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Decoupling of CO_2 Emissions from Growth with Energy Transition and Eco-Innovations in OECD: Novel Fourier-CS-ARDL and Fourier-DH-Causality Analyses

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Abstract

Decoupling between CO_2 emissions and economic growth is critical to reversing climate change. The OECD plays a crucial role in this regard, given its considerable share of global CO_2 emissions and GDP. This study examines the decoupling performance and the roles of renewable energy transition, as well as specific eco-innovations on climate change mitigation and environmental technology development across the OECD economies. The preliminary tests on a large panel of OECD countries identify cross-sectional dependence, structural breaks and heterogeneity. For robustness, the study proposes Fourier-CS-ARDL, Fourier-AMG, and Fourier–Dumitrescu–Hurlin methods as generalizations of their linear counterparts. After identifying cointegration and its singularity with Fourier-bootstrapping bounds and Fourier–Johansen tests, the modeling stage suggested a positive, but significantly inelastic long- and short-run elasticity of emissions to economic growth. Most of these effects are reversed by renewable energy transition in the long run and partially reversed in the short run. These CO_2 mitigation effects are also evident across different eco-innovations with varying temporal impacts. Novel Fourier causality tests identify feedback loops between CO_2 and CO_2-mitigating factors, as well as unidirectional causality from growth to all mitigating factors, confirming the indirect effect of growth on CO_2 mitigation. Overall, these results clearly suggest "relative" decoupling in OECD accompanied by CO_2e mitigation effects from eco-innovations and energy transition, and highlight the potential for green growth following the successful adaptation of energy transition and eco-innovations. Policymakers in OECD are encouraged to leverage the identified feedback mechanisms and establish international technology transfer policies to homogenously curb CO_2 emissions.

Keywords: decoupling; clean energy transition; energy economics; eco-innovation; endogenous growth; sustainable development; causality; Fourier; cointegration

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1. Introduction

One of the most urgent issues facing the world today is climate change, to which greenhouse gas emissions from human activities—especially from economic production and fossil fuel energy consumption—are pushing global temperatures upward to critical thresholds, thereby contributing to climate change. The OECD report in 2024 [1] confirms unsatisfactory clean energy transition and clean production achievements so far, with limited commitment to the targets put forth by the Paris Agreement and the Kyoto Protocol three decades ago [2]. Today, carbon dioxide emissions (CO_2e) are rising globally in lockstep

with economic growth (Y); in fact, global CO_2e increased by 7% between 2015 and 2022 in response to a 22% increase in the global GDP. In recent years, which also included the COVID-19 shutdown, only 40 countries experienced some years with growth in Y without a rise in CO_2e [1]. In response, the "beginning of the end of fossil fuel energy era" motto was put into motion by COP28 [3], and international cooperations were suggested to overcome the challenges faced in breaking the causation between Y and environmental deterioration.

It is evident that, to achieve the goals of environmental sustainability and to combat climate change, countries should effectively decouple CO_2e rises from their Y. However, decoupling exists in two forms [4]. The first form is "absolute" decoupling, which can be achieved by reversing the effect of Y on CO_2e, and thereby observing a negative association between Y and CO_2e. The second form is "relative" decoupling, which requires a diminished positive association, accomplished by clean energy transition, eco-innovations (EIs), and efficient material use. In the former, a strict negative association between Y and CO_2e still exists; however, the inclines in Y no longer result in equivalent inclines in CO_2e. In this form, a positive relation between Y and CO_2e exists; however, the growth rate of Y is not fully but partially transferred to growth in CO_2e, with a lessened growth-led CO_2e effect [4].

According to the IPCC report conducted on 115 countries in 2019, only 32 countries had a state of "absolute" decoupling, whereas 41 had "relative" decoupling, and among the 115, 36 countries did not have any form of decoupling at all for the period between 2015 and 2018 [5]. A more recent study analyzed 164 countries; this time, the sample covers the pre-COVID-19 period again [6]. Their results pointed to 49 countries, which had decoupling, and 115 had no form of decoupling [6]. Furthermore, the majority of the countries that decoupled their Y from CO_2e experienced "relative" decoupling; whereas, "absolute" decoupling only existed for a selected group of high-income economies, and only for data before 2018 [6].

Vogel and Hickel highlight the relation of decoupling to green growth [7]. Accordingly, green growth is defined as the equivalent of absolute decoupling [7]. To achieve it, a negative association between Y and CO_2e should have existed. After examining empirically, they identified only 11 high-income countries with absolute decoupling, and this decoupling existed between 2011 and 2019 [7]. Their projections suggested an optimistic scenario with 50% chance to limit global warming to the two degrees Celsius target set forth by the Paris agreement if countries persist in maintaining their existing performances [7]. Another projection required an effective reduction in CO_2e by more than 90% in 220 years, if countries persist in their existing decoupling performances [7]. Mazzai [4] discusses that, after the recent energy crisis, countries are becoming more reluctant to invest in clean energy, as they have started to shift their energy production to fossil fuels, especially coal, which will soon eliminate their pre-2019 successes on decoupling [4]. The findings of [4] identified that CO_2e surpassed pre-COVID-19 levels already, for the countries that had relative decoupling before [4]. IEA confirms that the positive link between Y and CO_2e in the world exists, and highlights the necessity to unlink Y from CO_2e with renewable energy transition (RET), clean technologies in the form of different EIs, and abandoning fossil fuels, especially coal [8]. In sum, the recent energy crisis further slows down energy transition and green innovation investments.

Examination of environmental sustainability performances of developed and industrialized nations is highly vital. The CO_2e from high-income and upper-middle-income industrialized nations summed up makes up 80 percent of the global CO_2e [9]. Industrialized economies, particularly the OECD members, play a decisive role in this context. Almost a third of global CO_2e originates from OECD economies. The OECD, as an economic organization, is also a prominent economic force in the world. Many countries in

OECD have an advantageous position in leading shifts toward eco-innovation (EI) and RET for sustainable development. As seen in Section 2, though OECD is a heterogeneous group, through effective international mechanisms and policies, OECD could influence its members to generate investments in EI, which a more homogenous transition with RET; hence, it is a more effective response to climate change with effective decoupling. Furthermore, OECD is also influential on non-OECD through its economic linkages in the global trade, as well as with its political influences, which could help to form coordination among OECD and non-OECD to more effectively achieve goals put in Kyoto [2] and Paris [7].

Ecological innovation, or eco-innovation (EI), is among the foremost drivers of sustainable development. Different EI types were identified in the literature [10]. At the firm and industry level, EI is an organizational and technological advancement that supports environmental sustainability [11]. EI is defined as any innovation that contributes to the decarbonization of production [12]. Green innovation is also used as a synonym, which defines EI as production processes that contribute to reductions in the use of energy and materials, and to the prevention of pollution [13]. EIs contribute to the achievement of clean production, and the OECD patent database distinguishes several categories of EI, including technology innovations on climate change mitigation (e.g., carbon-capture, renewable energy storage, green transportation) and environmental technology development (e.g., waste reduction, resource efficiency, pollution control) [14]. Hence, these two EI types, climate change mitigation (CCM) and environmental technology development (ETD), are at the central focus of this study in addition to their linkages with RET, Y and CO_2e.

The relationship between EI, RET, and CO_2e has been the subject of multiple studies. In this study, for robustness and to examine the effects of two critical EIs, the study focuses on CCM and ETD EIs, which cover several categories stated above. Furthermore, as seen in Section 3, a large body of literature employs an aggregate EI measure; however, the application of disaggregated measures has a set of benefits. The accumulation of the effects of different EIs on a single measure would average their temporal effects. Moreover, the employment of different measures helps in distinguishing their marginal effects, as well as varying temporal effects of different EIs.

The paper aims to provide two contributions. The first aim is to provide an extensive analysis of the (in)existence of decoupling, and if it exists, to distinguish between relative and absolute forms for the OECD. Due to the group's prominent role in global production and CO_2e, unbiased measurement of interlinkages among Y, CO_2e, RET, and EIs is highly vital. In line with this goal, the study examines different temporal roles of CCM, ETD, and RET on the achievement of effective mitigation of CO_2e. The second aim of the study is both empirical and methodological, which also supports the first contribution regarding effective measurement. The second contribution of the study is the suggestion and the employment of novel robust methods that lead to efficiency under a set of panel data characteristics. In fact, the major conventional methods in panel econometrics rely on linearity and the existence of no structural breaks (SBs). However, recent methods have become popular in empirical literature due to their effectiveness in estimations with panels with heterogeneity and cross-sectional dependence (CSD). Among these methods, the study focuses on Cross-Sectional Autoregressive (CS-ARDL) and Dumitrescu–Hurlin (DH) panel Granger-causality tests. By generalizing CS-ARDL with Fourier, the study establishes a novel Fourier-CS-ARDL model and its two variants under CCE and AMG estimators, followed by a Fourier-DH (FDH) causality test, which generalizes the DH test to SBs. Therefore, these suggested methods address three well-known issues in panels simultaneously, namely heterogeneity, CSD, and SBs, while relaxing the linearity and no SBs assumptions under CS-ARDL and DH. Furthermore, the OECD dataset, consisting of EIs, RET, CO_2e, and Y, is subject to all three factors, and PMG-type estimators are not

feasible under CSD and SBs, leading to biased parameter estimates and inefficiency, which happen with deflated standard errors and inflated t statistics, leading to both inconsistency and inefficiency. After the generalization with Fourier terms, the FDH causality test is effective in identifying contemporaneous causality effects in the dataset under SBs, in addition to its effectiveness under heterogeneity and CSD in panels.

The above-mentioned models are also important for future studies, which will focus on CO_2e and ecological variables, due to a set of reasons. Most importantly, CO_2e necessitates methods capable of modeling structural changes with smooth forms and allows the examination of long-run relations. In fact, certain characteristics of CO_2e and EIs are also in line with model capabilities. Accordingly, CO_2e is subject to "carbon-lock-in" [15] and to "ecological overshoot" [16], which significantly reduces the effects of the adopted policies on sustainability in the short run. EIs and their effects on CO_2e are highly delayed due to adaptation to technological change in production and due to endogenous growth that occurs in the long run [17]. Additional factors that affect the non-responsiveness of CO_2e to technological change and energy mix alterations include "technology lags" and "appropriability problems", in addition to heterogeneous implementation lags in different countries due to the variation in laws on intellectual property rights, and heterogeneity in technology adaptation on clean energies in OECD, which is detailed in Section Research Questions.

