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RESEARCH ARTICLE

Assessing the impact of energy R&D on green growth in OECD countries: a CS-ARDL analysis

Ashraf Galal Eid[1] · Zouhair Mrabet[1] · Mouyad Alsamara[1]

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Abstract

Since the introduction of the OECD innovation and green growth strategies in 2007 and 2011, respectively, the OECD countries have been actively engaged in supporting green energy R&D to accelerate the development of clean energy technologies. Specifically, the OECD recognizes that both renewable energy R&D and energy efficiency R&D are key components of a low-carbon and sustainable energy system. This study aims to assess the impact of disaggregated energy R&D on green growth in 21 high-income OECD countries, from 1990 to 2021. Two key green growth indicators, namely energy productivity and CO_2 productivity, are used as response variables. The long-run CS-ARDL model results show that renewable energy R&D and fossil fuel R&D have a positive and significant impact on energy productivity in all model specifications, with renewable energy R&D exhibiting a relatively stronger impact compared to fossil fuel R&D. The long-run effects of the disaggregated energy R&D variables on CO_2 productivity align with the results of the energy productivity model. Based on the study's findings, policymakers should consider reallocating the energy R&D budget towards renewable energy R&D, fostering international collaboration between OECD countries in renewable energy R&D, and implementing technology-specific policies to encourage investment in renewable energy technologies.

Keywords Energy R&D · Green growth · Energy productivity · CO_2 · Productivity · OECD · Renewable energy · CS-ARDL

✉ Ashraf Galal Eid
ashraf.eid@qu.edu.qa

[1] Finance and Economics Department, College of Business and Economics, Qatar University, Doha, Qatar

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1 Introduction

In recent decades, environmental degradation has become increasingly prominent, leading to a focus on green economic growth, which aims to "improve human well-being and promote social equity while reducing environmental risks and scarcities".[1] To ensure this, a holistic approach that considers economic, social, and environmental factors is necessary to guarantee environmentally sustainable and socially inclusive growth (Urbaniec et al. 2017; Barrett and Grizzle 1999; Nieto 1997).

Green growth refers to an economic development process that aims to promote economic growth and development while ensuring that natural assets continue to provide the resources and environmental services on which our well-being relies.[2] There is a large body of literature that analyzes various determinants of green growth and emphasizes the key role of research and development (R&D) in fostering environmental innovation (Dogan et al. 2022; Wong et al. 2013a, b; Cheng et al. 2021; Huang et al. 2017; Wang and Wei 2016; Liu et al. 2018; Bhattacharya et al. 2020; Chen et al. 2019; Chen et al. (2021); Zhang and Li (2022); Filipovic et al. 2015).

The 2009 OECD Green Growth Declaration, together with the launch of the OECD Innovation Strategy in 2007 that aim to promote innovation as a crucial driver of economic growth and social progress, represented a significant shift in OECD strategies that recognized the need for a new approach to economic growth that is sustainable, environmentally friendly, and socially inclusive. As indicated in the OECD green growth reports (2009)[3] and (2011), the 2009 declaration delineated a roadmap for countries to move towards green growth by adopting policies that promote innovation, investment in clean technologies, and sustainable resource management practices.

Following the 2009 Green Growth Declaration, the OECD launched the Green Growth Strategy in 2011. The strategy identified several key sectors, including energy, transport, and agriculture, where policy interventions could have the most significant impact on reducing greenhouse gas emissions, increasing resource efficiency, and promoting sustainable development. Furthermore, the OECD is actively engaged in supporting green energy R&D to accelerate the development and deployment of clean energy technologies. For instance, data from the OECD's Government Budget Allocations for R&D (GBARD) reveals a strong commitment by OECD countries to support innovation in the energy sector. After a long period of stagnation from 1990 to 2012, the government budget allocations for energy R&D nearly doubled within a decade, rising from USD 558.56 million in 2012 to USD 1087.39 million in 2022. This rise aligns with the OECD's recognition of renewable energy and energy efficiency R&D as crucial aspects of a sustainable, low-carbon energy

[1] The Green economy. United Nations Environment Programme. Retreived from: https://www.unep.org/pt-br/node/23750.

[2] OECD (2011). Towards Green Growth—A Summary for Policy Makers.

[3] OECD (2009). Declaration on Green Growth.

system. Such a system can help reduce greenhouse gas emissions and mitigate climate change impact (OECD 2023).[4] As shown in Fig. 1 of the "Appendix", following the implementation of the Green Growth Strategy in 2011, renewable energy and energy efficiency R&D spending has surpassed half of the total energy R&D budget over the past decade.

In recent years, the OECD has shifted its energy R&D strategy towards a disaggregated approach, emphasizing a broad range of technologies and innovations rather than solely focusing on traditional energy sources. This approach acknowledges the diversity of energy technologies and aims to create a more balanced R&D portfolio covering the entire energy system. In general, green R&D involves the development of new technologies, products, and processes that are environmentally friendly and contribute to sustainable development. The effect of green R&D on green growth can be understood through various channels. On the one hand, green R&D can stimulate the use of renewable energies, reduce CO_2 emissions, drive innovation and the development of new environmentally friendly technologies (Shao et al. 2021; Habiba and Anwar 2022; Hailemariam et al. 2022; Fernández et al. 2018). As a consequence, new markets will be created, which in return will create new opportunities for investors as well as new jobs for workers. On the other hand, by incorporating green R&D in their processes, companies will be able to reduce their costs, increase their productivity, and hence improve their efficiency. This in return will improve their competitiveness in domestic and international markets.

The study objective is to analyze the impact of energy-related green R&D on green growth in 21 high-income OECD countries, over the years 1990–2021. Among the four groups of green growth indicators in OECD countries, this study focuses on environmental and resource productivity indicators. Two key green growth indicators, namely energy productivity and CO_2 productivity, are utilized as response variables in this paper since they reflect the extent to which OECD countries achieve greener economic growth. The study's main hypothesis is that energy R&D variables have a positive but disproportionate effect on green growth indicators in OECD countries.

The importance of this study lies in the use of disaggregated energy R&D (energy efficiency R&D, fossil fuel R&D, renewable energy R&D, and nuclear energy R&D) as the primary variables of interest to explore their impact on major green growth indicators. By specifying the type of energy R&D, we believe our analysis can provide a better understanding of the factors that drive green growth. Furthermore, we employ the Cross-Sectional Autoregressive Distributed Lags (CS-ARDL) approach to estimate both the long-run and short-run cointegration relationships between green growth indicators and energy R&D variables. The CS-ARDL approach is advantageous due to its robust assumptions regarding cross-sectional dependency, endogeneity, and slope heterogeneity, which make it a superior method compared to other cointegration techniques. Finally, we test whether the launch of OECD innovation and green growth strategies in 2007 and 2011 helped improve the OECD green growth indicators.

[4] OECD (2023). Renewable Energy (indicator). https://doi.org/10.1787/aac7c3f1-en.

The long-run CS-ARDL model results indicate that renewable energy R&D and fossil fuel R&D have a positive and significant impact on energy productivity in all model specifications. Interestingly, investments in renewable energy R&D seem to have a stronger impact than fossil fuel R&D. This result also holds when examining the impact of the disaggregated energy R&D variables on CO_2 productivity.

The remainder of the paper is organized as follows, Sect. 2 provides an overview of the literature on energy R&D and green growth, Sect. 3 shows the variable description and summary statistics, Sect. 4 discusses the econometric methodology, Sect. 5 illustrates the empirical results, Sect. 6 delivers the conclusion and policy implications.

2 Literature review

Most of the traditional economic models prioritize increasing GDP and maximizing profit, and may not take into consideration the impact of economic activities on natural resources. The annual World Economic Forum Global Risks Report states that "current resource use models fail to underpin a stable economy and long-term human being".[5] Sustainability for such models might be considered a hindrance to economic growth, rather than an opportunity. In contrast, the 2011 OECD Green Growth Strategy suggests that promoting economic growth and fostering development can be achieved through sustainable, environmentally friendly practices (Jacobs 2012). As a result, economists, as well as policymakers, are all exploring new economic models that prioritize both economic growth and environmental sustainability because they recognize that green growth is not only possible but also necessary for long-term prosperity and well-being.

Within this context, the decoupling and circular economy models are worth mentioning. Both models share the primary goal of achieving economic growth without further environmental degradation. To achieve this goal, Churchill et al. (2021), Dinda (2004), and Song and Jia (2019) believe that investing in R&D is crucial, as more efficient technologies decrease dependence on natural resources and emissions. This aligns with the 'technology-push' hypothesis, which suggests that R&D investments can drive the development of green technologies, promoting environmental sustainability (Söderholm 2020; Shen and Lin 2020). As Nemet (2009) argues, this hypothesis is often used to justify public funding for green technology R&D, as it has the potential to yield positive economic and environmental outcomes.

In this section, we categorize existing studies on green R&D and green growth according to their focus on green growth indicators (energy and CO_2 productivity) and energy R&D spending.

