***[1.06]	−0.62***[-11.27]	−0.36***[-10.43]	−0.2***[-11.22]
FERT	−0.01***[5]	−0.01***[-1.70]	0.03***[12.98]	0.04***[9.96]	0.03***[13.65]	0.01***[2.82]
CATT	1.05***[16.04]	0.04***[-2.62]	0.5***[13.48]	0.76***[9.26]	0.5***[4.84]	0.31***[12.41]
Biofuel	0.18***[2.77]					
GEOB		−2.13***[-14.45]				
Hydropower			−5.28***[-6.34]			
Nuclear				−0.01***[-16.95]		
Solar					−3.64***[-4.37]	
Wind						−1.25***[-23.33]

Notes: p-value <0.01***. T-statistics in brackets. The estimations for FMOLS and DOLS models are computed using the STATA command "xtcointreg" (Khodzhimatov, 2018). The optimal lag and lead length are chosen using Akaike's information criterion (AIC).

Table 9
Results from CCEMG estimator.

Variables	CCEMG	CCEMG	CCEMG	CCEMG	CCEMG	CCEMG
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	−9.2303 [12.3427]	5.3678 [7.0713]	18.3581*** [6.4442]	10.2732 [12.7484]	14.3032 [11.2175]	18.849** [9.0679]
EC	0.0011*** [0.0002]	0.0009*** [0.0002]	0.0007*** [0.0002]	0.0008*** [0.0003]	0.0007*** [0.0001]	0.0008*** [0.0001]
PD	0.04 [0.0414]	−0.0074 [0.0411]	−0.0435 [0.0406]	−0.0309 [0.0594]	−0.0287 [0.0207]	−0.0182 [0.0247]
AGRI	−0.0776 [0.0899]	−0.0461 [0.0457]	−0.0348 [0.0477]	0.1077 [0.0661]	−0.0338 [0.0455]	−0.0124 [0.0374]
FERT	−0.0086 [0.0071]	0.0054 [0.0051]	0.0042 [0.0055]	0.0145 [0.0102]	0.0009 [0.0051]	0.002 [0.0054]
CATT	−0.0373 [0.0603]	0.0377 [0.0292]	0.0325 [0.0275]	0.0422 [0.0382]	0.0453 [0.029]	0.0601** [0.0253]
Biofuel	0.013 [0.0196]					
GEOB		−0.0032 [0.0434]				
Hydropower			−0.0215** [0.0101]			
Nuclear				−0.0072** [0.0033]		
Solar					−0.1389** [0.0677]	
Wind						−0.0651*** [0.0245]
RMSE	0.1455	0.2627	0.2822	0.2289	0.27	0.2662
CD test p-value	0.038	0.299	0.24	0.08	0.616	0.09
N. of groups	15	27	27	14	27	27
Observations	465	1372	1482	772	1482	1482

Notes: p-value <0.01***; p-value <0.05**. The estimations for CCEMG models are computed using the STATA command "xtmg" (Eberhardt, 2011).

is used as a robustness check. The test statistics are computed using the STATA command "xtgcause", developed by Lopez and Weber (2017). Each test is run with 500 bootstrap replications to reduce cross-sectional dependence. Because Akaike's information criterion (AIC) and Bayesian information criterion (BIC) model selection methods produce different lag orders, both are used as a conservative strategy (Table 12). The tests based on the AIC reveal unidirectional causality from biofuel to CO_2 emissions at a 1% level of significance, from GEOB to CO_2 at a 1% level of significance, and from CO_2 emissions to wind at a 5% level of significance.[27] Solar and CO_2 emissions show bidirectional causality, while at a 10% level of significance, a weak unidirectional causality from hydropower to CO_2 emissions is detected. There is no causality between nuclear and CO_2 emissions (Table 12, part A).