The remainder of the paper's sections are as follows. Section 2 reviews OECD for its CO_2e and heterogeneity in energy transition achievements. Section 3 presents theoretical and empirical literature. Section 4 outlines methodology. Section 5 describes the data and reports the results, and Section 6 concludes and reports a set of policy implications.

2. Decoupling, Clean Energy Transition, and EI in OECD

OECD is argued to target sustainable development by decoupling its CO_2e from its Y to achieve its sustainability policies with policy tools, including clean energy transition and EIs [1]. This section provides an overlook of the recent developments in CO_2e, Y, and RET between 1990 and 2023.

Figure 1 presents CO_2e and real GDP in OECD, followed by their respective yearly growth rates for 1990–2023 in Figure 2. The overview suggests an upward trend between 1990 and 2023, with a lessened trend after the year 2008 for the real GDP, which also coincided with the trend followed by the CO_2e. Figure 2 presents their growth rates. Accordingly, we observed a significant positive association between Y and CO_2e growth rates. Furthermore, both were subject to sharp declines during the 2008–2009 Great Recession and after the COVID-19 shutdown. After these years, CO_2e growth follows an upward trend again, along with a set of fluctuations, which are positively correlated with fluctuations in Y growth rates. These findings point to the significant level of positive association, which coincided with the strong coupling of CO_2e and Y before the 2000s, followed by a lessened positive relationship. These findings hint at a "relative" decoupling between CO_2e and Y instead of an absolute decoupling, which would be evident only after observing negative associations between CO_2e and Y.

In addition to these developments in CO_2e and real GDP, another point we want to highlight is the relative differences in the path followed by CO_2e in OECD and the world. In Figure 3, CO_2e in the world had a continuous upward trend with breaks in 2009 and 2020; the upward trend maintained with a lesser slope after the 2000s. For the OECD, however, the pace of the upward trend slowed effectively, leading to a horizontal path followed by its CO_2e after the mid-2000s. The critical factors that contributed to the slowdown in the CO_2e included the Paris agreement and the Kyoto protocol, whereas economic crises, COVID-19, and the recent energy crisis led to short-term declines in Y and CO_2e.

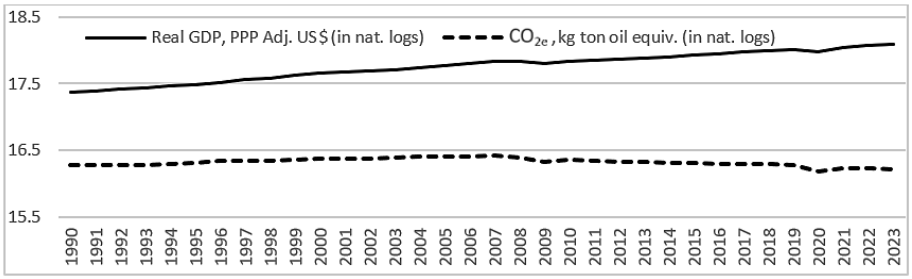


Figure 1. Real GDP and CO_2 emissions in OECD, in logarithms, 1990–2023. Notes: Real GDP is PPP adjusted and is in constant 2015 US$. CO_2 emissions are in kg ton of oil equivalent. Source: OECD Database, https://data-explorer.oecd.org/ (accessed on 22 December 2025).

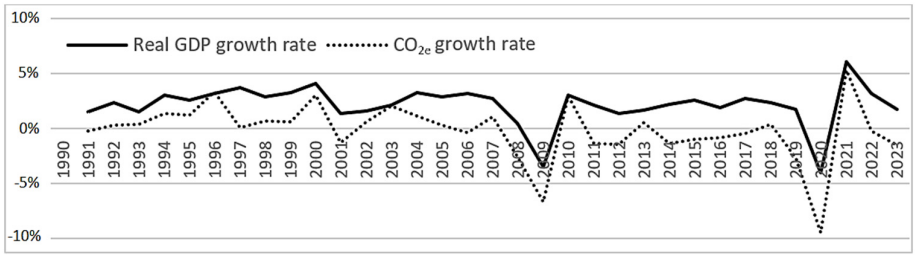


Figure 2. Yearly real GDP and CO_2e % growth rates in OECD, 1990–2023. Note: Growth rates reflect logarithmic first differences. Source: OECD Database, https://data-explorer.oecd.org/ (accessed on 22 December 2025).

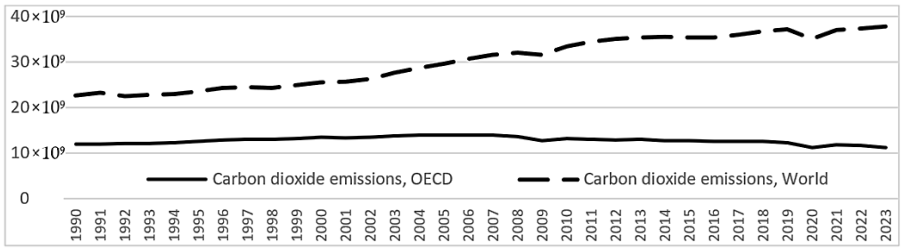


Figure 3. CO_2 emissions from the OECD and the world, in billion tons. Source: Our World in Data, https://ourworldindata.org/co2-emissions (accessed on 22 December 2025).

The CO_2e emitted from the OECD was more than one-fourth of global CO_2e. This makes OECD an important economic force in combating global climate change. However, the group is diverse in terms of their economic size, measured by GDP, and their economic structures. Furthermore, they also vary in terms of the level of CO_2e emitted from each country, not to mention their highly heterogeneous commitment to RET. The group also includes the top emitters, such as the USA, which released 41.90% of the OECD's total CO_2e in 2023, followed by the EU (23.4%), and Japan (8.6%) [18].

Figure 4 presents the renewable energy in energy mixes measured with RET and different EIs in the form of CCM and ETD. RET increased from 23% to 43% between 1990 and 2023, indicating a significant transition to clean energies. The significant incline in CCM- and ETD-type EIs is also evident in the period. The upward trend in EIs slowed after the 2009 Global Recession, and became horizontal afterward, with small fluctuations in 2015 and 2020 due to economic recessions and COVID-19. As EIs peaked in 2012 and 2018, RET also achieved an upward trend. These findings highlight the linkages between RET, EI, and Y.

RET surpassed 43% in the OECD in 2023, and significant heterogeneity still exists among its members. Figure 5 depicts RET in selected OECD members. In OECD, Iceland and Norway are the top performers in RET with 99.99% and 99.08%, respectively. New

Zealand, Luxembourg, Denmark, and Austria come afterward with their RETs ranging between 85.09% and 79%. Next comes the group with RETs over 60–65%: Finland (52%), followed by Chile, Spain, Greece, and Italy with RETs around 50%. After these countries, a decline occurs. The RET of Türkiye is 35.35%, followed by the Netherlands (33%). Afterward, countries with RETs equal to 20–27% are Australia (26.5%), Belgium, Mexico, France, Slovakia, Japan, and the USA (23–20%). Hungary, Poland, and Czechia's RETs are between 19.26 and 12.6%. Lowest RETs are in Israel (7.66%) and South Korea (6.3%) [14]. Accordingly, heterogeneity is an evident characteristic of the 34 OECD countries examined in this study.

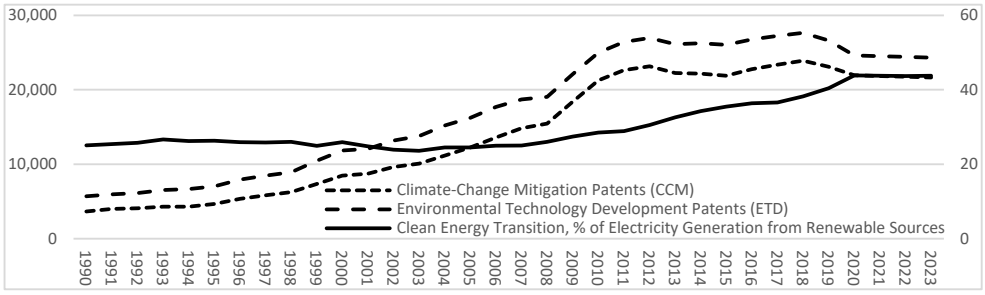


Figure 4. Clean energy transition (right lane), CCM and ETD patents (left lane) in OECD, 1990–2023. Source: OECD Patents Database and World Bank WDI.

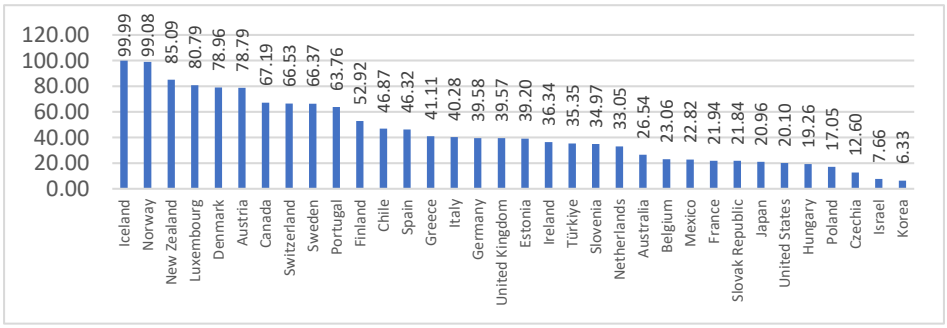


Figure 5. Energy mixes of selected OECD nations, 2023. Source: World Bank WDI Database.

The heterogeneity in OECD could significantly hinder efforts to reverse environmental degradation, and a more homogeneous shift to clean energies would improve the existing efforts to reverse climate change. Furthermore, in a heterogeneous OECD, it is extremely critical to assess the EI and RET policies and their effects on CO_2e that helped with decoupling.

Research Questions

Following the discussion on OECD above, the study aims to empirically examine the following research questions.

(1) Under heterogeneity and SBs, does RET effectively mitigate CO_2e, and what are the long-run and short-run effects of RET on CO_2e?
(2) Do ETD and CCM innovations help to reverse environmental degradation? If so, what are the contemporaneous causality directions between CCM and ETD with RET, Y, and CO_2e?
(3) What are the signs and sizes of the effects of Y on CO_2e? Robust determination is necessary to examine the effectiveness (or ineffectiveness) of decoupling policies. If so, do results point to "relative" or "absolute" decoupling?

(4) If Y has a positive effect on CO_2e, does relative decoupling exist, and if so, how does Y influence RET, CCM and ETD, which are the three factors that mitigate CO_2e through different causality channels?