[5] World Economic Forum (2019), "The Next Frontier: Natural Resource Targets". Retrieved from: https://www3.weforum.org/docs/WEF_The_Next_Frontier_Natural_Resource_Targets_Report.pdf.

2.1 Determinants of energy productivity

Energy productivity, defined by the OECD as total output per unit of total primary energy supply, is a crucial indicator of green growth that has been extensively studied in the context of achieving sustainable development, as highlighted by the European Union's Sustainable Development Goals (SDGs 7 and 12).[6] Several studies have investigated the determinants of energy productivity (e.g., Yu et al. 2022; Liu et al. 2018; Wang 2007; Parker and Liddle 2017; Ball et al. 2015; Wang and Wei 2016; Bhattacharya et al. 2020; Jin et al. 2021; Lin and Sai 2022). A review of these papers reveals that technological innovation is the most significant factor in improving energy productivity. This improvement stems from the positive impact of technological innovation, which not only reduces energy costs but also accelerates the shift towards more sustainable energy sources (Yu et al. 2022; Parker and Liddle 2017; Bhattacharya et al. 2020; Wang 2007).

Furthermore, the findings of Hussain et al. (2022) indicate that green growth is positively affected by green technology and negatively affected by energy consumption, particularly fossil fuel. In the same trend, Yasmeen et al. (2023) use the percentage of patents on environmental technology to total patents as a proxy of green technology to test its impact on energy productivity in OECD countries. The study results confirm the commonly believed positive relationship between green technology and energy productivity.

Additionally, regulations on carbon emissions control, industrial structure, openness index, domestic trade, mining agglomeration, and per capita income are significant factors that promote energy productivity growth (Wang and Wei 2016; Liu et al. 2018; Jin et al. 2021; Bhattacharya et al. 2020; Lin and Sai 2022; Ben Youssef and Dahmani 2024). However, there are differing opinions on the effects of energy prices and government regulation on energy productivity growth. While Liu et al. (2018) suggest that these factors harm energy productivity, The findings of Wang and Wei (2016) and Bhattacharya et al. (2020) suggest that both higher energy prices and stricter government regulations are positively associated with energy productivity.

2.2 Determinants of CO_2 productivity

CO_2 productivity, as defined by the OECD, refers to the total output generated per unit of CO_2 emitted. This is the second indicator used in our study as a proxy for green growth, which is selected by the OECD to track advancements toward green growth and help policymakers make informed decisions.[7] Examining and understanding the determinants of CO_2 productivity is an essential step toward promoting green growth. However, most of the existing literature concentrates on the different factors that affect CO_2 emissions rather than on the factors that affect CO_2

[6] United Nations Development Programme (UNDP). Sustainable Development Goals in the European Union. Retrieved from https://www.undp.org/european-union/sustainable-development-goals.

[7] OECD Green Growth Indicators.

productivity. The major factors that influence CO_2 emissions can generally be grouped into two categories. The first category includes factors that mitigate CO_2 emissions and promote the shift to economies based on renewable energy, such as environmental taxes, higher energy productivity, and eco-innovation. The second category comprises factors that increase carbon emissions, including imports, GDP, and public–private partnerships in energy (Cheng et al. 2021; Ding et al. 2021; Dogan et al. 2022; Khan et al. 2022; Koçak and Ulucak 2019; Wong et al. 2013a, b). For example, studies that conducted a comparison between the impact of renewable energy and nuclear energy on CO_2 emission found that renewable energy reduces carbon emissions and promotes economic growth, unlike nuclear energy, which is less environmentally and economically advantageous (Cheng et al. 2021; Jin and Kim 2019; Wong et al. 2013a, b). These findings are consistent with the study conducted by Wong et al. (2013a, b), which concluded that renewable energy helps reduce CO_2 emissions and promotes real economic growth, leading to the transition from coal to cleaner energy sources. However, they contradict the study by Koçak and Ulucak (2019), which presented an insignificant relationship between research and development expenditures in renewable energy and CO_2 emissions. In addition, the study by Petrović and Lobanov (2020) showed mixed results. They found that the relationship between R&D investment and CO_2 emissions could be positive, negative, or neutral. The outcome depends on whether policymakers focus on promoting R&D programs that directly aim to reduce CO_2. Ben Youssef and Dahmani (2024) highlight how digitalization, environmental taxes, and energy resource management impact environmental quality, measured by the Greenhouse gas (GHG) emissions, within the Environmental Kuznets Curve framework across 88 countries from 2000 to 2021 using the CS-ARDL method. The study reveals varying effects based on country income levels, indicating significant contributions of technology to environmental quality in high-income countries. Using the Nerlove partial adjustment model (NPAM), Wong et al. (2013a, b) found that income elasticity for oil and gas consumption is positive, while for coal consumption, it is negative. However, some papers, such as Hickel and Kallis (2020), suggest that it is more realistic to assume that the reduction in resource use and emissions can be achieved without growth rather than with growth.

2.3 The role of energy R&D expenditures

Another dimension of the energy R&D literature relates to research examining the effects of both aggregated and disaggregated R&D expenditures on energy intensity. Chen et al. (2019) find that R&D in the experimental and development phase and R&D activities conducted by industrial companies have a more pronounced impact on decreasing energy intensity. Teng (2012) focuses on industries and finds that domestic R&D can mitigate energy intensity significantly in industries with high energy consumption only. Huang et al. (2017) show that China's ability to benefit from a positive spillover effect from foreign direct investment is challenging if its level of domestic R&D activities is low.

Furthermore, previous studies have shown that public R&D expenditures play a crucial role in reducing energy intensity and promoting the generation of green patents. According to Bointner (2014) and Vona et al. (2012), the largest contribution to this effort came from nuclear energy, followed by energy efficiency, fossil fuels, and renewable energy. These findings are consistent with those of Klaassen et al. (2005), who suggest that public R&D policy was more effective in fostering energy innovation in Denmark than in the UK or Germany.

The impact of energy R&D on energy intensity in OECD countries is also examined by several researchers including Wong et al. (2013a, b), Dogan et al. (2022), and Churchill et al. (2021), to mention a few. The findings indicate that increasing renewable energy R&D can lead to a decrease in carbon emissions and fossil fuel consumption. It can also facilitate the transition toward green economies (Wong et al. 2013a, b). That is why many researchers believe that prioritizing the promotion of renewable energy through research funding, subsidies, and government incentives is not an option but a necessity (Dogan et al. 2022). Churchill et al. (2021) see that the impact of energy R&D varies over time. Specifically, the impact of R&D on renewable energy consumption was positive and significant until 1996 but turned negative afterward. Dahmani et al. (2023) analyze the relationship between renewable and non-renewable energy consumption, financial development, ICT diffusion, and economic growth in MENA countries from 1980 to 2018 using the CS-ARDL technique. The findings suggest positive impacts of energy consumption on economic growth, while financial development has a negative effect.

Green R&D can also enhance the reputation and social responsibility of firms, which can improve their access to finance and markets and strengthen their long-term competitiveness. This goes along with the findings of Lee et al. (2015) and Lee and Min (2015), which reveal that green R&D and the firms' profitability are positively related, while it is negatively related to CO_2 emissions. Furthermore, green R&D turns out to be a positive determinant of firms' market value as shown by Ganda (2018).

Based on a review of the literature, it becomes apparent that existing literature explores technological innovation's impact on green growth, but a gap exists regarding the impact of disaggregated energy-related R&D spending on green growth. Additionally, current studies overlook the potential role of the OECD's innovation and green growth strategies in promoting energy R&D. This motivates our investigation into whether disaggregated energy-related green R&D investments enhance environmental and economic sustainability in OECD countries. Our study contributes to the green growth literature by offering a comprehensive analysis of how different types of energy R&D spending affect green growth in high-income OECD countries over the past three decades. By categorizing energy R&D, this research provides valuable insights into the efficacy of various energy research avenues in promoting sustainable growth. Furthermore, incorporating energy productivity and CO_2 productivity as key green growth indicators strengthens the analysis, enabling a detailed understanding of the connection between energy R&D and green growth.

3 Variable description and summary statistics

Table 1 below presents the variables' definitions, expected signs of the explanatory variables, and data sources. Since energy R&D is expected to play a crucial role in enhancing OECD countries' green growth indicators, we expect a positive impact of all disaggregated energy R&D variables on green growth. Additionally, we follow the literature and add energy intensity as a determinant of energy productivity. A decrease in energy intensity signifies an improvement in energy productivity. Therefore, we expect the coefficient for energy intensity to be negative. Moreover, we investigate the impact of energy price, general government final consumption, and real GDP growth rate on green growth indicators. We expect a positive impact of real GDP growth rate on both green growth indicators since countries experiencing high economic growth rates are likely to have the financial ability to invest in green technologies, thereby promoting a greener economy. Conversely, we expect the coefficient for the energy price index to be negative, suggesting that higher energy prices may have a dampening effect on green growth indicators. Finally, the impact of the general government final consumption share of GDP on green growth might be positive or negative, depending on whether a bigger government size leads to a higher energy consumption, and thus energy supply, than the increase in GDP.