The test based on the BIC reveals a unidirectional causality from hydropower to CO_2 at a 1% level of significance and a weak unidirectional causality from CO_2 to nuclear. There is bidirectional causality between CO_2, and GEOB, solar, and wind. In contrast, there is no causal relationship between biofuel and CO_2 (Table 12, part B). As a result, these tests are substantially consistent with the results of PVAR models, lending support to prior findings. They show that nuclear power is unsuccessful at cutting CO_2 emissions, whereas GEOB, hydropower, and solar, can play an important role in lowering CO_2 emissions in OECD countries. Biofuel evidence is somewhat unclear, while the relationship between wind and CO_2 appears to be bidirectional as a whole. The key findings of ARDL and PVAR are depicted in Fig. 12 as a summary.

[27] The alternative hypothesis states that output does Granger-cause CO_2 emissions for at least one panelvar.

Table 10
Results from PVAR-Granger non-causality models.

Null hypothesis	Chi-square	P-value	Direction of causation
Biofuel $\nRightarrow$ CO_2	40.371***	0.000	Biofuel $\Leftrightarrow$ CO_2
CO_2 $\nRightarrow$ Biofuel	53.168***	0.000	
GEOB $\nRightarrow$ CO_2	27.023***	0.000	GEOB $\Leftrightarrow$ CO_2
CO_2 $\nRightarrow$ GEOB	5.352**	0.021	
Hydropower $\nRightarrow$ CO_2	5.102**	0.024	Hydropower $\Rightarrow$ CO_2
CO_2 $\nRightarrow$ Hydropower	2.866*	0.09	
Nuclear $\nRightarrow$ CO_2	0.471	0.79	CO_2 $\Rightarrow$ Nuclear
CO_2 $\nRightarrow$ Nuclear	8.555**	0.014	
Solar $\nRightarrow$ CO_2	4.816**	0.028	Solar $\Rightarrow$ CO_2
CO_2 $\nRightarrow$ Solar	0.169	0.681	
Wind $\nRightarrow$ CO_2	81.915***	0.000	Wind $\Rightarrow$ CO_2
CO_2 $\nRightarrow$ Wind	0.417	0.518	

Notes: p-value <0.01***; p-value <0.05**; p-value <0.1*. A $\nRightarrow$ B indicates the null hypothesis that A does not Granger cause B; $\Rightarrow$ indicates unidirectional causality from A to B, $\Leftrightarrow$ indicates bidirectional causality. Each model includes the following control variables: energy consumption, population density, agricultural land, fertilizer, and cattle density. The STATA "pvar" package is used to compute the estimates (Abrigo and Love, 2016). The option "fod" is used to account for panel-specific fixed effects.

Table 11
Diagnostic test results for PVAR-Granger non-causality models.

Causality	Eigenvalue's modulus	Hansen's J statistics	p-value
Biofuel $\nRightarrow$ CO_2 CO_2 $\nRightarrow$ Biofuel	0.2353–0.8819	210.96	0.22
GEOB $\nRightarrow$ CO_2 CO_2 $\nRightarrow$ GEOB	0.0187–0.6328	204.03	0.33
Hydropower $\nRightarrow$ CO_2 CO_2 $\nRightarrow$ Hydropower	0.0594–0.8337	169.29	0.92
Nuclear $\nRightarrow$ CO_2 CO_2 $\nRightarrow$ Nuclear	0.0346–0.9421	127.93	0.87
Solar $\nRightarrow$ CO_2 CO_2 $\nRightarrow$ Solar	0.1011–0.9927	103.51	0.33
Wind $\nRightarrow$ CO_2 CO_2 $\nRightarrow$ Wind	0.0692–0.9955	183.1	0.78

Notes: A $\nRightarrow$ B indicates the null hypothesis that A does not Granger cause B. The diagnostic tests refer to the PVAR models estimated in Table 10.

7. Discussion

7.1. Biofuel

This section discusses the policy implications of each of the renewable energy sources studied in this paper. Biofuel has an overall low effect on CO_2 emissions. A one-unit TWh increase in biofuel energy generation results in a 0.02 metric tons reduction in CO_2 emissions per capita. Furthermore, the direction of causality between biofuel and CO_2 emissions is somewhat unclear. This could be because, while plants used to produce biofuel help to sequester CO_2 from the atmosphere (Aljaafari et al., 2022), converting vegetation and forest to biofuel feedstock cultivation can increase the risk of biodiversity loss, soil erosion, and forest and land degradation, all of which result in increased GHG emissions (Jeswani et al., 2020). As a result, it appears that biofuel is not the best solution for enhancing environmental sustainability and mitigating climate change, particularly when compared to other options.