In fact, once we determine the sign and size effects of Y on CO_2e with robust methods, we can effectively examine the existence or inexistence of decoupling, and if it exists, we can distinguish between its types. As discussed before, if the association between Y and CO_2e is strictly negative, evidence would suggest "absolute decoupling" evident with inclines in Y translating into declines in CO_2e. A second case is "relative decoupling," which indicates a positive association among Y and CO_2e; however, the relationship is significantly less than a one-by-one relation. In this case, one should expect a long-run elasticity (LRE) of CO_2e to Y to be positive but highly inelastic, and inclines in Y lead to inclines in CO_2e, but it could still help in combating climate change if Y also occurs along with an energy transition and positive influence on clean energies.

Conversely, the ceteris-paribus effect of Y on CO_2e could be positive and large, but close to one; however, Y could have indirect effects on CO_2e deceleration through its effects on CO_2e mitigation factors, i.e., different EIs (CCM and ETD) and clean energy transition. As a result, the study examines these dynamic linkages carefully with robust causality tests. After the identification of the long-run elasticities of CO_2 to Y, RET, CCM, and ETD with model results, PGC testing provides vital information about the dynamics between Y, CO_2e, RET, ETD and CCM. Nevertheless, though Y results increase in CO_2e in model results, Y could also help by supporting EIs and RET. As a result, the direct effect of Y on CO_2e reduces with its indirect effects on CO_2e through EIs and RET, contributing to relative decoupling. Therefore, the four conditions for relative decoupling are as follows: a. positive and significant effect of Y on CO_2 with less than +1 LRE in the long run; b. coupled with negative LRE of CO_2e to both EIs and to RET; c. Granger-causality dynamics should identify the existence of PGC from Y to factors contributing to CO_2e mitigation (RET, EI, and CCM); d. after identifying the expected PGC directions in (c), one should compare the size of long-run elasticities to RET, EI, and CCM, if they could lessen the effect captured by the LRE of Y in (a).

We should note that, if expected directions of causality hold as in (c), the examination of partial effects in all factors in the main model would help in identifying decoupling and its type. If the positive LRE of Y occurs with negative LREs of CO_2e mitigation factors for which Y is their Granger-cause, in the long run, the positive effect of Y on CO_2 could be lowered further by indirect mitigation effects of Y on CO_2e through improving EIs and RET, contributing to relative decoupling. Furthermore, it is evident that if condition (a) does not hold and if the LRE of CO_2e on Y is significantly negative along with conditions (b) and (c), evidence would suggest absolute decoupling. In sum, by comparing the size/sign of parameter estimates of Y, RET, and EIs in addition to PGC tests with necessary conditions, a more effective examination of decoupling is possible by incorporating the contemporaneous causality effects into the analysis.

The study specifically proposes the examination of long-run relations and PGC under the robust methods proposed. The reasons are linked to the following theoretical foundations. As shown by endogenous growth theories, technological change is a significant driver of Y [17], and technology-driven Y leads to inclines in CO_2e in the long and short run [19]. As a result, the size and sign of the effects of Y on CO_2e are under the influence of technological change and energy transition. Furthermore, as the effects of RET and Y could occur both in the long and short run, technological change is a long-run phenomenon, and the effects of EIs in the short run could be either nonexistent, extremely limited, or even negative. The reasons are as follows: i. technology adaptation lags; ii. varying levels in intellectual property rights in nations; iii. insufficiency of implementation of patents due to

appropriability problems. Further, the levels of EIs and the length of technology adaptation vary among nations and periods, contributing to heterogeneity.

In addition, the nature of CO_2e is subject to smooth changes that occur in the long run. Further, green technological or economic changes, or CO_2e mitigation efforts with RET and Eis, would even occur unexpectedly, with a positive association with CO_2e and rises in CO_2e, and the literature defines a set of reasons. Among these, the first is the "carbon-lock-in" nature of CO_2e [15]. CO_2e is not likely to decrease in the short run, and the changes take place in the exceptionally long run. Because of carbon lock-in, clean technologies or eco-friendly steps could fail to stop the upward trend of CO_2e in the short run. Second is "ecological overshoot," which results from the cumulative nature of CO_2e. In fact, CO_2e will continue to rise for a long time, even if, hypothetically, the economic activities of humans were to halt today without decline due to "ecological overshoot." [16].

Furthermore, international agencies, including IPCC, warn OECD countries to take action, especially after 2019 [20]. The recent energy crisis and disputes today have also brought about warnings for nations to increase investments for RET and EIs, and not to divert from RET by increasing fossil fuels, especially coal in the mix [4]. Following these developments, decoupling is questioned, especially given the nature of CO_2e, since a deference from RET and R&D on EIs could easily reverse the sustainability achievements achieved so far [20].

3. Literature Review

The increasing urgency of climate change and environmental degradation has raised the role of innovations in generating sustainable and clean economic development. In this regard, EI emerged as a central concept in the literature. Kemp and Pearson define EI as encompassing various technologies and practices that aim at the reduction in environmental risks, enhancing resource efficiency and supporting the decarbonization of economies [12]. According to the UN, EIs are also vital for corporations to attract investments and stay ahead of regulations, as well as for corporate sustainability, which will also help in the reduction in disasters such as flooding and the protection of biodiversity. Afterward, the reversal of environmental degradation at the aggregate level in nations characterizes the value added from EIs [21].

The increasing interest in the reversal of climate change also brought up an increasing amount of literature on EIs, energy types, and environmental degradation with different measures, countries examined, years covered, and methodological approaches.

3.1. OECD's Decarbonization, Growth, EI, and Environmental Degradation

Seminal literature on the environment and economic production nexus highlighted the existence of a trade-off, or a dilemma between economic growth and environmental sustainability, popularized after the influential research by Grossman and Krueger [22,23], and Stern [24], which suggested an existence of a nonlinear relation defined as an inverted-U curve known as the environmental Kuznets curve (EKC) hypothesis. These studies also generated an examination of decarbonization efforts in more-developed countries, including OECD countries that went through Rostow's development stages. As countries prosper, through the pace of economic growth, environmental degradation initially worsens; after a certain level of income, it may eventually improve in OECD [22]. Recent advancements further highlighted the existence of nonlinearity in the income–environment nexus with smooth transitions in a panel of developed nations, which are also OECD members [25], and nonlinearity in long-run relationships [26].

In fact, early studies highlight the role of not controlling SBs in empirical results, leading to biased estimates. Moomaw and Unruh questioned the validity of EKC, and they

found 16 countries that went through the EKC-type transition empirically (mostly OECD members) [27]. However, in this result, historical events such as the 1973 oil shock had been responsible for leading to results that spuriously suggest EKC [27]. In a more recent study that surveys the relevant literature, Dinda investigates the environment–income relationship with studies on OECD members, various high-income nations, and developing countries [28]. Dinda's literature survey indicated the negative effects of continued growth that increases emissions further in the majority of results, indicating no reversal towards a negative correlation [28]. The importance of "pollution-reducing innovations" and energy transition is an important outcome obtained from a thorough analysis of the literature [28]. Even though the emissions continue to be positively related to the continuation of industrial production, technology policies targeting the development of more environment-friendly technologies could be effectively used to reverse the environmental degradation both in home countries and in pollution havens [29].

In the context of OECD, the organization underlines such decoupling effects between economic growth and environmental degradation in various reports [1,30]. As depicted in the next section, the decoupling effect is visible in the OECD data [14]; however, though the pace of emissions slowed down, the levels of yearly emissions are maintained at steady levels. In this success, the roles of EI and energy transition cannot be disregarded. However, it is also argued that part of OECD's emissions occurs in their trade partners, the non-OECD nations, which continue to have an upward-trending emissions curve. In a recent study on EU members, Bildirici et al.'s recent findings on the EU cover a large set of OECD countries as well; as a result, it is of importance. With Fourier-ARDL and Fourier causality methods, they confirmed the carbon-leakage effect and its interrelation with environmental policy stringency after controlling for SBs [31]. Their findings are also in line with the "race-to-bottom" hypothesis, i.e., high standards on the environment leading to a passage of CO_2e to those with relatively lax environmental laws, in addition to "pollution-haven" and "displacement" hypotheses, which underline mechanisms to shift pollution from relatively more-developed and developing nations [28]. In the context of China, Du et al. examine the effects of green city and EI policies with data on 248 cities covering 14 years [32]. By examining DID models, they obtained differentiation between before and after effects, with results indicating the importance of the synergy between ecological policies and EI [32].

As discussed in Section Research Questions, cointegration testing is critical to inspect the connection between CO_2e and Y and to examine decoupling and the effects of mitigation factors, including EIs and energy transition in OECD. However, cointegration tests are not prone to various data structures. On the inconsistency of results obtained for environment–income relations, certain data properties could play crucial roles. Perman and Stern provide an early analysis of data properties for environment and economic growth variables for future studies, testing the income–environmental degradation relationship [33]. They showed that the majority of the literature on EKC is incorrect, particularly due to panel econometrics tests on cointegration, which indicated a long-run relation after confirming that both income and emissions variables are integrated of the same order at the panel level, while at the individual time series level for countries, integration properties varied, and cointegration did not exist [33].

In a recent study on OECD, Erdoğan and Acaravcı examined OECD with second generation unit root tests to control CSD in panel, followed by Fourier-stationarity tests to control SBs and findings suggested non-stationarity of emissions per capita in OECD panel as a whole, though at individual level, a set of OECD countries' data was stationary and displayed non-stationarity, further questioning the sustainability of CO_2 per capita emissions [34].

Studies also highlighted results favoring the non-existence or the existence of decoupling in the OECD panel, once heterogeneity was controlled for or not [35]. Technological efforts can mitigate emissions if supported with green EI [36]. EI is advocated further for the reduction in footprints [37]. Though the non-existence of a decoupling that translated to the whole OECD cannot be rejected, as well as the carbon transmission linkages with the rest of the world, given the heterogeneity of OECD with various levels of policies towards environmental measures, EIs and renewable energy transition are critical to counterbalance the effects on the environment [35]. Technological efforts can mitigate emissions if supported with green EI and complemented by structural policy changes, as shown for different environmental sectors, including waste treatment [36] and EI for the reduction in footprints in the manufacturing sector [37].

3.2. Aggregated EI, Renewable Energy Consumption, and CO_2e

In the literature that employs primary nation-level data, our literature search showed that the empirical studies apply an aggregate EI measure, the number of environmental patents, or EI per one thousand people, thereby mostly neglecting the varied EI processes. Furthermore, the studies that apply secondary data aim at collecting data on EI at the firm or industry level, either by focusing on a specific type of EI or its aggregation. Furthermore, the data on EI, as well as economic growth and energy consumption or production measures, are subject to heterogeneity, CSD, and structural breaks (SBs) or nonlinearity. However, SBs and nonlinearity are not generally taken into account [19]. Analyses on disaggregated EI with primary data also exist but there are few.