Table 2 displays the summary statistics for the selected model variables for 21 high-income OECD countries based on GNI per capita (according to the World Bank Country and Lending Groups classification). The study sample includes the following countries: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom, and the United States. Over the period of study (1990–2021), the average values for energy efficiency R&D, fossil fuel R&D, renewable energy R&D, and nuclear energy R&D as a percentage of the total energy R&D budget are 20.5, 12.1, 23.6, and 22.5, respectively.

When comparing the total energy R&D budget composition over the last decade (after introducing the OECD green growth strategy in 2011) with the energy R&D budget compositions before the green growth strategy implementation, we observe an obvious gradual increase in the proportion of both renewable energy R&D and energy efficiency R&D relative to the total energy R&D budget. In contrast, there has been a continuous reduction in the proportion of nuclear energy R&D and fossil fuel R&D budgets, as shown in Fig. 1 in the "Appendix". However, while the renewable R&D budget share of the total energy R&D budget increased from 19.9 percent on average in the last decade of the twentieth century to 24.5 percent in the first decade of the twenty-first century, we noticed a modest increase in renewable energy R&D budget after the implementation of the OECD green growth strategy to reach 25.7 percent, over the period 2011–2021.

Table 1 Variable description

Variable	Definition	Expected sign	Data source
Energy efficiency R&D (EEFF)	Energy efficiency R&D expenditure as a percent of total energy R&D budget	+	OECD iLibrary
Fossil fuel R&D (FFL)	Fossil fuel R&D expenditure as a percent of total energy R&D budget	+	OECD iLibrary
Renewable energy R&D (RENS)	Renewable energy R&D expenditure as a percent of total energy R&D budget	+	OECD iLibrary
Nuclear energy R&D (NUC)	Nuclear energy R&D expenditure as a percent of total energy R&D budget	+	OECD iLibrary
Energy price Index (EPI)	Consumer price index for energy	−	OECD Statistics
Government share of GDP (GE)	General government final consumption expenditure as a percent of GDP	−/+	World Development Indicators
Energy intensity (ENSITY)	Total primary energy supply per capita	−	OECD iLibrary
GDP growth (RGDP)	Real GDP growth rate	+	World Development Indicators
CO_2 productivity (CO_2PRO)	Production-based CO_2 productivity is equal to real GDP generated per unit of CO_2 emitted (constant USD/kg)	Dependent variable	OECD iLibrary
Energy productivity (ENGPRO)	Energy productivity is equal to real GDP per unit of total primary energy supply (constant USD/ton of oil equivalent)	Dependent variable	OECD iLibrary

Table 2 Panel data summary statistics

Variable	Mean	Max	Min	SD
Energy productivity (ENGPRO)	10,710	36,501	4093	4058.8
CO_2 productivity (CO_2PRO)	5.47	17.98	1.96	2.62
Energy efficiency R&D (EEFF)	20.5	67.6	0	13.9
Fossil fuel R&D (FFl)	12.1	72.7	0	18.3
Renewable energy R&D (RENS)	23.6	70.9	0	14.6
Nuclear energy R&D (NUC)	22.5	100	0	22.4
Energy intensity (ENSITY)	3.93	18.21	0.55	2.39
Real GDP growth (RGDP)	0.5	2.11	−3.82	0.28
Energy price index (EPI)	81.1	207.4	22.1	24.5
Share of government expenditure to GDP (GE)	19.69	27.93	10.33	3.54

4 Methodology

Following the presentation of the econometric model, we will conduct a series of tests to justify the use of CS-ARDL. This includes examining cross-sectional dependence and unit root tests for all variables, such as the Levin-Lin-Chu test or the Im–Pesaran–Shin test, to determine their order of integration and stationarity. If the variables are found to be integrated, cointegration tests like Pedroni or Johansen will be employed. Finally, if the data exhibits cross-sectional dependence and cointegration, the cross-sectionally augmented ARDL (CS-ARDL) technique will be utilized.

4.1 Econometric model

The study examines the role of disaggregated energy R&D in enhancing green growth in OECD countries using two econometric model specifications. The first one (the basic model) includes the disaggregated energy R&D and energy intensity variables (Eq. 1), while the second model extends the basic model by including the following control variables: energy price, general government final consumption, and real GDP growth rate (Eq. 2).

4.1.1 The basic model

$$\begin{aligned} lnGG_{it} = \alpha_0 + \alpha_1 lnRDS_{it} + \alpha_2 lnEI_{it} + \alpha_3 Dum_j \\ + \alpha_4 Dum_j * lnRDS_{it} + \varepsilon_t \quad j = 2007 \quad \text{or} \quad 2011 \end{aligned} \tag{1}$$

where $lnGG_{it}$ denotes the natural logarithm of the green growth indicators (energy productivity and CO_2 productivity, respectively), $lnRDS_{it}$ is the share of each specific energy R&D (energy efficiency R&D, fossil fuel R&D, renewable energy R&D, and nuclear energy R&D) in total energy budget, $lnEI_{it}$ denotes the natural logarithm of energy intensity, and ε_t shows the error disturbance term. α's denotes variable coefficients.

4.1.2 The extended model

$$lnGG_{it} = \beta_0 + \beta_1 lnRDS_{it} + \beta_2 lnEI_{it} + \beta_3 Dum_j + \beta_4 Dum_j * lnRDS_{it} + \sum_{s=3}^{6} \beta_s x_{sit} + \pi_t, j = 2007 \quad \text{or} \quad 2011 \tag{2}$$

In Eq. 2, the time is denoted by t. β′s denotes variable coefficients, x_{sit} represents the additional control variables (energy price, general government final consumption, and real GDP growth rate), and π shows the error disturbance term. In both models, we include two dummy variables, Dum_j, for the year 2007 and 2011 and an interaction term between the dummy variable and each energy R&D variable.

4.2 Cross-sectional dependence

A preliminary analysis of the data involves testing for the presence of cross-sectional dependence (CSD). This step is crucial in selecting the appropriate unit root techniques that can effectively handle CSD. In studies focusing on a specific region or group of countries with similar economic environments, it is possible to encounter shared influences among the countries in that region. These shared factors may include inter-regional policies, financial crises, oil prices, and other relevant variables. While certain techniques can account for some of this shared variation, there may still be unexplained variation remaining. Ignoring the issue of cross-sectional dependence in such cases can lead to biased and inaccurate results, making interpretations ambiguous. To address the issue of CSD in this study, we employ the CSD test proposed by Pesaran and Smith (1995). This test helps us account for and appropriately handle cross-sectional dependence, ensuring the reliability and validity of our findings.

4.3 Panel unit root testing

The next step involves proceeding with the unit root analysis of the variable series. We utilize the Cross-sectional Independence Im–Pesaran–Shin (CIPS) unit root test developed by Pesaran (2007), which accounts for cross-sectional dependence. The equation for the CIPS test is as follows:

$$\widehat{CIPS} = N^{-1} \sum_{i=1}^{n} CADF_i$$

where CADF represents the Cross-Sectionally Augmented Dickey-Fuller test.

4.4 Testing for Co-integration

After completing the assessment of stationarity, the subsequent stage involves investigating potential cointegration relationships among the variables. To conduct this analysis, we employ the Pedroni panel cointegration test (Pedroni 2004), which extends the Engle-Granger test to examine cointegration relationships within panel data. This robust test employs seven statistical measures to assess the null hypothesis of no cointegration. These measures take into account variations in the long-term slope and intercept coefficients, as well as in the short-term dynamics throughout different cross-sections. The overall structure of the test can be defined as follows:

$$y_{it} = \alpha_i + \beta_{1i}x_{1i,t} + \beta_{2i}x_{2i,t} + \cdots + \beta_{Ki}x_{Ki,t} + \omega_{it} \tag{3}$$

where $t=1, \ldots, T$; $i=2, \ldots, N$; $k=1, \ldots, K$; the vector y and x are assumed to be integrated of order one i.e. I(1). The estimated parameters α_i are the individual effects. These effects can be eliminated by setting them equal to zero.

Under the null hypothesis of no cointegration, the residual ω_{it} will follow an I(1). This can be examined by performing a supplementary regression on the residuals obtained from Eq. (3) for each cross-section expressed by the following equation.

$$\omega_{it} = \pi_i \omega_{i,t-1} + \varepsilon_{it} \tag{4}$$

The residuals from Eq. (4) can be utilized to compute the test statistics for Pedroni panel cointegration *N, T*.