7.2. GEOB

Geothermal and biomass technologies are the most effective in lowering CO_2 emissions. A one-unit TWh increase in GEOB energy generation results in a 0.12 metric tons reduction in CO_2 emissions per capita. The direction of causality is bidirectional, implying that when CO_2 emissions decline, GEOB energy generation rises and vice versa. Investing in geothermal development has both benefits and drawbacks. On the one hand, it may be effecting in boosting decarbonization

Table 12
(part A). Results from Dumitrescu and Hurlin's (2012) panel non-causality test.

Null hypothesis	Lag (AIC)	W-bar	Z-bar	Z-bar tilde	Direction of causation
Biofuel $\nRightarrow$ CO_2	8	40.3087	31.2827*** (0.000)	4.7251*** (0.000)	Biofuel $\Rightarrow$ CO_2
CO_2 $\nRightarrow$ Biofuel	8	14.604	6.3943 (0.254)	0.2226 (0.756)	
GEOB $\nRightarrow$ CO_2	14	30.6784	16.3779*** (0.002)	3.0877*** (0.002)	GEOB $\Rightarrow$ CO_2
CO_2 $\nRightarrow$ GEOB	14	13.3719	−0.6168 (0.938)	−1.7359* (0.054)	
Hydro $\nRightarrow$ CO_2	16	28.6998	7.777* (0.088)	0.6067 (0.542)	Hydro $\Rightarrow$ CO_2 [weak]
CO_2 $\nRightarrow$ Hydro	16	25.265	5.6736(0.21)	0.1633(0.9)	
Nuclear $\nRightarrow$ CO_2	16	23.4962	4.9583 (0.366)	−0.0703 (0.948)	Nuclear $\neq$ CO_2
CO_2 $\nRightarrow$ Nuclear	16	17.1474	0.7589 (0.886)	−0.9555 (0.26)	
Solar $\nRightarrow$ CO_2	1	4.3291	8.1545*** (0.000)	7.5029*** (0.000)	Solar $\Leftrightarrow$ CO_2
CO_2 $\nRightarrow$ Solar	16	43.6141	16.9101*** (0.000)	2.5322*** (0.000)	
Wind $\nRightarrow$ CO_2	16	27.1428	6.8236* (0.096)	0.4057 (0.734)	CO_2 $\Rightarrow$ Wind
CO_2 $\nRightarrow$ Wind	16	53.1232	22.7332** (0.014)	3.7598** (0.014)	

Notes: p-value <0.01***; p-value <0.05**; p-value <0.1*. Hydro, hydropower; A $\nRightarrow$ B indicates the null hypothesis that A does not Granger cause B; $\Rightarrow$ indicates unidirectional causality from A to B, $\Leftrightarrow$ indicates bidirectional causality; $\neq$ indicates no causality. The test is based on the Akaike's information criterion (AIC). The test statistics are computed using the STATA command "xtgcause", developed by Lopez and Weber (2017). The critical values are determined by performing 500 bootstrap replications with the random-number seed set to "1234567" for replication purposes.

Table 12
(part B). Results from Dumitrescu and Hurlin's (2012) panel non-causality test.