With the aggregated EI measure, and by applying robust techniques for CSD and heterogeneity, but not for SBs, studies showed the importance of EI in reversing the adverse effects of economic growth on per capita CO_2 emissions. A typical study is the one that showed the importance of EI with an aggregated measure and its importance for the sustainability of the environment, emissions, and natural resources, as well as relations with renewable energy consumption (REC) [38].

There could be problems due to omitting key factors and information if a single aggregated EI measure is employed. Aggregation could result in ambiguity in the effects of different EI types, omission of time lags, and variation in the amounts of individual EIs in the aggregated EI measure, and inconsistent determination of contributions of specific EI types. Other than the studies that employed nation-level primary data, studies employed firm-level secondary datasets, and examples include Costantini et al., Borghesi et al., and Lee and Min, which provided important insights into the role of green technologies in emissions mitigation [39–41].

However, the use of a single EI measure also resulted from the unavailability of different forms of EI data. Furthermore, we noted that very limited studies employ methods robust to heterogeneity, CSD, SBs, or nonlinearity simultaneously; among these factors, SBs are mostly not taken into account [19]. With robust techniques for CSD and heterogeneity, studies showed the importance of aggregated EI in reversing the adverse effects of economic growth on CO_2e. With CCE and AMG estimators as robust panel methods, Ahakwa et al. showed the positive effects of EI for the sustainability of the environment and in terms of reducing emissions and pressure on natural resources with REC, and with DH tests, they showed bidirectional PGC between Y and CO_2e, natural resources and CO_2e, REC and CO_2e, as findings pointed to unidirectional PGC from aggregated EI to Y [38]. The role of green technologies and causality effects on CO_2e and their mitigation were also confirmed in a set of studies with various methods [39–41]. To overcome it, numerous studies suggest the employment of proxy variables for green innovation instead. Typically, Berrone et al. utilized a market-based environmental regulation measure [42], and Borsatto and Bazani

used two measures, namely the ratios of investments on environmental pollution control and environmental protection within fiscal expenditures [43], and afterward, by combining different proxies of these two proxies into a single EI measure, Lu et al. employed an entropy method to form a single EI variable for green innovation, which is a proxy produced from investments and environmental regulations instead of the innovations themselves [44]. With this respect, due to data unavailability on Eis, we observed that a set of studies focused on the green innovation investments and supports, instead of directly employing datasets on EIs themselves. Therefore, to overcome data unavailability, after employing proxies, part of the literature assumed that the investments and incentives that targeted green innovations, and the amount of effective number of regulations, would generate successful EIs. As a result, due to data availability in sectors, firms, and nations, except for few studies, aggregate EI measures or proxies were utilized. Furthermore, the nonlinear relations as well as the effects of SBs have also been investigated only by few studies.

3.3. Firm- and Industry-Level EIs

Here, we focus on a strand of literature that focuses on firm-level secondary datasets. Their significant contributions include the achievement of measures of EI or proxies that help in examining the EI–environment nexus. Horbach et al. examined determinants of EIs as well as their environmental effects on various greenhouse gas emissions with extensive secondary data in Germany, using discrete choice models [11]. Their findings show that different EIs are influenced by regulatory, market, and technology push–pull effects, among which regulations are highly effective for companies to reduce their GHGs and water pollution, circumvent the use of hazardous materials, and encourage recycling [11]. Borsatto and Amui examined a sample of 186 companies with structural equation modeling, and their findings point to the significance of green innovation for sustainability, influenced by governmental policies, whereas company size and internationalization had negative moderating effects on green innovations [45].

By examining an extensive dataset on Japanese manufacturing companies for 2001–2010, Lee and Min (2015) provided results for firm-level efforts linked to their macro-level outcomes, hence providing a bridge between sectoral and macroeconomic results. In their findings, Lee and Min show the importance of green research and development investments of firms to achieve EI, and their findings also point to the positive contributions of EI to financial performances, then to environmental sustainability, given the identified negative effects of EI on CO_2e with national-level effects [41]. Costantini et al. studied energy-related EIs and showed their significant emission reduction effects, particularly when supported by consistent policies on environmental sustainability [40]. Another study of Costantini et al. studied the GHG reduction effect of different EIs for patents applied by residents and non-residents for a panel consisting of 27 EU and 13 non-EU countries for 1995–2009 with CSD-robust methods, and their findings confirm the GHG reduction effects of EIs [46]. Ahakwa et al. examined green innovation, REC share, economic growth, natural resources, urbanization, and their relations to per capita CO_2 emissions, with findings pointing to the importance of EI in reducing negative effects on the environment [38].

3.4. Renewable Energy Production, EI, Growth, and CO_2e

A strand of literature has explored the transition to renewable energies collected under various renewable energy measures, including the level of REC and their nexus with environmental degradation and economic production [47,48], renewable energy intensity, and renewable energy productivity measured as renewable energy production (REP) per 1$ of output produced. Studies also highlighted nonlinearity in such relations, as recently, by employing quantile panel regression methods and by focusing on renewable electricity

productivity per output in the context of Industry 4.0, Bildirici et al. examined REP's role as well as various factors, and they identified the importance of clean energy and its relations to industrial structure, R&D, financial development and economic growth [47].

A set of studies highlighted the importance of specific and new renewable energy sources for their economic feasibility and their roles in improving environmental sustainability, such as biomass [49,50], biofuels [51], and wind [52] and solar energy [53] for their feasibility. Furthermore, research highlighted the importance of energy transition, measured as the % of clean energy production in total energy generation [51,54]. In this respect, studies examined the effects of variations in the transition to clean energies and the environmental outcomes.

Ren et al. investigated spatial and dynamic impacts of energy transition and economic growth on CO_2e in the EU with a fixed effects dynamic spatial Durbin model, and their findings confirmed significant negative effects of renewable energy on CO_2 without significant spatial effects on CO_2 in other EU members [55]. Long et al. explored the differentiated effects among various energy types, including gas, coal, hydro, and nuclear, with cointegration tests and Granger-causality tests, and their linkages with economic growth and CO_2e in China, and they highlighted the importance of altering energy policies and energy mix towards renewable energies as a policy suggestion [56].

3.5. Energy Transition with EI and Economic Growth

Zhang et al. explored the linkages between technology innovation, green energy transition, economic growth, energy consumption, and sectoral CO_2e in different industries for a sample of 1982–2022 of the USA, and they highlighted the importance of policies encouraging investments directed to innovations towards renewable energy and to improving access to clean energies to achieve the 2030 sustainable development targets [57]. Khan et al. studied the relations among EI, green economic growth, and environmental policies for 26 EU countries [58], which are also members of the OECD, in the context of our study. Their empirical results with second generation unit root tests after the identification of CSD led to the existence of cointegration afterwards, and their model results showed the effectiveness of green growth policies and EI in reducing CO_2 emissions.

For BRICS nations, Fatima et al. studied green technology innovations, renewable energy consumptions and environmental policy stringency as a measure of environmental policies targeting ecological footprint reduction [59]. Their study did not center on CSD and heterogeneity, and by employing FMOLS and MMQR regressions, their results indicated the significant role of green technologies in the long run on CO_2 reduction, which is an effect that further advances with interaction effects among green technology innovations with enhanced environmental policies [59].

Barak and Koçoğlu employed a panel dataset of 30 OECD countries for 1995–2018, for which they found significant contributions of both environmental R&D expenditures and REC on curbing the upward trend of the environmental Kuznets curve by lowering CO_2e [60]. In the context of China, as a major emitter of CO_2 emissions, Chien et al.'s results for 1990–2018 indicated long-run cointegrated effects between renewable energy, EI, and CO_2e, and they suggested more investments in EI and solar energy, which are the most important sources of CO_2 reduction effects [61].

Following the discussion above, it is evident that the examination of interrelations among CO_2e and Y, as well as RET and different EIs, is of crucial importance with a focus that aims at a broad coverage of countries for environmental sustainability. However, within the panel context, data structures as well as empirical methods focusing on modeling long- and short-run relations and Granger-causality tests could require robustness to CSD, SBs, and heterogeneity for unbiasedness and efficiency in analysis. As discussed in Sections 1–3,

as a recent model, CS-ARDL [62] integrates CS terms to control CSD in panels; however, the model requires testing SBs first, and obtaining results that no SBs exist in the data. This assumption does not hold for many datasets. Ecological variables such as ecological footprints and CO_2e have necessitate models capable of capturing smooth forms of SBs. For Granger-causality testing in panels, it is evident that the DH causality test found significant applications under CSD and heterogeneity [63]. The DH test also requires the establishment of no SBs in panels. By relaxing linearity and panels with evident heterogeneous SBs, this study adapts the Fourier-CS-ARDL and Fourier-AMG models and the FDH causality tests.