4.5 Cross-sectional ARDL

If cross-sectional dependence and slope heterogeneity exist in our dataset, which we anticipate observing in OECD countries, then the panel autoregressive distributed lag (ARDL) model will be insufficient in addressing the potential errors that may arise from this dependence. Therefore, we should utilize the cross-sectionally augmented autoregressive distributed lag model (CS-ARDL) to estimate the coefficients for both short-run and long-run effects. This approach effectively tackles the issue of CSD by incorporating the cross-section averages of each regressor into the model. In our specific case, unobserved common characteristics may influence the productivity of the energy sector. If these unobserved common components in energy productivity are related to the independent variables, the estimation process may suffer from inefficiency and produce invalid test statistics. To ensure the appropriate application of the CS-ARDL model, a large time dimension (T) is required to estimate the model for each cross-sectional unit. Given that the time series dimension exceeds the cross-sectional dimension in our sample (T > N), opting for the CS-ARDL model is the appropriate decision (Rizvi et al. 2022). The CS-ARDL equation can be expressed as follows

$$\Delta lnGG_{it} = \alpha_i + \sum_{k=1}^{p} \delta_{k,i} \Delta lnGG_{i,t-k} + \sum_{k=0}^{q} \rho_{k,i} X_{i,t-k} + \sum_{k=0}^{z} \vartheta_i k\overline{X}_{i,t-k} + \theta_{i,t} \tag{5}$$

Table 3 CSD analysis

Variable	CD test	prob-values
EEFF	60.072***	0.000
FFL	36.398***	0.000
RENS	71.05***	0.000
NUC	46.212***	0.000
EPI	80.66***	0.000
GE	81.905***	0.000
ENSITY	79.675***	0.000
RGDP	9.216***	0.000
CO_2PRO	81.168***	0.000
ENGPRO	81.967***	0.000

***Significant at the 1% level, **Significant at the 5% level, and *Significant at the 10% level

where $\overline{X}$ indicates cross-sectional means of the independent variables (such as energy intensity, and energy R&D variables) and dependent variables (*GG*).

5 Empirical results

5.1 Panel unit root and panel cointegration tests

As an initial analysis, we examine the presence of cross-sectional dependency among the variables. The results of the cross-sectional dependency (CSD) test of Pesaran and Smith (1995) are presented in Table 3. The findings indicate that the probability values are below 0.05, leading us to reject the null hypotheses associated with the absence of CSD. Therefore, we can conclude that cross-sectional dependency is present among the variables under investigation.

Given the presence of cross-sectional dependence (CSD3), we utilize the second-generation unit root test developed by Pesaran. The Cross-sectional Independence Im–Pesaran–Shin (CIPS) test addresses the problems of cross-sectional dependence and heterogeneity within the panel. This test is specifically designed to assess the null hypothesis of the presence of a unit root. The results are shown in Table 4, and Panel C showcases the outcomes of the CIPS test at the level. In most instances, the null hypothesis of a unit root cannot be rejected. This shows that all variables are stationary only when considered in their first difference form, implying an order of integration of I(1).

After conducting unit root tests on all variables, the next step is to investigate whether the variables exhibit cointegration. This is accomplished by utilizing the Pedroni panel cointegration test (Pedroni 1999, 2004). The test decisively rejects the null hypothesis of "No Panel Cointegration" and provides compelling evidence to support the adoption of the Autoregressive Distributed Lag (ARDL) model, along with its error correction specification, for the analysis of both

Table 4 Results of panel unit-root tests

Panel A-LLC test	Level	*P*-value	Diff	*P*-value
EEFF	0.094	0.537	−3.433***	0.000
FFL	0.328	0.628	−4.363***	0.000
RENS	2.342	0.990	−4.541***	0.000
NUC	2.919	0.998	−5.541***	0.000
EPI	−1.263	0.103	−7.027***	0.000
GE	−0.801	0.211	−10.41***	0.000
ENSITY	−0.813	0.208	−10.810***	0.000
RGDP	−1.09	0.14	−5.802***	0.000
CO_2PRO	−2.882***	0.002	−10.242***	0.000
ENGPRO	−2.208**	0.013	−8.292***	0.000
Panel B-IPS				
EEFF	0.182	0.57	−12.19	0.000
FFL	2.303	0.1	−14.186	0.000
RENS	0.575	0.71	−13.685	0.000
NUC	2.919	0.998	−5.541	0.000
EPI	2.698	0.99	−12.775	0.000
GE	0.700	0.758	−12.511	0.000
ENSITY	2.337	0.990	−14.681	0.000
RGDP	−0.658	0.255	−13.582	0.000
CO_2PRO	−5.658***	0.000	−15.378	0.000
ENGPRO	−6.342***	0.000	−15.329	0.000
Panel C-CIPS test statistics				
EEFF	0.182	0.57	−12.19***	0.000
FFL	2.303	0.1	−14.186***	0.000

Table 4 (continued)

Panel A-LLC test	Level	*P*-value	Diff	*P*-value
RENS	0.575	0.71	−13.685***	0.000
NUC	2.919	0.998	−5.541***	0.000
EPI	−1.47	0.99	−4.187***	0.000
GE	−1.92	0.758	−5.13***	0.000
ENSITY	−1.93	0.990	−5.6***	0.000
RGDP	−1.75	0.255	−4.57***	0.000
CO_2PRO	−2.7***	0.000	−5.541***	0.000
ENGPRO	−2.53***	0.000	−5.58***	0.000

LLC test: is the unit root test of Levin-Lin-Chu. IPC test: is the unit root test of Im–Pesaran–Shin

***Significant at the 1% level, **Significant at the 5% level, and *Significant at the 10% level

Table 5 Results of Pedroni's residual-based panel cointegration tests

	Within dimension statistic		Between dimension statistic	
	Statistic	*P*-value	Statistic	*P*-value
Modified variance ratio	−8.5632***	0.000		
Modified Phillips–Perron t	3.7249***	0.000	5.5715***	0.000
Phillips–Perron t	−5.5317***	0.000	−3.9424***	0.000
Augmented Dickey–Fuller t	−7.6325***	0.000	−5.2125***	0.000

***Significant at the 1% level

long-term and short-term dynamics. The Pedroni's residual-based panel cointegration tests' results are shown in Table 5.

5.2 CS-ARDL model results and discussion

5.2.1 The basic model

As shown in Eq. 1, we estimate two basic models. Each model uses energy R&D and energy intensity variables as the primary variables of interest and alternately assesses their effects on energy productivity (Table 6) and CO_2 productivity (Table 7). Furthermore, we estimate the long-run and short-run relationships of each basic model using eight different model specifications. For each of the four energy-related green R&D variables, we estimate two separate interactions. These interactions reflect the relationship between the two key years: the year of launching the OECD innovation strategy (2007) and the year of launching the OECD green growth strategy (2011), and each of the four energy-related green R&D variables.

The results of the long-run CS-ARDL cointegration model for energy productivity, as reported in Table 6, suggest that the impact of disaggregated energy R&D on energy productivity varies depending on the type of energy R&D. Specifically, while the coefficients of energy efficiency R&D and nuclear energy R&D are found to be insignificant, the impact of fossil fuel R&D and renewable energy R&D is positive and significant, with renewable energy R&D exhibiting a relatively stronger impact compared to fossil fuel R&D. The estimation of the basic model indicates that increasing fossil fuels R&D intensity by one percent leads to a 0.0052 and 0.00345 percent increase in energy productivity in model specifications 3 and 4, respectively. Additionally, raising renewable R&D intensity by one percent leads to a 0.011 and 0.007 percent increase in energy productivity in model specifications 5 and 6, respectively. These findings are consistent with the results of Yasmeen et al. (2023), Yu et al. (2022), Parker and Liddle (2017), Bhattacharya et al. (2020), Wang (2007), Jin et al. (2021), and Wang et al. (2021), which indicate a positive relationship between green technology and energy productivity.

This positive effect is anticipated because both types of R&D can lead to advancements in technologies that extract and use energy more efficiently. As indicated by the OECD Green Growth Strategy in 2011, advancements in fossil fuel

Table 6 CS-ARDL long-run and short-run results: basic model

Variables	ENGPRO	ENGPRO	ENGPRO	ENGPRO	ENGPRO	ENGPRO	ENGPRO	ENGPRO
Long-run	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable: energy productivity								
lr_ENGPRO	−0.840***	−0.77***	−0.81***	−0.913***	−0.96***	−0.88***	−0.819***	−0.827***
	(0.0838)	(0.047)	(0.033)	(0.0373)	(0.089)	(0.052)	(0.0372)	(0.0660)
lr_EEFF	0.0314	0.001						
	(0.0264)	(0.0031)						
lr_EEFF11	0.0503*							
	(0.0256)							
lr_EEFF07		0.01*						
		(0.0053)						
lr_FFL			0.0052*	0.00345*				
			(0.0027)	(0.00201)				
lr_FFL11			0.0095*					
			(0.0056)					
lr_FFL07				0.00977*				
				(0.00548)				
lr_RENS					0.011**	0.007**		
					(0.005)	(0.0035)		
lr_RENS11					0.019*			
					(0.01)			
lr_RENS07						0.024**		
						(0.011)		
lr_NUC							0.00751	0.0164
							(0.0104)	(0.0180)
lr_NUC11							0.0221***	
							(0.00623)	

Table 6 (continued)