Null hypothesis	Lag (BIC)	W-bar	Z-bar	Z-bar tilde	Direction of causation
Biofuel $\nRightarrow$ CO_2	1	0.9253	−0.2054 (0.856)	−0.3747 (0.754)	Biofuel $\neq$ CO_2
CO_2 $\nRightarrow$ Biofuel	1	0.6645	−0.9189 (0.43)	−0.9933 (0.332)	
GEOB $\nRightarrow$ CO_2	1	1.8036	2.9527** (0.03)	2.5742** (0.03)	GEOB $\Leftrightarrow$ CO_2
CO_2 $\nRightarrow$ GEOB	1	1.694	2.55**(0.05)	2.2021* (0.052)	
Hydro $\nRightarrow$ CO_2	1	3.663	6.5231*** (0.000)	5.9832*** (0.000)	Hydro $\Rightarrow$ CO_2
CO_2 $\nRightarrow$ Hydro	1	0.8764	−0.3027 (0.76)	−0.3751 (0.698)	
Nuclear $\nRightarrow$ CO_2	1	0.9719	−0.0743 (0.94)	−0.1698 (0.864)	CO_2 $\Rightarrow$ Nuclear [weak]
CO_2 $\nRightarrow$ Nuclear	1	0.306	−1.8361* (0.092)	−1.8109* (0.07)	
Solar $\nRightarrow$ CO_2	1	4.3291	8.1545*** (0.000)	7.5029*** (0.000)	Solar $\Leftrightarrow$ CO_2
CO_2 $\nRightarrow$ Solar	16	43.6141	16.9101*** (0.000)	2.5322*** (0.000)	
Wind $\nRightarrow$ CO_2	1	2.9683	4.8212*** (0.008)	4.3979*** (0.008)	Wind $\Leftrightarrow$ CO_2
CO_2 $\nRightarrow$ Wind	16	53.1232	22.7332** (0.014)	3.7598** (0.014)	

Notes: p-value <0.01***; p-value <0.05**; p-value <0.1*. Hydro, hydropower; A $\nRightarrow$ B indicates the null hypothesis that A does not Granger cause B; $\Rightarrow$ indicates unidirectional causality from A to B, $\Leftrightarrow$ indicates bidirectional causality; $\neq$ indicates no causality. The test is based on the Bayesian information criterion (BIC). The test statistics are computed using the STATA command "xtgcause", developed by Lopez and Weber (2017). The critical values are determined by performing 500 bootstrap replications with the random-number seed set to "1234567" for replication purposes.

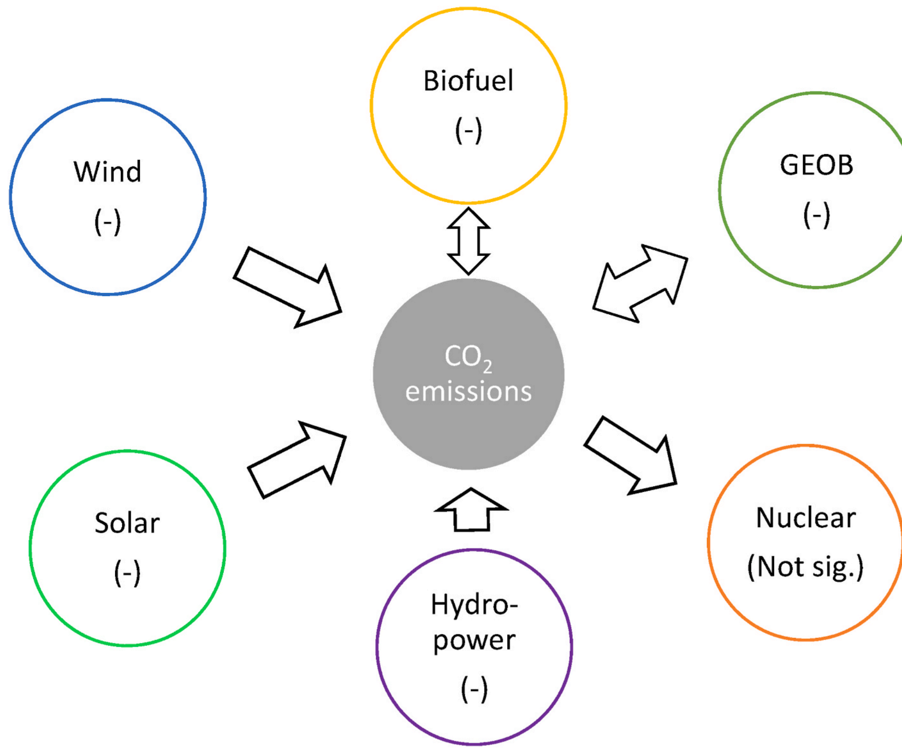

Fig. 12. A summary of the results of the ARDL and PVAR models.
Notes: Not sig., not significant; ⇒ indicates unidirectional causality; ⇔ indicated bidirectional causality. The sign of the long-run coefficients of the ARDL models is shown in brackets.