4. Methodology

4.1. Fourier-CS-ARDL Model

The starting point for Fourier-CS-ARDL is Panel ARDL [64],

$$\Delta Y_{it} = \theta_0 + \theta_1 Y_{it-1} + \theta_2 X_{it} + \sum_{p=1}^{p} \vartheta_{ip} \Delta Y_{it-p} + \sum_{q=0}^{q} \sigma_{iq} \Delta X_{it-q} + \varepsilon_{it} \quad (1)$$

which allows the modeling of long- and short-term relations, and country-specific error-correction dynamics. The model could suffer from CSD [62] and to control it, Equation (1) is augmented with cross-sectional (CS) terms by incorporating a variable matrix $\overline{Z}_{it-r}$ to achieve CS-ARDL [65],

$$\Delta Y_{it} = \theta_0 + \theta_1 Y_{it-1} + \theta_2 X_{it} + \sum_{p=1}^{p} \vartheta_{ip} \Delta Y_{it-p} + \sum_{q=0}^{q} \sigma_{iq} \Delta X_{it-q} + \sum_{r=0}^{r} \tau_{ir} \overline{Z}_{it-r} + \varepsilon_{it} \quad (2)$$

Fourier-augmented versions of Panel ARDL in Equation (1) are well-established [66,67]. Fourier-ARDL model is as follows:

$$\Delta Y_{it} = \theta_0 + \theta_1 Y_{it-1} + \theta_2 X_{it} + \sum_{p=1}^{p} \vartheta_{ip} \Delta Y_{it-p} + \sum_{q=0}^{q} \sigma_{ip} \Delta X_{it-q} + f_k(\lambda_{0,k}, \lambda_{1,k}) + \varepsilon_{it} \quad (3)$$

for efficiency and consistency under SBs and heterogeneity, readers are referred [66,67]. CS-ARDL in Equation (2) is not robust to SBs; with a similar strategy, the model is extended with Fourier terms to achieve the following novel Fourier-CS-ARDL

$$\Delta Y_{it} = \underbrace{\theta_0 + \theta_1 Y_{it-1} + \theta_2 X_{it}}_{long-run} + \underbrace{\sum_{p=1}^{p} \vartheta_{ip} \Delta Y_{it-p} + \sum_{q=0}^{q} \sigma_{iq} \Delta X_{it-q}}_{short-run} + \underbrace{\sum_{r=0}^{r} \tau_{ir} \overline{Z}_{it-r}}_{CS\ terms} + \underbrace{f_k(\lambda_{0,k}, \lambda_{1,k})}_{Fourier\ terms} + \varepsilon_{it} \quad (4)$$

with a discrete Fourier form as in [68,69].

$$f_k(\lambda_{0,k}, \lambda_{1,k}) = \sum_{k=1}^{k\max} \lambda_{i0,k} \sin(2\pi k \times t/T) + \sum_{k=1}^{k\max} \lambda_{i1,k} \cos(2\pi k \times t/T) \quad (5)$$

After substituting Equation (5), the Fourier-CS-ARDL is

$$\begin{aligned} \Delta Y_{it} = {} & \theta_0 + \theta_1 Y_{it-1} + \theta_2 X_{it} + \sum_{p=1}^{p} \vartheta_{ip} \Delta Y_{it-p} + \sum_{q=0}^{q} \sigma_{iq} \Delta X_{it-q} + \sum_{r=0}^{r} \tau_{ir} \overline{Z}_{it-r} \\ & + \sum_{k=1}^{k\max} \lambda_{i0,k} \sin(2\pi k \times t/T) + \sum_{k=1}^{k\max} \lambda_{i1,k} \cos(2\pi k \times t/T) + \varepsilon_{it} \end{aligned} \quad (6)$$

for which the error-correction representation is

$$\Delta Y_{it} = \gamma_i ecm_{i,t-1} + \sum_{p=1}^{p} \vartheta_{ip} \Delta Y_{it-p} + \sum_{q=0}^{q} \sigma_{iq} \Delta X_{it-q} + \sum_{r=0}^{r} \tau_{ir} \overline{Z}_{it-r} + \sum_{k=1}^{kmax} \lambda_{i0,k} \sin(2\pi k \times t/T) + \sum_{k=1}^{kmax} \lambda_{i1,k} \cos(2\pi k \times t/T) + \varepsilon_{it}. \quad (7)$$

In Equation (7), $\gamma_i ecm_{i,t-1}$ is the error-correction mechanism, γ_i is the speed of convergence that should be statistically significant and non-positive, and $1 < \gamma_i < 0$ so that convergence to the long-run equilibrium takes $1/|\gamma_i|$ periods [19]. Fourier-CS-ARDL allows heterogeneity in error-correction, short-run dynamics, and SBs. Furthermore, π is the number pi, t is a variable that behaves like trend for $t = 1, 2, \ldots, T$, whereby T is the length of time dimension. Lastly, $\lambda_{i0,k}$ and $\lambda_{i1,k}$ are Fourier parameters. The order of Fourier terms, k, is selected from $k = 1, 2, \ldots, k_{\max}$ by sequential Fourier nonlinearity tests following [19,68]. The asymptotic normality of Fourier regressions is well-established [70].

A bi-variate Fourier-CS-ARDL with $k = 1$ is

$$\Delta Y_{it} = \theta_0 + \theta_1 Y_{it-1} + \theta_2 X_{it} + \sum_{p=1}^{p} \vartheta_{ip} \Delta Y_{it-p} + \sum_{q=0}^{q} \sigma_{iq} \Delta X_{it-q} + \sum_{r=0}^{r} \tau_{ir} \overline{Z}_{it-r} + \lambda_{i0} \sin(2\pi k \times t/T) + \lambda_{i1} \cos(2\pi k \times t/T) + \varepsilon_{it} \quad (8)$$

for which the error-correction representation becomes

$$\Delta Y_{it} = \gamma_i ecm_{i,t-1} + \sum_{p=1}^{p} \vartheta_{ip} \Delta Y_{it-p} + \sum_{q=0}^{q} \sigma_{iq} \Delta X_{it-q} + \sum_{r=0}^{r} \tau_{ir} \overline{Z}_{it-r} + \lambda_{i0} \sin(2\pi k \times t/T) + \lambda_{i1} \cos(2\pi k \times t/T) + \varepsilon_{it}. \quad (9)$$

As seen in the empirical section, the omission of CSD and SBs could point toward biased parameter estimators, inflated/deflated standard errors, and t statistics, leading to inefficiency under CSD and SBs for the dataset examined in this study. As for the CS-ARDL, Fourier-CS-ARDL is estimated with the CCE of [65]. An AMG variant of the model can also be estimated with the AMG estimator as a robust generalization of AMG [71] to Fourier-CS-ARDL. Hence, this model is a Fourier-AMG, as a second suggested model that employs country-specific Fourier terms to capture SBs along with robustness to CSD and heterogeneity.

4.2. Modeling Stages

The four stages are as follows:

Stage 1: Specification. Testing unit roots, cointegration, CSD, heterogeneity, and SBs.
Stage 2: Modeling and Estimation. If stage 1 suggests

Case one. SBs and CSD rejected, heterogeneity accepted: Panel-ARDL.
Case two. CSD and heterogeneity exist, SBs do not: CS-ARDL.
Case three. SBs and heterogeneity exist, CSD does not: Fourier-ARDL.
Case four. Simultaneous existence of SBs, CSD, and heterogeneity: Fourier-CS-ARDL. An alternative model is Fourier-AMG for moderate panel sizes.

Stage 3: Evaluation. Diagnostic tests aim at examining remaining CSD, SBs, and heterogeneity. This stage also includes testing Fourier terms. For robustness and with a comparative perspective, evaluate the estimation results for Fourier-CS-ARDL, Fourier-AMG, Panel ARDL and Fourier-ARDL.
Stage 4: Examining dynamic causality relations with the FDH causality test. Fourier-CS-ARDL, Fourier-AMG, and FDH test results will lead to policy implications.

4.3. Study's Models

Model 1 of this study is

$$CO_{2eit} = \theta_0 + \theta_1 ETD_{it} + \theta_2 RET_{it} + \theta_3 Y_{it} + \varepsilon_{it} \quad (10)$$

which focuses on the effects of RET, Y, and ETD as an EI variable.

Model 2 replaces ETD with CCM,

$$CO_{2eit} = \theta_0 + \theta_1 CCM_{it} + \theta_2 RET_{it} + \theta_3 Y_{it} + \varepsilon_{it} \quad (11)$$

5. Empirical Results

5.1. Dataset

After examining data availability for different EI types, while aiming to preserve the largest country and year coverage in a balanced panel, the study focuses on thirty-four countries from the OECD for the period covering 1990 and 2023. Table 1 presents data and sources. The study focuses on five variables. The first variable is carbon dioxide omissions (CO_2e) in thousand tons, and CO_2e is obtained from the OECD Air and Pollution Statistics. To measure economic growth (Y), the study employs real gross domestic product, and purchasing power parity (PPP) adjusted, in 2015 U.S. dollars. For renewable energy transition (RET), the study employs the % of renewable energy in total electricity generation. RET and Y are obtained from the World Bank's World Development Indicators database.

Furthermore, the study utilizes the two eco-innovation measures discussed in the previous section. The former utilizes the patents on environmental technology development (ETD), and the latter utilizes the patents for climate change mitigation technologies (CCM), and are obtained from the OECD Patents Database. Afterward, a balanced panel of thirty-four countries is established for the period between 1990 and 2023. The countries included are the UK, the USA, Canada, Belgium, Austria, Netherlands, New Zealand, Norway, Poland, Australia, Italy, Luxembourg, Sweden, Czechia, Spain, Denmark, Switzerland, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Japan, Korea, Israel, Mexico, Portugal, Slovak Republic, Slovenia, Türkiye and Chile. These countries that we included for the analysis were also presented in Figure 5.

The selection is based on the existence of EI data for 1990–2023, in addition to the aim of achieving variety in terms of RET. We did not include countries with 0% RET, which were mostly petrol-abundant nations, for which RET data had no variation. In the remaining OECD members, the EI data is either nonexistent for 1990–2023, or the data had observations with zeros for certain years, especially before the 2000s. As a result, by employing countries for which data existed for EIs, and by omitting petrol-rich nations, a balanced panel was formed with thirty-four countries in the cross-section, and thirty-four years in the time dimension.

5.2. Preliminary Tests

5.2.1. Descriptive Statistics and CSD Tests

Table 2 reports descriptive statistics, CSD tests, and unit root test results for variables in levels and for variables in first differences, respectively.

In analyses, variables are subject to natural logarithms to achieve distributional properties. Δ is the first difference operator. The log-first-differenced variables also represent their yearly % changes. The first part of Table 2 presents descriptive statistics. For variables in levels, third, and fourth moments of CO_2e are close to ideal values, and the same holds for Y. JB test confirms normal distribution followed by CO_2e and Y. The test rejects normality for ETD, CCM, and RET. For first-differenced variables, kurtosis statistics indicate leptokurtic

distributions, skewness points to negative and positive skewness, and JB suggests rejection of the normal distribution for variables in first differences.

In the second part of Table 2, we report a battery of CSD tests, and findings indicate CSD at 1% level of significance for both variables in levels and in first differences. In the third part of Table 2, due to the existence of CSD, second generation tests are reported as MW [72] and CIPS [73], in addition to the traditional tests of LLC [74] and IPS [75]. Findings suggested that these variables are first-difference, stationary at 1% and 5% levels of significance.

Table 1. Variable definitions and sources.