Variables	ENGPRO	ENGPRO	ENGPRO	ENGPRO	ENGPRO	ENGPRO	ENGPRO	ENGPRO
Long-run	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
lr_NUC07								0.0252*
								(0.0137)
lr_dm_11	−0.142		−0.035		−0.073		−0.00660	
	(0.111)		(0.032)		(0.056)		(0.105)	
lr_dm07		−0.02		−0.0349		−0.09**		0.0147
		(0.05)		(0.0266)		(0.043)		(0.180)
lr_ENSITY	−1.479***	−0.89***	−0.82***	−0.789***	−0.96***	−0.87***	−0.851***	−1.138***
	(0.462)	(0.086)	(0.10)	(0.0779)	(0.89)	(0.098)	(0.0769)	(0.126)
Short-run	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EEFF	0.00220	−0.00019						
	(0.00448)	(0.0018)						
EEFF11	0.0209							
	(0.0130)							
EEFF07		0.0047						
		(0.0032)						
FFL			0.004*	0.00230				
			(0.0021)	(0.00176)				
FFL11			0.006*					
			(0.004)					
FFL07				0.00725*				
				(0.00417)				
RENS					0.0093**	0.0063**		
					(0.0042)	(0.0031)		

Table 6 (continued)

Short-run	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RENS11					−0.013			
					(0.0089)			
RENS07						0.013		
						(0.0083)		
NUC							0.00207	−0.00174
							(0.00580)	(0.00437)
NUC11							0.0176***	
							(0.00548)	
NUC07								0.0109**
								(0.00485)
ENSITY	−0.753***	−0.67***	−0.68***	−0.717***	−0.74***	−0.72***	−0.716***	−0.804***
	(0.0940)	(0.062)	(0.08)	(0.0710)	(0.065)	(0.076)	(0.0714)	(0.0599)
dm_11	−0.0758		−0.02		−0.046		−0.0182	
	(0.0571)		(0.024)		(0.042)		(0.0734)	
dm_07		−0.0041		−0.0262		−0.061**		0.00197
		(0.035)		(0.0199)		(0.03)		(0.0705)
L.ENGPRO	0.160*	0.22***	0.18***	0.0873**	0.18***	0.11**	0.181***	0.173***
	(0.0838)	(0.047)	(0.033)	(0.0373)	(0.047)	(0.052)	(0.0372)	(0.0660)
Observations	546	630	588	588	546	546	609	567
Number of groups	21	21	21	21	21	21	21	21

***Significant at the 1% level, **Significant at the 5% level, and *Significant at the 10% level

Table 7 CS-ARDL long-run and short-run results: basic model

VARIABLES	CO_2PRO	CO_2PRO	CO_2PRO	CO_2PRO	CO_2PRO	CO_2PRO	CO_2PRO	CO_2PRO
Long-run	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable: CO_2 *productivity*								
lr_CO_2PRO	−0.919***	−0.805***	−0.889***	−0.901***	−0.859***	−0.822***	−0.805***	−0.710***
	(0.0579)	(0.0636)	(0.0474)	(0.0422)	(0.0563)	(0.0663)	(0.0568)	(0.0504)
lr_EEFF	0.00954	0.0128*						
	(0.00781)	(0.00717)						
lr_EEFF11	0.0257							
	(0.0202)							
lr_EEFF07		0.00177						
		(0.00908)						
lr_FFL			0.0118*	0.0109*				
			(0.00643)	(0.00569)				
lr_FFL11			0.0291*					
			(0.0159)					
lr_FFL07				0.0113*				
				(0.00618)				
lr_RENS					0.0130*	0.0146*		
					(0.00720)	(0.00873)		
lr_RENS11					0.0337*			
					(0.0182)			
lr_RENS07						0.00928		
						(0.0169)		
lr_NUC							0.0240	0.0139
							(0.0286)	(0.0103)
lr_NUC11							0.0303*	

Table 7 (continued)

VARIABLES	CO_2PRO	CO_2PRO	CO_2PRO	CO_2PRO	CO_2PRO	CO_2PRO	CO_2PRO	CO_2PRO
Long-run	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
							(0.0156)	
lr_NUC07								0.0106
								(0.0183)
lr_dm_11	−0.149		0.0198		−0.0359		−0.106	
	(0.109)		(0.0921)		(0.126)		(0.125)	
lr_dm07		0.0133		−0.0528*		−0.0561		−0.0987
		(0.0403)		(0.0300)		(0.182)		(0.132)
lr_ENSITY	−0.894***	−0.633***	−0.854***	−0.729***	−0.860***	−0.845***	−0.857***	−0.333***
	(0.152)	(0.178)	(0.179)	(0.146)	(0.136)	(0.185)	(0.141)	(0.107)
Short-run	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EEFF	0.0111	0.00748						
	(0.00672)	(0.00466)						
EEFF11	0.0228							
	(0.0206)							
EEFF07		0.00235						
		(0.00747)						
FFL			0.0113*	0.00995*				
			(0.00590)	(0.00559)				
FFL11			0.0249**					
			(0.0118)					
FFL07				0.00966**				
				(0.00435)				
RENS					0.0104	0.0115**		

Table 7 (continued)

Short-run	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
					(0.00701)	(0.00560)		
RENS11					0.0357**			
					(0.0153)			
RENS07						0.00726		
						(0.0119)		
NUC							0.0112	0.00827
							(0.0146)	(0.00599)
NUC11							0.0254**	
							(0.0120)	
NUC07								0.00411
								(0.00985)
ENSITY	−0.735***	−0.534***	−0.711***	−0.662***	−0.702***	−0.695***	−0.658***	−0.276***
	(0.109)	(0.122)	(0.158)	(0.139)	(0.129)	(0.137)	(0.117)	(0.0841)
dm_11	−0.121		−0.0174		−0.0424		−0.0867	
	(0.107)		(0.0650)		(0.105)		(0.104)	
dm_07		0.00957		−0.0427*		−0.0471		−0.0447
		(0.0318)		(0.0217)		(0.121)		(0.0669)
L.CO_2PRO	0.0811	0.195***	0.111**	0.0994**	0.141**	0.178***	0.195***	0.290***
	(0.0579)	(0.0636)	(0.0474)	(0.0422)	(0.0563)	(0.0663)	(0.0568)	(0.0504)
Observations	567	567	588	588	567	588	588	588
Number of groups	21	21	21	21	21	21	21	21

***Significant at the 1% level, **Significant at the 5% level, and *Significant at the 10% level

technologies, such as carbon capture and storage, along with increased deployment of renewable energy are expected to improve overall energy efficiency. This will be achieved by reducing energy waste throughout the consumption process, ultimately leading to increased energy productivity. The stronger impact of renewable energy R&D could be explained by the fact that renewable energy technologies are relatively new and have a bigger room for efficiency improvement compared to fossil fuel R&D. Moreover, in line with the growing focus on sustainability, renewable energy R&D has captured the largest share of total energy R&D budget among all other energy R&D categories over the past decade, as illustrated in Fig. 1 of the "Appendix".

The analysis of the interaction between fossil fuel R&D and renewable energy R&D with the key years 2007 and 2011 reveals a positive and significant impact on energy productivity. On the other hand, although the coefficients of energy efficiency R&D and nuclear energy R&D are found to be insignificant, the interaction terms involving energy efficiency R&D and nuclear energy R&D for the years 2007 and 2011 are found to be positive and significant. In all model specifications, the interaction terms were found to be significant with coefficients higher than those of the individual energy-related green R&D variables. This suggests that both OECD innovation and green growth initiatives contributed to improving the impact of all energy-related green R&D variables on energy productivity during the specified years. Furthermore, the coefficients of the interaction terms are found to be stronger than those of the individual energy R&D variables. Additionally, in all model specifications, we observe a significant negative impact of the energy intensity variable on energy productivity, in line with our initial expectations (when energy intensity decreases, less energy is needed to produce the same amount of output, which implies improved energy productivity).

The analysis of the long-term effects of the four energy-related R&D variables on CO_2 productivity produces results that are consistent with those obtained from the energy productivity model. However, one notable difference arises in the case of energy efficiency R&D, where its significance is evident in one of the CO_2 productivity model specifications. Specifically, both fossil fuel R&D and renewable energy R&D are found to have a significant positive effect in all model specifications. Again, renewable energy R&D shows a stronger impact than fossil fuel R&D. The CO_2 productivity model results reported in Table 7 indicate that a one percent increase in fossil fuel R&D intensity is estimated to increase CO_2 productivity by 0.0118 and 0.0109 percent in model specifications 3 and 4, respectively. Similarly, a one percent increase in renewable energy R&D intensity leads to an increase in CO_2 productivity by 0.013 and 0.0146 percent in model specifications 5 and 6, respectively. As mentioned above, energy efficiency R&D is found to be positive and significant only in one specification, with an estimated increase in CO_2 productivity of 0.0128 percent. In addition, the estimated effect of nuclear energy R&D is still positive but insignificant.

This could be explained by the significant reduction in the growth of both nuclear energy consumption and the nuclear energy R&D budget in the last decade. Data from the IEA (2024) Energy Technology RD&D Budgets shows a substantial reduction in the nuclear R&D share of the total energy R&D budget, from 29.2 percent in the last decade of the twentieth century to 15 percent during the period 2011–2021, as illustrated in Fig. 1 in the "Appendix". Additionally, the Energy Institute (2023) report indicates that the growth rate of nuclear energy consumption was − 1.4 percent during the same period (2011–2021). As mentioned above, the rise of renewable energy consumption and R&D investment might overshadow the contributions of nuclear energy R&D to overall energy productivity.