because, unlike wind and solar energy, it is not dependent on weather factors since it is available worldwide (Vargas et al., 2022), and has a high capacity factor of 77%.[28] On the other hand, compared to other renewable energies, it has high installation and electricity production costs.[29] Along with hydropower, it is the only renewable energy source to have seen a significant increase in average total installation costs, which have risen from 2714 USD/kW in 2010 to 3991 USD/kW in 2021, as well as an increase in the cost of producing electricity from 0.05 USD/kWh to 0.068 USD/kWh over the same period (International Renewable Energy Agency, 2022, p. 15).

Furthermore, the earliest stages of geothermal energy exploration and drilling are very capital-intensive and financially risky, taking up to four years to complete (Abidin et al., 2020, p. 54). This poses a clear financial barrier that may prevent geothermal energy from being widely used.

In 2021, total installation costs for biomass energy were 2353 USD/kW, with electricity generation costs of 0.067 USD/kWh (International Renewable Energy Agency, 2022, p. 15). However, at 0.088 USD/kWh and 0.097 USD/kWh, respectively, the average cost of producing power from biomass in Europe and North America was much higher than the global average (International Renewable Energy Agency, 2022, p. 163). As a result, while biomass and geothermal energy are both effective in reducing CO_2 emissions, they are both difficult to adopt. The cost and availability of feedstock heavily influence biomass expenses. An alternative is to increase the use of wood pellets, which have a high bulk density (Tumuluru, 2016)[30] and generally stable and competitive pricing (Bioenergy Europe, 2022).

Future geothermal energy regulations may provide public companies with a greater role in funding and assisting with initial exploration expenditures. This is especially crucial for countries with near-zero GEOB electricity outputs, such as Cyprus, Greece, Israel, Mexico, and Norway (Table 2).

7.3. Hydropower

According to the findings, hydropower is the second greatest renewable option for lowering CO_2 emissions in OECD countries. A one-unit TWh increase in hydropower energy generation results in a 0.09 metric tons reduction in CO_2 emissions per capita. Furthermore, the direction of causality shows that hydropower is a strong predictor of CO_2 emissions. The use of hydropower is particularly desired since the cost of producing hydroelectricity is quite low when compared to geothermal and biomass generation and was 0.048 USD/kWh in 2021 (International Renewable Energy International Energy Agency, 2022, p.15). It also has a technical yearly electricity generation potential of 52 PWh per year, which would cover roughly 33% of global annual energy consumption (Hoes et al., 2017).

Europe, on the other hand, has a substantially lower hydropower potential of 73 GW, having already utilized 79.1% of its full potential (International Hydropower Association, 2022, p. 11). Not all countries, however, pursue the same policy. For example, the United States added only 0.34 GW of hydroelectric capacity between 2018 and 2021, whereas Canada added 1.6 GW, nearly five times as much. Only Norway and Austria added large amounts of hydropower capacity in 2018–2021,

[28] The capacity factor is defined as the ratio of a plant's annual electric power generated to its theoretical continuous maximum output, expressed as a percentage ranging from 0 to 100 (International Renewable Energy Agency, 2022b, p. 24).

[29] The first measure refers to the global weighted average total installed cost required for project completion (International Renewable Energy Agency, 2022b, p. 15 and 24). The second measure refers to the levelized cost of electricity and is calculated by the ratio of a certain technology's lifetime power production to its lifetime costs. More details on this measure can be found in International Renewable Energy Agency (2022b, p. 24).

[30] The bulk density is the ratio of biomass volume to biomass mass.

with increases of 0.86 GW and 0.56 GW, respectively (International Hydropower Association, 2019, 2020, 2020, 2021, and 2022).