Annotation	Variable	Definition and Source
		Dependent variable:
CO_2e	CO_2 emissions	Carbon dioxide emissions, tons of CO_2, in thousands Source: OECD Database on Air and Pollution Statistics https://www.oecd.org/en/data/indicators/air-and-ghg-emissions.html (accessed on 22 December 2025)
		Explanatory variables:
RET	Renewable energy transition	Renewable energy % in total electricity production. RET is also in line with SDG7—"Affordable, sustainable clean energy for all", and SDG7.2—"Increase renewable energy share in global energy mix." Source: World Bank WDI Database https://data.worldbank.org/indicator/EG.ELC.RNEW.ZS (accessed on 22 December 2025)
Y	Economic growth	Real gross domestic product, PPP, 2015 prices, in US dollars. Source: World Bank WDI Database https://data.worldbank.org/indicator/NY.GDP.MKTP.KD (accessed on 22 December 2025)
ETD	Environmental technology development	Environmental technology development innovations, measured with "patents for environmental technologies" under the domain of "development of environment-related technologies". Unit: Patent count per one thousand people Source: OECD Patent Database https://data-explorer.oecd.org/?lc=en&pg=0&bp=true&snb=36&tm=patent (accessed on 22 December 2025)
CCM	Climate-change mitigation technologies	Climate change mitigation innovations, measured with sets of patents for "climate change mitigation" under "OECD technology domains." The unit is the set of patents. Source: OECD Patent Database https://data-explorer.oecd.org/?lc=en&pg=0&bp=true&snb=36&tm=patent (accessed on 22 December 2025)

5.2.2. Heterogeneity and Structural Breaks

Table 3 reports heterogeneity and the SB test results. The heterogeneity tests of PY [76] and BW [77] are robust to CSD, and the results favored rejection of homogeneity ($p < 0.01$). DKW multiple structural break tests are examined under CSD [78]. The former is the default, the latter is the HAC-augmented version of the DKW test, which achieves robustness under heteroskedasticity. These findings identified SBs that vary between three and four depending on the method. The identified SB dates correspond to 1994, 1996, 2008, 2010, and 2018, which coincide with the 1994 and 1997 Financial and Asian Crisis. The years 1996–1998 are the years that followed either the Kyoto protocol, or the expansionary period

before the 1998 Crisis; 2008 and 2010 are for the Great Recession and Great Moderation; 2018 is an economic recession.

Table 2. Descriptive statistics, CSD, and unit root tests.

Descriptive Statistics (Levels)					
Statistic:	**CO_2e**	**ETD**	**CCM**	**RET**	**Y**
Mean	11.63848	1.881021	3.496377	2.692963	26.85395
Sd	1.516110	1.692169	2.797070	1.558156	1.505091
Skewness	0.131066	−1.017949	−0.750695	−1.548064	−0.127814
Kurtosis	3.106192	4.028751	4.158720	6.355119	3.073609
JB	3.739541	243.2499 ***	168.1506 ***	974.4022 ***	3.308231
CSD Tests (levels)					
BP-LM	7458.865 ***	11,899.91 ***	11,917.08 ***	8385.874 ***	16,660.83 ***
PS-LM	205.9294 ***	338.5125 ***	339.0254 ***	233.6043 ***	480.6455 ***
BCS-LM	205.3981 ***	337.9813 ***	338.4941 ***	233.0731 ***	480.1143 ***
P-CSD	31.69467 ***	106.8947 ***	107.2137 ***	68.48936 ***	128.3754 ***
Unit Root Tests (levels)					
LLC	−0.7989	10.791	0.161	−0.807	−1.152
IPS	3.6985	8.248	−1.459	0.576	1.287
CIPS	1.019	−2.098 *	−1.599	1.276	−0.5281
MW	39.612	59.274	38.833	62.436	51.236
Descriptive Statistics (first differences)					
	ΔCO_2e	ΔETD	ΔCCM	ΔRET	ΔY
Mean	−0.002443	0.035931	0.091368	0.047719	0.025319
Sd.	0.055150	0.442423	0.969108	0.191496	0.031788
Skewness	−0.723165	−0.088015	0.431448	0.871997	−0.696967
Kurtosis	7.891525	11.99082	20.47347	12.59567	6.837888
JB	1179.523 ***	3665.916 ***	13,875.03 ***	4312.036 ***	755.8170 ***
CSD Tests (first differences)					
BP-LM	2632.768 ***	1986.934 ***	874.5608 ***	969.5342 ***	6081.344 ***
PS-LM	61.85072 ***	42.56993 ***	9.361065 **	12.19641 **	164.8047 ***
BCS-LM	61.30233 ***	42.02154 ***	8.812678 **	11.64802 **	164.2564 ***
P-CSD	44.42989 ***	29.52568 ***	9.804062 **	6.447306 **	73.7834 **
Unit Root Tests (first differences)					
LLC	−23.101 ***	−16.459 ***	−24.313 ***	−21.795 ***	−17.762 ***
IPS	−28.487 ***	−23.133 ***	−30.431 ***	−27.154 ***	−18.901 ***
CIPS	−6.246 ***	−12.901 ***	−12.525 ***	−8.657 ***	−9.920 ***
MW	153.428 ***	158.521 ***	254.282 ***	218.327 ***	157.729 ***

Notes: JB is the Jarque–Bera test statistic. Sd is the standard deviation. BP-LM: Breusch–Pagan Lagrange-multiplier (LM) test; PS-LM: Pesaran's scaled-LM; BCS-LM: bias-corrected scaled-LM; P-CSD: Pesaran's CSD test. *, **, *** denote statistical significance at 10%, 5%, 1% levels of significance.

Table 3. Heterogeneity and structural break test results.

Slope Heterogeneity Tests:				
Model No:	**Model 1**		**Model 2**	
Test/Statistic:	**PY**	**BW**	**PY**	**BW**
D	13.236 *	7.475 *	13.026 *	23.765 *
AD	14.975 *	8.457 *	14.737 *	27.590 *
DKW Structural Break Test:				
H_0 vs. H_1	a	b	a	b
0 vs. 1 Break (B)	85.37 *	28.14 *	91.82 *	34.42 *
1 vs. 2 Bs	16.98 *	9.54 *	18.49 *	11.36 *
2 vs. 3 Bs	15.40 *	7.14 *	15.86 *	8.07 *
3 vs. 4 Bs	4.74	6.09 *	4.75	7.51 *
4 vs. 5 Bs	3.40	4.55	2.85	3.60
No. of Breaks:	3	4	3	4
Break dates:	2018, 2008, 1996	2010, 2018, 1994,2006	2008, 1996, 2018	1994, 2018, 2006, 2010

Note: D and AD are delta and adjusted delta statistics, where the null hypothesis is homogeneity with Bartlett kernel and HAC kernel specifications. The results are robust to CSD. In the DKW test, the two versions reported are (a) F without HAC and (b) F with HAC. In all tests, * indicates rejection of the null hypothesis at 1% level.

5.2.3. Fourier-Bootstrapping Panel ARDL Bounds Test Approach for Cointegration

At this stage, we test cointegration among CO_2e, RET, Y, and two EIs (CCM, ETD) with the Fourier-Bootstrapping-ARDL test of [47], which generalizes McNown et al.'s bootstrapping ARDL test [79] with Fourier functions to control SBs. In addition, this test also helps in distinguishing between cointegration, spurious cointegration, and degenerate cases 1 and 2. Table 4 reports these test results.

The test overcomes a set of problems encountered with traditional ARDL bounds tests. The bounds test has sensitivity to the order of integration of variables, and in many cases, unit root tests would point to uncertainty in the order of integration. Pesaran's ARDL bounds test requires dependent variables to be integrated of order 1 to remove the possibility of any degenerate cases. Furthermore, similar to the ARDL, CS-ARDL and Fourier-ARDL, the novel Fourier-CS-ARDL model also necessitates the existence of a single cointegration vector.

In this test, we vary the dependent variable and examine cointegration conditional on the remaining variables. Then, we report a series of tests; these are F1, F2, and t tests, along with their bootstrapped critical values at 5% and 1% levels. The first section focuses on Model 1. The first row takes Y as the dependent variable, conditional on CO_2e, ETD, and RET, and findings indicate no cointegration. If RET or ETD is the dependent variable, results indicate degenerate case 1 at the third and fourth rows. In the first row, findings indicate cointegration only if CO_2e is the dependent variable, since both F1 and F2 significantly surpass the bootstrap critical values, and the t statistic is significantly more negative than its bootstrap critical value at conventional levels of significance.

For Model 2, if either Y or RET is the dependent variable, the results indicate no cointegration at 1%. If CCM is at 5%, results point to a degenerate case 1, and no cointegration at 1% level. Instead, if CO_2e is the dependent variable, tests confirm cointegration. Thus, in both Models 1 and 2, test findings supported cointegration for models with CO_2e as their dependent variable.

Table 4. Fourier-bootstrapping Panel ARDL test results.

Model 1: Dep. var. | Indep. var.	**F1** [1]	**C.V. @ 5%, 1%**	**F2**	**C.V. @ 5%, 1%**	**t**	**C.V. @ 5%, 1%**	**Result:**
Y | ETD, RET, CO_2e	3.73	4.55, 5.32	2.60	4.84, 5.11	−1.23	−3.21, −3.48	No cointegration
CO_2e | ETD, RET, Y	9.43	4.67, 4.99	12.37	4.61, 5.26	−6.03	−3.23, −3.57	Cointegration
RET | Y, CO_2e, ETD	7.85	7.24, 7.89	1.37	7.88, 9.49	−4.65	−3.77, −3.89	DC1 [2]
ETD | Y, CO_2e, RET	6.63	5.75, 7.27	1.09	4.31, 4.81	−5.33	−3.48, −3.64	DC1
Model 2: Dep. var. | Indep. var.	F1 [1]	C.V. @ 5%, 1%	F2	C.V. @ 5%, 1%	t	C.V. @ 5%, 1%	Result:
Y | CCM, RET, CO_2e	2.78	4.64, 5.75	2.31	4.73, 5.30	−1.21	−3.36, −3.64	No Cointegration
CO_2e | CCM, RET, Y	10.30	5.73, 6.24	13.44	5.69, 6.67	−6.29	−3.54, −3.81	Cointegration
RET | Y, CO_2e, CCM	5.85	6.08, 7.31	1.59	6.36, 7.25	−4.76	−3.65, −3.80	No Cointegration
CCM | Y, CO_2e, RET	6.01	5.72, 7.19	1.22	4.42, 4.90	−3.49	−3.44, −3.61	DC1 [3]

[1] F1, F2, t are Fourier-bootstrapping bounds test statistics. F1, F2, and t tests help to distinguish between cointegration/no cointegration/degenerate cases 1 and 2. C.V. represents the 5% bootstrapping critical values followed by 1%. Bootstrapping replications = 1000. For the decision process, readers are referred to [47,79]. [2] DC1 denotes the degenerate case 1. [3] In the last row, the test suggests DC1 at 5%, and no cointegration at 1%.