The estimation of the interaction between the energy-related R&D variables and the two OECD initiative years under investigation yields mixed results. Our findings indicate that the introduction of the OECD innovation strategy in 2007 had a notable effect on CO_2 productivity, but solely through fossil fuel R&D, while the interaction with the other energy-related R&D variables is found to be insignificant. On the other hand, the 2011 OECD green growth strategy was found to have a positive and significant impact on CO_2 productivity through all the energy-related R&D variables, except for energy efficiency R&D.

The short-run results of the CS-ARDL model for the energy productivity specifications confirm the findings of the long-run model. We find an insignificant short-run effect of energy efficiency R&D and nuclear energy R&D on energy productivity, while the impact of fossil fuel R&D and renewable energy R&D is estimated to be positive and significant. The only exception is that fossil fuel R&D is significant in one model specification (specification 3) but not in the other (specification 4).

As mentioned earlier, the interactions between the four energy-related R&D variables and the years of launching the two OECD innovation and green growth strategies are consistently estimated to have a positive and significant effect in the long run across all model specifications. However, in the short run, these interactions have a positive and significant effect only through fossil fuel R&D and nuclear energy R&D. These results are expected since the full impact of the OECD innovation and green growth strategies through the four energy-related R&D variables is more likely to take effect on energy productivity in the long-run.

The same conclusion is reached when examining the short-run results for the CO_2 productivity model specifications. Only fossil fuel R&D and renewable energy R&D exhibit a significant positive effect in at least one model specification. In addition, the short-run estimation of the impact of the interaction between the energy-related R&D variables and the two OECD initiative years under investigation produced similar results to those obtained from the long-run model estimation.

5.2.2 The extended model

In Eq. 2 above, we follow the energy productivity literature and expand the basic model by incorporating the following relevant control variables: real GDP growth, government share of GDP, and energy price index. The results from the extended model are used to test the robustness of the impact of the primary variables of interest, namely, the disaggregated energy-related green R&D variables and energy intensity, on OECD green growth indicators. Tables 8 and 9 indicate that the extended model results for both the energy productivity and CO_2 productivity models support certain findings of the basic model. Specifically, the positive and significant impact of fossil fuel R&D and renewable energy R&D

on both green growth indicators is reinforced. However, contrary to our initial estimation in the basic model, energy efficiency R&D exhibits a positive and significant impact across all model specifications for both green growth indicators. Also, nuclear R&D demonstrates a positive and significant effect, but only in model specification 7. On the other hand, the results obtained from the estimation of energy R&D interaction terms were similar to those obtained from the basic model for the energy productivity model but not for the CO_2 productivity model, as there were differences in the level of significance.

The estimated impact of the control variables shows that there is a positive and significant effect of GDP growth on both green growth indicators in the long run. This outcome aligns with the conclusions drawn by Mahmoud and Ahmed (2018), Atalla and Bean (2017), Rajbhandari et al. (2018), Sener and Karakas (2019), and Deichmann et al. (2018), who reported that higher economic growth rates lead to lower energy intensity and higher energy productivity in high and upper-middle-income countries. The primary explanation behind this result is that as countries develop, they shift from the high energy-intensive industrial sector to the low energy-intensive service sector. Furthermore, high-income countries have the financial means to allocate more resources to energy-related green R&D, which results in higher energy productivity.

Given that the size of the government can affect energy consumption, and thus energy supply, in the economy, we examine the relationship between government share of GDP and green growth indicators. The long-run impact of the government share of GDP is found to be negative and significant in all specifications of the energy productivity model. This finding suggests that government spending has a notable impact on increasing energy consumption and energy supply in OECD countries, which appears to outweigh the governments' efforts to promote energy efficiency measures. This result is consistent with the conclusions of Movahedi et al. (2022) and Liu et al. (2018), which indicate that an increase in government size leads to higher energy intensity, ultimately leading to a decrease in energy productivity. Nonetheless, we found the long-run effect of government consumption expenditure share of GDP on CO_2 productivity to be negative but insignificant in almost all the CO_2 productivity model specifications.

The long-run effect of energy price on energy productivity is estimated to be negative in all the energy productivity model specifications. However, this negative effect is significant in four out of the eight specifications. The inverse relationship between energy price and energy productivity is consistent with the findings of Liu et al. (2018). One of the reasons for this negative effect is that higher energy prices are expected to reduce economic activity. Industries may be forced to reduce their energy consumption to balance the increase in energy costs, especially if the cost of adopting more energy-efficient technologies is higher than the rise in energy prices (Liu et al. 2018). This reduction in economic activity results in a decrease in energy productivity. On the other hand, the long-run impact of the energy price index on CO_2 productivity is found to be inconclusive. While it is estimated to be negative and significant in two specifications, in all other specifications it is either estimated to be positive and significant or insignificant.

Table 8 CS-ARDL long-run and short-run results: extended model

VARIABLES	ENGPRO	ENGPRO	ENGPRO	ENGPRO	ENGPRO	ENGPRO	ENGPRO	ENGPRO
Long-run	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable: energy productivity								
lr_ENGPRO	−0.771***	−0.748***	−0.841***	−0.91***	−0.756***	−0.795***	−0.822***	−0.889***
	(0.0891)	(0.0547)	(0.0513)	(0.05)	(0.0526)	(0.0509)	(0.0554)	(0.0628)
lr_CO_2PRO								
lr_EEFF	0.0105*	0.0108*						
	(0.00541)	(0.00576)						
lr_EEFF11	0.0291*							
	(0.0169)							
lr_EEFF07		0.0204**						
		(0.00828)						
lr_FFL			0.00651**	0.0055**				
			(0.00307)	(−0.0024)				
lr_FFL11			0.0148*					
			(0.00812)					
lr_FFL07				0.0071**				
				(−0.0042)				
lr_RENS					0.00985***	0.00813**		
					(0.00365)	(0.00352)		
lr_RENS11					0.0166*			
					(0.00861)			
lr_RENS07						0.0112*		
						(0.00676)		
lr_NUC							0.0192*	0.00446
							(0.00974)	(0.00590)
lr_NUC11							0.00382	
							(0.00932)	

Table 8 (continued)

VARIABLES	ENGPRO	ENGPRO	ENGPRO	ENGPRO	ENGPRO	ENGPRO	ENGPRO	ENGPRO
Long-run	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
lr_NUC07								0.0266*
								(0.0134)
lr_dm_11	−0.140*		−0.0290		−0.0888*		0.139	
	(0.0794)		(0.0348)		(0.0485)		(0.190)	
lr_dm_07		−0.0958**		−0.041		−0.0686**		0.0407
		(0.0465)		(0.2)		(0.0303)		(0.159)
lr_ENSITY	−1.164***	−1.252***	−1.161***	−1.02***	−1.231***	−1.136***	−1.124***	−1.092***
	(0.234)	(0.120)	(0.114)	(0.094)	(0.111)	(0.111)	(0.170)	(0.0948)
lr_GE	−0.466**	−0.186*	−0.128*	−0.19*	−0.165**	−0.162*	−0.0653	−0.216**
	(0.210)	(0.0971)	(0.0738)	(0.062)	(0.0786)	(0.0940)	(0.147)	(0.1000)
lr_RGDP	0.972*	0.910***	0.832***	0.42**	0.939***	0.702***	0.355**	0.295**
	(0.509)	(0.210)	(0.248)	(0.099)	(0.184)	(0.106)	(0.135)	(0.131)
lr_EPI	−0.309	−0.195**	−0.120	−0.13**	−0.162*	−0.173**	−0.0215	−0.0700
	(0.286)	(0.0935)	(0.109)	(0.057)	(0.0839)	(0.0782)	(0.100)	(0.0573)
Short-run	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EEFF	0.00695***	0.00479**						
	(0.00242)	(0.00231)						
EEFF11	0.0115							
	(0.00856)							
EEFF07		0.0109***						
		(0.00398)						
FFL			0.00509**	0.0052**				
			(0.00250)	(0.0023)				
FFL11			0.00851					

Table 8 (continued)

Short-run	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
			(0.00588)					
FFL07				0.0063**				
				(0.0039)				
RENS					0.00658***	0.00506**		
					(0.00228)	(0.00220)		
RENS11					0.0137**			
					(0.00626)			
RENS07						0.00899**		
						(0.00452)		
NUC							0.00976	0.000248
							(0.00601)	(0.00405)
NUC11							0.00235	
							(0.00714)	
NUC07								0.0188*
								(0.00946)
dm_11	−0.0497		−0.0144		−0.0717*		0.0179	
	(0.0501)		(0.0201)		(0.0368)		(0.0688)	
dm_07		−0.0464**		−0.034**		−0.0497**		0.00489
		(0.0219)		(0.017)		(0.0200)		(0.0938)
ENSITY	−0.864***	−0.848***	−0.876***	−0.88***	−0.838***	−0.834***	−0.834***	−0.901***
	(0.0564)	(0.0540)	(0.0482)	(0.053)	(0.0427)	(0.0489)	(0.0747)	(0.0715)
RGDP	0.427***	0.552***	0.500***	0.34***	0.566***	0.503***	0.236***	0.199**
	(0.0860)	(0.0817)	(0.0990)	(0.078)	(0.0653)	(0.0664)	(0.0751)	(0.0981)
GE	−0.158*	−0.106	−0.0970	−0.18	−0.0981**	−0.0946*	−0.100	−0.220**