As a result, countries in North America, in particular, are encouraged to use hydropower energy. However, in the United States, the hydroelectric permission procedure is difficult and time-consuming (Energy Efficiency and Renewable Energy, 2021). By minimizing the number of agencies/institutions involved and lowering licensing costs for smaller hydropower projects, the procedure can be simplified and made more economically viable. In fact, there are not very significant scale economies in hydropower plants, except for projects with a very high capacity (International Renewable Energy Agency, 2022, p. 143–144). Meanwhile, European countries should gamble more on other renewable sources, even considering that environmental policies and social pressure have limited the period of hydropower plant permits in Europe (Kampa, 2022).

7.4. Nuclear

According to the empirical analysis, the influence of nuclear energy production on CO_2 emissions reduction is negligible. This suggests that nuclear energy is ineffective in combating environmental degradation and climate change, and it directly contradicts the International Energy Agency's recent recommendation (2022), which identified nuclear power as a tool for reducing reliance on fossil fuels and achieving a future clean energy system. Furthermore, when compared to other renewable energy sources, nuclear has somewhat high average overall installation costs, despite being relatively cheap to run (International Energy Agency, 2020a).

The OECD's environmental policies appear to be following the route suggested in this paper's conclusions. For example, Germany abandoned nuclear energy on April 17, 2023, shutting down its final three nuclear reactors (American Nuclear Society, 2023). Except for South Korea and Japan, which are currently building three and two reactors, respectively, OECD countries currently have only four nuclear reactors under construction, with the UK having two and France and Slovenia each having one.

However, nuclear energy is still a long way from being completely phased out. Although 143 nuclear reactors in OECD countries have been permanently shut down, there are still 258 active nuclear reactors, particularly in the US, France, and South Korea, which have 93, 56, and 25 operational nuclear power reactors, respectively, and rely heavily on this source of energy (International Atomic Energy Agency, 2023).

7.5. Solar

Solar energy ranks third among renewable energy sources in terms of lowering CO_2 emissions. A one-unit TWh increase in solar power is associated with an average reduction of about 0.08 metric tons of CO_2 emissions per capita from 1965 to 2020. Moreover, the direction of causality reveals that solar energy is a significant predictor of CO_2 emissions.

While weather-dependent, solar energy appears to be of interest due to recent technological breakthroughs in generation capacity, efficiency, and storage capacity (Hayat et al., 2019). Overall installation and PV solar energy production costs were reduced by 82.2% and 88.5%, respectively, between 2021 and 2010. In 2021, solar PV had the lowest total installation costs of any renewable energy source, at 857 USD/kW, whereas electricity generation costs were the same as hydropower, at 0.048 USD/kWh (International Renewable Energy Agency, 2022, p. 15). In addition, solar facilities, unlike geothermal and hydropower plants, are less cost-sensitive to location (International Renewable Energy Agency, 2022, p. 156).

Despite this, solar energy is underutilized, particularly in OECD countries with more favorable weather conditions. Germany, for example, had a total cumulative PV capacity of 58.5 GW in 2021 but only a long-term daily global PV power potential (PVOUT) of 3.[31] Despite having a higher PVOUT and a larger area than Germany, Chile, Mexico, and Spain had cumulative PV capacity of just 4.4 GW, 7 GW, and 13.6 GW in 2021, respectively (Energy Sector Management Assistance Program, 2020, p. 29–31; International Renewable Energy International Energy Agency, 2022a, p. 24–25). As a result, there is a lot of room for increasing the quantity of electricity supplied by PV panels. Specific incentives and environmental policies, such as personal income tax deductions, VAT exemption, feed-in tariffs, and competitive solar loans, may be employed in these countries to enhance and promote the use of solar energy.

7.6. Wind

Wind energy generation contributes slightly to CO_2 emissions, similar to the influence of biofuel energy on CO_2 emissions. A one-unit TWh increase in wind power is associated with an average reduction of 0.02 metric tons of CO_2 emissions per capita. Furthermore, the causality tests appear to imply that wind and CO_2 have a likely bidirectional relationship.

On the other hand, wind energy is particularly cost-effective. In fact, between 2010 and 2021, both onshore and offshore wind saw considerable decreases in total installation costs and power production costs. Onshore wind, in particular, appears to be economically sustainable, with a cost of producing power of 0.033 USD/kWh in 2021, the lowest among primary renewable sources. Furthermore, it had the second lowest average total installation cost (1325 USD/kW) in the same year, which was only higher than solar PV (International Renewable Energy Agency, 2022, p. 15).