In addition to the Fourier-Bootstrapping ARDL test results, we evaluate the existence of a single cointegration vector with the Fourier–Johansen test in Table 5. These results also suggest a single cointegration vector at 1% and 5% levels. For confirmation, the Westerlund [80] test is applied, and findings also support cointegration under SBs and CSD.

Table 5. Johansen test for single cointegration vector.

Fourier-Augmented Johansen Cointegration Test				
Model:	**1**		**2**	
H_0:	**Trace**	**Max Eigen**	**Trace**	**Max Eigen**
none	313.6 *** [1] [0.00]	251.1 *** [0.00]	260.8 *** [0.00]	159.0 *** [0.00]
$r \leq 1$	128.7 *** [0.00]	102.1 *** [0.005]	139.8 *** [0.00]	95.21 ** [0.02]
$r \leq 2$	67.53 [0.25]	61.03 [0.38]	75.55 * [0.08]	66.36 [0.53]
$r \leq 3$	54.70 [0.27]	52.01 [0.34]	53.08 [0.65]	53.01 [0.65]
Westerlund Structural Break Cointegration Test				
	F	t	F	t
Test statistics:	12.801 *** [0.002]	−2.7656 *** [0.003]	11.993 *** [0.003]	−2.5972 *** [0.004]

[1] ***, **, * denote statistical significance at 1%, 5% and 10% levels of significance, respectively. Probability values are in brackets.

5.3. Model Estimation Results

Following the establishment of a single cointegration relation, Table 6 reports model estimations. We report on two models. The former employs ETD, the latter employs CCM as the EI variable. At the first stage, we examine the long-run elasticity (LRE) of CO_2e to the explanatory variable set. Regarding decoupling, the LRE of CO_2e to Y in Models 1 and 2 is estimated as 0.353 and 0.271, indicating a significantly lower effect relative to a unit elastic

relationship between CO_2e and Y. Accordingly, a 1% incline in Y results in a significantly lower incline in CO_2e than a one-to-one relationship; however, the effect is still positive.

Table 6. Fourier-CS-ARDL results.

Model:	**1**		**2**	
EI Variable:	**ETD**		**CCM**	
Long-run equation:				
Explanatory variable:	coef. [1]	t	coef.	t
RET_{it}	−0.258 **	−2.50	−0.244 ***	−2.70
Y_{it}	0.353 ***	10.72	0.271 ***	7.15
ETD_{it}	−0.022 **	−2.06	-	-
CCM_{it}	-	-	−0.043 **	−2.50
Short-run equation:				
ect_{it-1}	−0.412 ***	−12.41	−0.309 ***	−9.95
ΔCO_2e_{ti-1}	0.587 ***	17.69	0.691 ***	22.26
ΔETD_{it}	−0.006	−1.46	-	-
ΔCCM_{it}	-	-	−0.014 ***	−2.64
ΔRET_{it}	−0.106 ***	−3.28	−0.109 ***	−3.67
ΔY_{it}	0.511 ***	6.32	0.431 ***	5.24
ΔY_{it-1}	−0.352 ***	−4.19	−0.333 ***	−3.84
$Fourier1_{it}$ (k = 1)	−0.0141 ***	−5.27	−0.0103 ***	−8.73
$Fourier2_{it}$ (k = 1)	−0.0169 ***	−9.98	0.0114 ***	−5.31
Diagnostics: [2]				
Adj. R-square	0.6604		0.7102	
Fourier NL Test [3]	63.68 [0.00]		52.20 [0.00]	
Pesaran's CSD test	0.98 [0.40]		1.15 [0.32]	
DKW test for unmodelled SBs	4.29 [0.15]		4.01 [0.27]	

[1] ***, ** denote 1%, 5% levels of significance. [2] *p*-values are in brackets. [3] Fourier NL is the Fourier nonlinearity F test statistic indicating statistical rejection of the null of Fourier parameters equal to zero.

So far, these results provide an earlier finding regarding the acceptance of relative decoupling instead of an absolute decoupling, which would only take place once one obtains a significantly negative LRE to Y. In the context of relative decoupling, we examine these preliminary findings together with Granger-causality results in the next section. However, so far, these early findings are in line with relative decoupling since these findings point to LREs in the range of 0.35 and 0.27, pointing to growth rates in Y that could translate into a significantly lessened % growth rate in CO_2e. Furthermore, as seen in Section 5.4, findings indicate the acceptance of economic growth-led energy transition and economic growth-led eco-innovation hypotheses, and given the LREs to RET and to the two EIs and their strict negativity, examining these findings together also highlights the role of Y in supporting the factors that help CO_2e mitigation.

These claims are supported statistically by the LREs of CO_2e to RET in Models 1 and 2, where we estimated these LREs as −0.258% and as −0.244 in these models. The sizes of these LREs also point to the inelasticity of CO_2e to RET. Accordingly, in contrast to Y, energy transition measured by RET significantly reduces CO_2e in the long run, and the respective

LREs of RET are close to those obtained for Y. Regarding the two EIs, LREs of CO_2e to CCM and to ETD are estimated as −0.043 and −0.022. These results support the significant CO_2e mitigation effects of the two EIs. Furthermore, among the two, CCM has a stronger mitigation effect. At this point, we should note that the sign of these LREs is negative, but their sizes are not as high as those obtained for RET. However, we should evaluate these results together with the Granger-causality results in the next section. The overlook is as follows: significant feedback effects are evident between both EIs, between EIs and RET, and between EIs and CO_2e, pointing to the importance of EIs on CO_2e mitigation as well as supporting energy transition. As a result, a common characteristic of RET, CCM, and ETD is the negativity and the inelasticity of CO_2e to these factors. Once we examine the size of these effects in detail, findings point to the significant CO_2e reduction effect from RET, followed by CCM and ETD. However, these findings also highlight the importance of CCM and ET on RET; in other words, it highlights the significant role of these green technologies on energy transition.

Models in Table 6 allowed current ΔY_t and first lag ΔY_{t-1} and ΔCO_2e_{ti-1}, ΔETD_{it}, ΔCCM_{it}, and ΔRET_{it} and their respective parameters in the short-run equations after model architecture selection conducted by Bayesian information criterion. In both models, variables included in the short-run equations were determined as ΔY_t and ΔY_{t-1} for economic growth, for which parameter estimates are +0.511 and −0.352 in Model 1, with positive and negative effects on ΔCO_2e_t. Signs and sizes of these variables are similar for Model 2. Therefore, for both models, to ease interpretation, we examined the accumulated effect of ΔY on ΔCO_2e. Accordingly, in the short run, 1% incline in ΔY results in a 0.159% and 0.098% increase in ΔCO_2e in Models 1 and 2, in the short run. However, as these results underline positive effects of Y on CO_2e also in the short run, so are the CO_2e mitigation effects from RET. In the short run, the parameter estimates for ΔRET_t are −0.106 and −0.109 in Models 1 and 2, which is statistically significant and negative in both models. These results stress the CO_2e mitigation effects of RET that also hold in the short run. Furthermore, like the long run, the size of parameter estimates of ΔRET is significantly close to those obtained for ΔY in absolute terms.

Among the two EIs, in the short run, parameters of both CCM and ETD have negative signs. Furthermore, CO_2e mitigation effects of these innovations were not expected to occur particularly in the short run, and their effects could be either insignificant, exceptionally low, or even negative. In the short-run results, the parameter estimate of ΔCCM is −0.014, indicating that a 1% incline in ΔCCM results in a 0.014% decline in ΔCO_2e, contributing to the mitigation of CO_2e. However, as discussed above, both CCM and ETD have significant CO_2e mitigation effects in the long run, and due to a set of forces including patent rights and technological lags in the short run, these results are in line with expectations. Other factors include the long-run nature of technological change and adaptation, and appropriability problems in the short run. Further, limitations in benefiting from technology spillovers, intellectual property rights, and technology lags are shown as characteristics of technology in endogenous growth theories [19]. Extremely limited technology adaptation in the short run is also another factor that contributes to these results.

In the last part of Table 6, the diagnostic tests and goodness-of-fit statistics indicated Fourier-F test results, suggesting the significance of Fourier terms and effectiveness in capturing SBs. Further, DKW and Pesaran-CSD tests confirm no SBs and no CSD in the remainders of these models, along with higher goodness-of-fit compared to methods including Panel ARDL and Fourier-ARDL in the next section.

Overall, if we evaluate these results together, positive but strictly inelastic LREs of CO_2e to Y, coupled with comparable LREs to RET in size in absolute terms, and LREs to both CCM and ETD, point to the existence of decoupling in the relative form. It should

be noted that the relations among variables are more complex than the regression results reported in this section, and as Granger-causality results are also taken into consideration, we better capture the dynamics among the three CO_2e mitigation factors, Y and CO_2e. The overlook suggests that, though LREs for Y were positive and inelastic, findings will point to growth-led energy transition and growth-led eco-innovations, which bring the important indirect effects of Y on factors mitigating CO_2e.

Nevertheless, the examination of error-correction mechanisms is also of vital importance. Parameter estimates for ect_{t-1} in Models 1 and 2 are -0.41 and -0.309, both satisfying the necessary conditions, i.e., strict negativity, statistical significance, and being bounded between zero and -1. In Models 1 and 2, after an external shock, 41% and 30.9% of the deviations from the long-run equilibrium are corrected within a year, and the convergence to the long-run equilibrium occurs in 2.4 and 3.24 years, respectively.

In the next section, novel methods provide a significant improvement over baseline Panel ARDL and Fourier-ARDL models. Furthermore, by omitting CSD and especially SBs, Panel ARDL resulted in significantly high LRE for Y and significantly lower LREs for RET, whereas diagnostic tests fail to support these models for controlling CSD or SBs on par with Fourier-CS-ARDL.

5.4. Robustness Checks and Comparative Analysis

To examine the robustness of findings, we compare these findings with a set of model architectures and estimators. Table 7 presents the robustness test results.

Model A in column 1 is Panel ARDL, estimated with the pooled mean group estimator (PMG), and the method omits SBs and CSD, while controlling heterogeneity. Comparatively, with models omitting CSD and SBs, the LRE of CO_2e to Y tends to bias upward, along with remarkably high t values, which are inflated due to CSD in the panel as the model is not designed to control CSD. Model B is a Fourier-ARDL. This model controls SBs and heterogeneity but omits CSD. In this case, LRE parameter estimates for Y are between 0.86 and 0.88, which is again significantly higher than LREs obtained for Y with Fourier-CS-ARDL. However, these LREs reduce with Fourier-ARDL. The upward bias observed by the Panel ARDL is the highest.