Table 8 (continued)

Short-run	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	(0.0909)	(0.0693)	(0.0707)	(0.062)	(0.0473)	(0.0507)	(0.0912)	(0.0851)
EPI	−0.0992	−0.105**	−0.0417	−0.11*	−0.0678*	−0.0914**	−0.0204	−0.0518
	(0.0710)	(0.0501)	(0.0602)	(0.044)	(0.0398)	(0.0414)	(0.0547)	(0.0415)
L.ENGPRO	0.229**	0.252***	0.159***	0.085***	0.244***	0.205***	0.178***	0.111*
	(0.0891)	(0.0547)	(0.0513)	(0.047)	(0.0526)	(0.0509)	(0.0554)	(0.0628)

***Significant at the 1% level, **Significant at the 5% level, and *Significant at the 10% level

Table 9 CS-ARDL long-run and short-run results: extended Model

Variables	CO_2PRO	CO_2PRO	CO_2PRO	CO_2PRO	CO_2PRO	CO_2PRO	CO_2PRO	CO_2PRO
Long-run	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable: CO_2 *productivity*								
lr_CO_2PRO	−0.916***	−0.856***	−0.784***	−0.823***	−0.93***	−0.942***	−0.866***	−0.786***
	(0.0534)	(0.0411)	(0.0676)	(0.0673)	(0.061)	(0.0730)	(0.0532)	(0.0543)
lr_EEFF	0.0108*	0.00979*						
	(0.00623)	(0.00590)						
lr_EEFF11	0.0541*							
	(0.0316)							
lr_EEFF07		0.0241**						
		(0.0103)						
lr_FFL			0.0140*	0.0151*				
			(0.00744)	(0.00849)				
lr_FFL11			0.0184					
			(0.0161)					
lr_FFL07				0.00613				
				(0.0136)				
lr_RENS					0.0154**	0.0186**		
					(0.0062)	(0.00908)		
lr_RENS11					0.043*			
					(0.023)			
lr_RENS07						0.0226*		
						(0.0132)		
lr_NUC							0.0194*	−0.00589
							(0.0116)	(0.0148)
lr_NUC11							0.0494***	

Table 9 (continued)

Variables	CO_2PRO	CO_2PRO	CO_2PRO	CO_2PRO	CO_2PRO	CO_2PRO	CO_2PRO	CO_2PRO
Long-run	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
							(0.0117)	
lr_NUC07								0.0263**
								(0.0130)
lr_dm_11	−0.296**		−0.148**		−0.192		−0.168***	
	(0.149)		(0.0655)		(0.13)		(0.0594)	
lr_dm07		−0.115**		−0.0821		−0.130*		−0.0772
		(0.0581)		(0.0766)		(0.0663)		(0.0541)
lr_ENSITY	−0.866***	−0.666***	−0.715***	−0.610***	−0.96***	−0.984***	−1.072***	−1.043***
	(0.170)	(0.101)	(0.108)	(0.168)	(0.159)	(0.155)	(0.162)	(0.203)
lr_GE	−0.0555	−0.0803	−0.0425	−0.181**	−0.136	−0.0920	0.0751	−0.134
	(0.160)	(0.0984)	(0.130)	(0.0700)	(0.093)	(0.0752)	(0.161)	(0.212)
lr_RGDP	0.103	0.395**	0.543*	0.350*	0.42***	0.391*	0.214	0.534**
	(0.149)	(0.175)	(0.278)	(0.189)	(0.145)	(0.222)	(0.195)	(0.229)
lr_EPI	−0.299***	−0.240***	0.202***	0.138**	−0.017	−0.115	0.0732	−0.0577
	(0.0905)	(0.0717)	(0.0763)	(0.0579)	(0.079)	(0.0998)	(0.130)	(0.125)
Short-run	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EEFF	0.00924*	0.00781*						
	(0.00559)	(0.00463)						
EEFF11	0.0410							
	(0.0250)							
EEFF07		0.0179**						
		(0.00748)						
FFL			0.0102*	0.00916				

Table 9 (continued)

Short-run	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
			(0.00573)	(0.00633)				
FFL11			0.00935					
			(0.00820)					
FFL07				0.00185				
				(0.00750)				
RENS					0.012**	0.0191**		
					(0.006)	(0.00834)		
RENS11					0.041*			
					(0.021)			
RENS07						0.0209*		
						(0.0120)		
NUC							0.0149*	−0.00598
							(0.00758)	(0.00994)
NUC11							0.0418***	
							(0.0107)	
NUC07								0.0198*
								(0.0108)
dm_11	−0.219*		−0.0934**		−0.20*		−0.151***	
	(0.113)		(0.0363)		(0.11)		(0.0482)	
Dm_07		−0.0773**		−0.0456		−0.126**		−0.0537*
		(0.0355)		(0.0381)		(0.0604)		(0.0320)
ENSITY	−0.727***	−0.569***	−0.550***	−0.476***	−0.85***	−0.869***	−0.857***	−0.756***
	(0.136)	(0.0990)	(0.0945)	(0.119)	(0.153)	(0.127)	(0.127)	(0.147)
RGDP	0.121	0.319**	0.208	0.196	0.29**	0.300	0.0875	0.413**

Table 9 (continued)

Short-run	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	(0.127)	(0.150)	(0.137)	(0.120)	(0.12)	(0.217)	(0.167)	(0.188)
GE	−0.0727	−0.0546	−0.0726	−0.157**	−0.1	−0.0756	−0.0193	−0.170
	(0.136)	(0.0839)	(0.0996)	(0.0628)	(0.095)	(0.0651)	(0.138)	(0.157)
EPI	−0.262***	−0.190***	0.151***	0.110**	(0.0032)	−0.0546	0.0869	−0.0131
	(0.0787)	(0.0623)	(0.0527)	(0.0428)	0.0687	(0.0913)	(0.111)	(0.0957)
L.CO_2PRO	0.0838	0.144***	0.216***	0.177***	0.062	0.0580	0.134**	0.214***
	(0.0534)	(0.0411)	(0.0676)	(0.0673)	(0.061)	(0.0730)	(0.0532)	(0.0543)
Observations	588	630	609	567	588	567	588	588
Number of groups	21	21	21	21	21	21	21	21

***Significant at the 1% level, **Significant at the 5% level, and *Significant at the 10% level

The short-run results obtained from the CS-ARDL model show similar results to those of the long-run results for both green growth indicators. It is worth noting that the year dummies for 2007 and 2011 are found to have either negative or insignificant effects on both green growth indicators.

6 Conclusion and policy implications

This paper examines the impact of disaggregated energy R&D on green growth, namely energy productivity and CO_2 productivity, in 21 high-income OECD countries over the years 1990 to 2021. The long-run CS-ARDL model results show that the impact of disaggregated energy-related green R&D on energy productivity varies depending on the type of energy-related green R&D. Specifically, the renewable energy R&D and fossil fuel R&D are found to have a positive and significant impact on energy productivity in all model specifications, with renewable energy R&D exhibiting a relatively stronger impact compared to fossil fuel R&D.

In addition, the analysis of the interaction between renewable energy R&D, fossil fuel R&D, energy efficiency R&D, nuclear energy, and the two key years (2007 and 2011) revealed a positive and significant impact on energy productivity suggesting that OECD innovation and green growth initiatives contributed to improving the impact of all energy-related green R&D variables on energy productivity during those years. The long-run effects of the energy R&D variables on CO_2 productivity are consistent with the energy productivity model results. These results highlight the importance of renewable energy for improving energy productivity and CO_2 productivity.

Besides, the positive and significant impact of renewable energy R&D and fossil fuel R&D on green growth indicators is reinforced when additional control variables (GDP growth, government share of GDP, and energy price index) are included in the extended model. The impact of GDP growth on both green growth indicators is found to be positive and significant in the long-run, indicating that higher economic growth rates lead to higher energy productivity and CO_2 productivity. On the other hand, the study results show a negative and significant impact of the government's share of GDP on energy productivity, suggesting that government spending leads to an increase in energy consumption and thus energy supply. However, the impact of the government's share of GDP on CO_2 productivity is mostly insignificant. Finally, the long-run effect of energy prices on energy productivity is estimated to be negative and significant, suggesting that higher energy prices can reduce economic activity and decrease energy productivity, while its impact on CO_2 productivity is found to be inconclusive.