Wind energy's low contribution to CO_2 reduction could be attributed to the fact that wind turbine construction requires complex operations such as raw material extraction, material processing, transportation, and maintenance, all of which emit significant CO_2 emissions into the atmosphere (Mello et al., 2020).

To successfully incorporate wind energy into a renewable energy mix, turbine blade raw materials should be replaced with novel and more sustainable materials, and logistical efficiency should be improved. This could be especially beneficial for countries with low renewable energy shares, such as Cyprus, Mexico, and Poland, which can benefit from the low prices of onshore wind energy generation.

8. Conclusions

This paper evaluated the long-run causal relationship between renewable energy sources and CO_2 emissions for a panel of 27 OECD countries from 1965 to 2020. The main strength of this analysis is the use of long-term data on electricity production from six renewable energy sources, as well as the use of a set of control variables and several econometric techniques to test the sensitivity of the findings. The study's major goal was to identify the ideal combination of renewable energy sources for reducing CO_2 emissions in advanced countries and so mitigating climate change.

The panel cointegration results reveal a negative and highly

[31] The PVOUT represents the amount of energy generated per unit of installed PV capacity over the long term, measured in kilowatt-hours per installed kilowatt peak (kWh/kWp), and ranges from approximately 2.5 for Ireland to around 5.5 for Namibia and Chile (Energy Sector Management Assistance Program, 2020).

significant long-run relationship between CO_2 emissions and GEOB, hydroelectric, nuclear, solar, and wind energy production. The results are consistent across a broad spectrum of econometric specifications, including MG, PMG, DFE, FMOLS, DOLS, and CCEMG estimators. According to the panel Granger non-causality testing approach, GEOB, hydropower, and solar, in particular, are key predictors of CO_2 emissions. As a result, policies that enhance and promote the production of electricity from these sources represent an effective strategy for reducing CO_2 emissions and may pave the way to the ambitious objective of carbon neutrality in OECD countries.

This is noteworthy in light of the recent large swings in worldwide fossil fuel prices caused by the Russia-Ukraine war, which increased global average energy household costs by 73.9% (Guan et al., 2023). This is especially important for Mediterranean European countries, as well as Germany and Ireland, which rely the most on energy imports to satisfy their energy needs (Eurostat, 2023). The use of renewable energy can effectively reduce the dependence on imports of fossil fuels and relieve the balance of payment problems. Furthermore, recent studies have shown that using renewable energy sources such as solar (Bulut and Apergis, 2021), geothermal (Doğan et al., 2022), biomass (Ohler and Fetters, 2014) and hydropower (Ummalla et al., 2019) can boost economic growth. All of these factors support the hypothesis that renewable energy sources can play a significant role in promoting sustainable economic development.

This study also has some limitations, which are outlined below. It just uses conventional CO_2 emissions as a proxy for environmental damage. Although it is the most commonly used metric in the literature, some researchers have suggested that other measures, such as the ecological footprint (EF) or load capacity factor (LCF), can be employed to better describe human resource exploitation. Indeed, the EF, for example, allows for the consideration of several aspects associated with environmental degradation, such as built-up, carbon, agricultural, forest land, and grazing land footprints (Destek et al., 2018; Altıntaş and Kassouri, 2020), while LCF is the ratio of biocapacity (BC) to EF (Hossain et al., 2023). Future studies could fill this void by comparing alternative proxy measures of environmental effects. Furthermore, this study is limited to high-income countries. Further research should look at differences in environmental and technology policies in emerging and developing countries to figure out if they matter and how much they affect renewable energy's ability to prevent or reduce environmental deterioration.

CRediT authorship contribution statement

Gaetano Perone: The author confirms sole responsibility for the following, study conception and design, data collection, analysis and interpretation of results, and manuscript preparation, Writing – review & editing.

Declaration of competing interest

The author declares that he has no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

I have included files containing the data and computer codes employed.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2023.139655.

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