Based on the study results, we can develop the following policy recommendations. Given the robust positive, and relatively strong, impact of renewable energy R&D on both green growth indicators in all model specifications compared to the non-renewable energy R&D, policymakers should consider reallocating the energy R&D budget towards renewable energy R&D. As mentioned earlier, despite the launch of the 2011 OECD green growth strategy, there has been only a minimal increase in the proportion of renewable energy R&D to the total energy R&D budget over the last decade in high-income OECD countries, as indicated in Fig. 1 in the "Appendix".

Moreover, Fig. 2 in the "Appendix" reveals that, during the past decade, 8 out of the 21 high-income OECD countries under investigation reduced their renewable energy R&D budget as a percentage of the total energy R&D budget. This could explain the modest increase in the renewable R&D budget share of the total energy R&D budget in the sample of the study. The reallocation of funds towards renewable energy R&D is expected to assist in overcoming the well-known problems of renewable energy, namely, the low reliability and efficiency of renewable energy sources and the high initial cost of their production, which will eventually improve the green growth indicators in OECD countries.

On the other hand, although the impact of the four energy R&D variables on both green growth indicators is found to be positive and statistically significant in the extended model specifications, especially when considering the interaction with the two key years (2007 and 2011), their impact is relatively weak compared to other factors like GDP growth, energy intensity, and the government's share of GDP. This relatively limited impact could be attributed to the limited energy R&D budgets in OECD countries as a percentage of gross domestic expenditure on R&D. According to Fig. 3 in the "Appendix", the average share of energy R&D budget to gross domestic expenditure on R&D from 1990 to 2021 ranged from as low as 0.9% in Portugal to as high as 6.9% in Norway. In addition, as shown in Fig. 4 in the "Appendix", six countries in our sample (Australia, Greece, Ireland, Japan, Netherlands, and New Zealand) experienced a decrease in the proportion of energy R&D budget to gross domestic expenditure on R&D in the last decade compared to the decade prior to the launch of the 2011 OECD green growth strategy. Therefore, since increasing energy productivity and CO_2 productivity require massive efforts in the area of technological improvements, which is apparently difficult to achieve given the current levels of energy R&D budgets in OECD countries, policymakers need to consider increasing the share of energy R&D budget as a proportion of the gross domestic expenditure on R&D. In addition, we recommend enhancing the international collaboration between OECD countries to benefit from the R&D spillover effect, which can lead to more effective and efficient advancements in energy-related technologies.

Also, it is crucial to review and enhance green energy R&D investment policies and incentives in OECD countries, including tax incentives, direct funding, subsidies, and public–private partnerships. The OECD (2022) Inventory of Support Measures for Fossil Fuels report indicates a sharp increase in support for fossil fuel production and consumption, almost doubling in 2021 and 2022. As shown by the aforementioned report, this surge can be attributed to the challenge faced by these countries in balancing the implementation of their longstanding policy to phase out inefficient fossil fuel subsidies with the need to protect households from rising energy prices, primarily caused by the Russian war against Ukraine. As a major consequence of this significant increase in fossil fuel subsidies, investments in green energy and energy efficiency have slowed down. To counter this, we recommend adopting technology-specific policies rather than technology-neutral policies in OECD countries. While both types of policies contribute positively to boosting green energy innovation, the technology-specific policies have been found to have a greater impact on promoting emerging technologies (Gerarden 2022; Calel and Dechezleprêtre 2016; Johnstone et al. 2010). By implementing such focused policies, OECD countries can boost investment in green energy innovation, which will, in turn, contribute to greener economic growth.

Appendix

See Figs. 1, 2, 3 and 4.

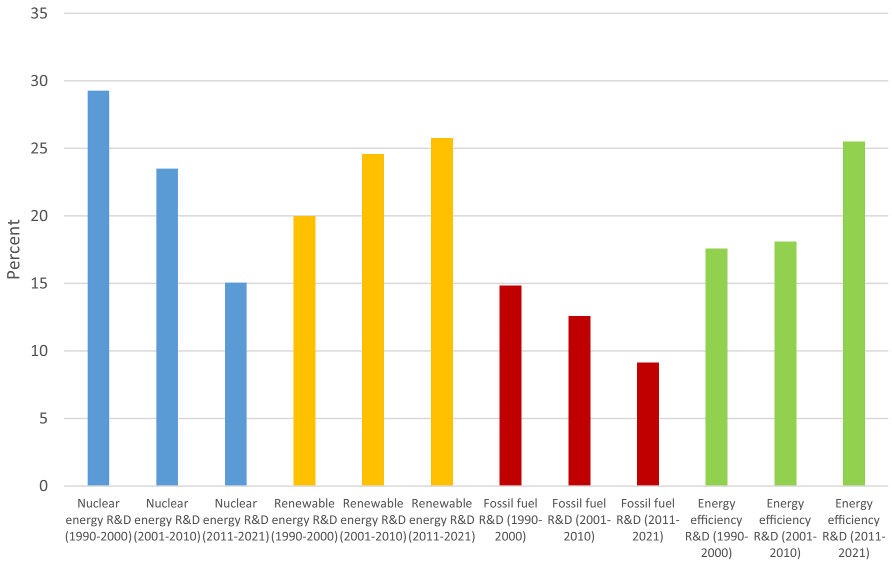

Fig. 1 Average disaggregated energy R&D to total energy budget over the last three decades (1990–2021). *Source*: Authors' calculations

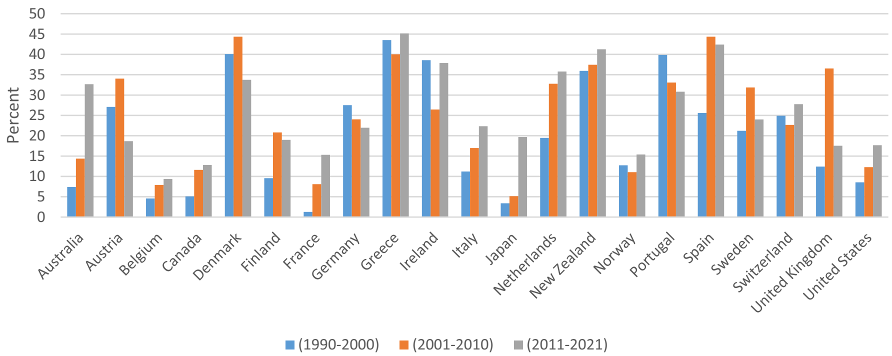

Fig. 2 The average share of renewable energy R&D to total energy budget in high-income OECD countries over the past three decades. *Source*: Authors' calculations

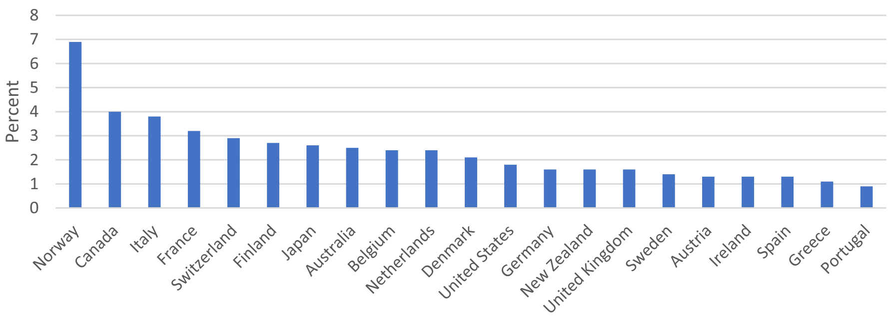

Fig. 3 Average Share of Energy R&D Expenditure to Gross Domestic Expenditure on R&D in OECD Countries (1990–2021). *Source*: Authors' calculations

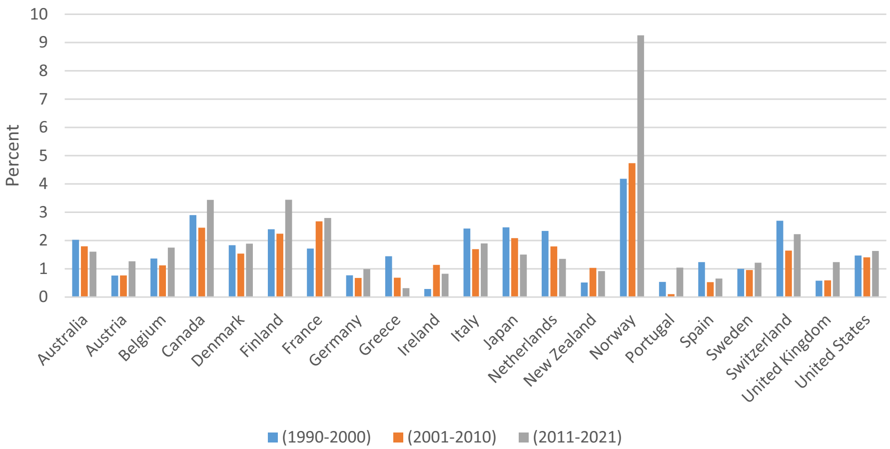

Fig. 4 The average share of total energy R&D budget to gross domestic expenditure on R&D. *Source*: Authors' calculations

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Data availability The data used in this study is available on the OECD iLibrary, OECD Statistics, and the World Development Indicators database.

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