For a comparative analysis and for robustness, we reported Model C, a Fourier-AMG model obtained in this study, which is a Fourier-generalized augmented mean group regression. AMG is known for robustness against CSD [71], and by including Fourier functions as exogenous factors, the model provides a comparative basis for the Fourier-CS-ARDL of this study, reported as Model D in Table 7 above, a model that generalizes CS-ARDL [65] with Fourier terms for SBs. These two models, Fourier-AMG and Fourier-CS-ARDL, led to close parameter estimates. Further, LREs of CO_2e to Y are almost one in Panel ARDL due to an upward bias in the PMG estimator after not controlling CSD and SBs. LREs to Y significantly reduce with Models C and D that control SBs and CSD simultaneously. In addition, LREs to RET significantly vary between Model A and B, and Model C and D. These findings with Panel ARDL followed by Fourier-ARDL could lead to the identification of almost no decoupling at all. However, CSD and SBs had significant effects on these results.

In addition, the last part of Table 7 provides DKW tests for the remaining SBs and the PCSD test for CSD. The findings at conventional levels indicate the effectiveness of Fourier-CS-ARDL and Fourier-AMG in controlling both CSD and SBs. Further, Panel ARDL fails to capture SBs as expected. Fourier-ARDL fails to control CSD at conventional levels of significance. However, for Fourier-ARDL, the DKW test suggests rejection of unmodelled SBs at 5% level as expected, which does not hold for Panel-ARDL. Among all models, Fourier-CS-ARDL has the highest goodness-of-fit, followed closely by Fourier-

AMG. However, the adjusted R-squares are lower for Fourier-ARDL and especially for Panel ARDL. Further, in addition to the biasedness of LREs by Panel ARDL under CSD and SBs, deflated standard errors and inflated t statistics lead to over-acceptance of parameters in hypothesis tests under the simultaneous existence of SBs and CSD.

Table 7. Robustness testing by altering methods and estimators.

Method:	**PMG**		**PMG**		**AMG**		**CCE**	
Model Controls:	**A. Panel-ARDL**		**B. Fourier-ARDL**		**C. Fourier-AMG**		**D. Fourier-CS-ARDL**	
H	Yes		Yes		Yes		Yes	
CSD	No		No		Yes		Yes	
SBs	No		Yes		Yes		Yes	
Long-run elasticities								
Models/LRE:	1	2	1	2	1	2	1	2
RET	−0.175 [a]	−0.122 [a]	−0.217 [a]	−0.208 [a]	−0.169 [a]	−0.1802 [a]	−0.258 [b]	−0.244 [a]
Y	0.950 [a]	0.951 [a]	0.859 [a]	0.883 [a]	0.359 [a]	0.354 [a]	0.353 [a]	0.271 [a]
ETD	−0.028 [a]	-	−0.025 [a]	-	−0.018 [b]	-	−0.022 [b]	-
CCM	-	−0.014 [a]	-	−0.028 [a]	-	−0.021 [b]	-	−0.043 [b]
Diagnostics tests								
Adj. R^2	0.5119	0.5204	0.6511	0.6870	0.6571	0.7093	0.6604	0.7102
PCSD	11.45 [a] [0.000]	10.66 [a] [0.000]	10.98 [a] [0.00]	9.33 [a] [0.00]	1.05 [0.38]	1.11 [0.34]	0.98 [0.40]	1.15 [0.32]
DKW	9.590 [a] [0.009]	9.85 [b] [0.012]	5.64 [c] [0.09]	5.24 [c] [0.07]	4.36 [0.18]	4.17 [0.23]	4.29 [0.15]	4.01 [0.27]

Notes: LRE: long-run elasticity. Adj. R^2 is the adjusted R-squared. H: slope heterogeneity. PCSD is Pesaran's CSD test. DKW is Ditzen et al.'s test for multiple breaks. "a, b, c": statistical significance at 1%, 5%, and 10%, respectively.

5.5. Endogeneity

Other than heterogeneity, CSD and SBs, the three factors that influence models in Section 5.5 in terms of efficiency, endogeneity could also affect panel regressions. Theoretically, studies suggested that AMG [81] and CCE [82] are robust estimators to endogeneity and the same holds for Fourier-AMG and Fourier-CS-ARDL. However, severe forms of endogeneity could still affect models. The models in Table 7 are tested for endogeneity with the Hausman test [83]. Table 8 reports these test results.

In Fourier-augmented models, namely Fourier-ARDL, Fourier-CS-ARDL, and Fourier-AMG, test results strongly suggested rejection of endogeneity at 1% level of significance. Endogeneity test results also indicated no endogeneity at the conventional 5% level of significance for the baseline Panel-ARDL. As a result, these findings showed the significant role of CSD and SBs in the deviation we observed in the parameter estimates of the baseline model. Furthermore, the same issue holds for the Fourier-ARDL, since this model also led to higher parameter estimates relative to Fourier-CS-ARDL and Fourier-AMG.

After controlling CSD and SBs simultaneously, findings with Fourier-CS-ARDL led to significant improvement in parameter estimates, especially for the LRE of CO_2e to Y, as discussed in the previous section. Further, the estimates from Fourier-AMG confirmed Fourier-CS-ARDL. Overall, in the context of the OECD panel studied, these findings highlighted the effectiveness of Fourier-CS-ARDL and Fourier-AMG in controlling the SBs and CSD.

Table 8. Endogeneity test results.

Model 1				
Tested Variable	**A. Panel-ARDL**	**B. Fourier-ARDL**	**C. Fourier-AMG**	**D. Fourier-CS-ARDL**
Y	−0.109 [0.913] [1]	1.447 [0.148]	1.485 [0.137]	1.392 [0.201]
ETD	1.744 * [0.082]	0.947 [0.344]	0.982 [0.321]	0.894 [0.442]
RET	−1.692 * [0.091]	−0.438 [0.661]	−0.416 [0.680]	−0.438 [0.669]
Model 2				
Tested Variable	**A. Panel-ARDL**	**B. Fourier-ARDL**	**C. Fourier-AMG**	**D. Fourier-CS-ARDL**
Y	−1.152 [0.249]	0.388 [0.698]	0.551 [0.664]	0.316 [0.712]
ETD	1.628 [0.114]	−0.264 [0.792]	0.467 [0.655]	−0.264 [0.792]
RET	−1.615 [0.121]	−0.412 [0.681]	−0.796 [0.614]	−0.412 [0.681]

[1] t statistics followed by *p*-values in brackets. The test accepts CO_2e as the dependent variable following Models 1 and 2. The independent variables are tested after forming auxiliary Fourier-CS-ARDL regressions. For test stages, readers are referred to [83,84]. * indicates statistical significance at 10% level only, whereas, endogeneity was rejected at conventional 5% and 1% levels.

5.6. Fourier-Augmented Dumitrescu–Hurlin Granger-Non-Causality Test

The DH test is a well-known test for Granger-non-causality testing for panels with heterogeneity and CSD [63]. Due to SBs, this study generalizes DH to Fourier. FDH causality test results are presented in Table 9.

Figure 6 summarizes these results. Blue arrows denote one-way, and black arrows denote two-way Granger-causality. Figure 6 also presents the sign of the effect as follows: the green circled variable has a negative effect on CO_2e, while the gray-colored variable has a negative effect on CO_2e. Accordingly, CCM, ETD, and RET significantly mitigate CO_2e, while Y accelerates CO_2e emissions; however, Y also affects CO_2e indirectly by supporting RET, CCM, and ETD.

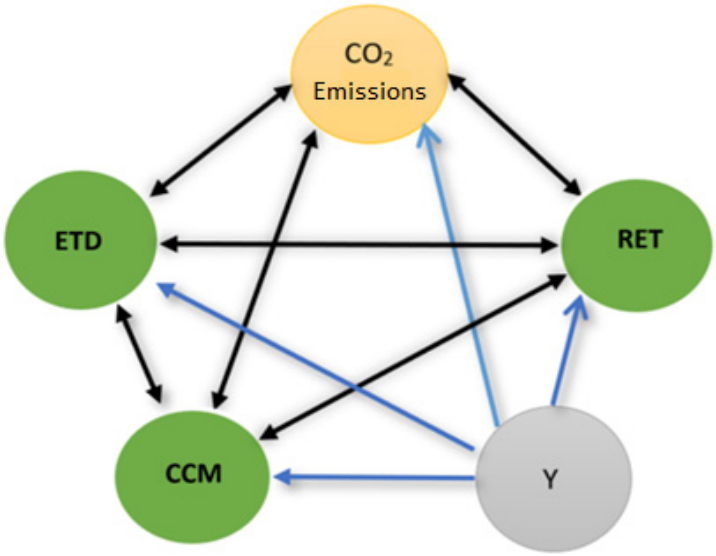


Figure 6. Fourier–Granger-causality results. Note: The black (blue) arrow indicates bidirectional (unidirectional) causality. The green (gray) circle indicates the CO_2e mitigation (acceleration) effect of the variable in the relevant circle.

Table 9. FDH causality tests.

H1: [1]	Zbar	Zbar Tilde	Decision
ETD ⟶ CO_2e	7.766 *** [0.00]	6.564 *** [0.00]	Bidirectional ETD ↔ CO_2e
CO_2e⟶ ETD	23.986 *** [0.00]	20.833 *** [0.00]	
CCM ⟶ CO_2e	8.871 *** [0.00]	7.535 *** [0.00]	Bidirectional CCM ↔ CO_2e
CO_2e⟶ CCM	10.585 *** [0.00]	9.043 *** [0.00]	
RET ⟶ CO_2e	11.012 *** [0.00]	9.419 *** [0.00]	Bidirectional CO_2e↔ RET
CO_2e⟶ RET	12.570 *** [0.00]	10.789 *** [0.00]	
Y ⟶ CO_2e	14.156 *** [0.00]	12.185 *** [0.00]	Unidirectional Y ⟶ CO_2e
CO_2e ⟶ Y	0.444 [0.66]	0.122 [0.90]	
CCM⟶ ETD	14.349 *** [0.00]	12.355 *** [0.00]	Bidirectional CCM ↔ ETD
ETD ⟶ CCM	16.641 *** [0.00]	14.371 *** [0.00]	
RET ⟶ ETD	17.483 *** [0.00]	15.112 *** [0.00]	Bidirectional RET ↔ ETD
EI ⟶ RET	12.004 *** [0.00]	10.292 *** [0.00]	
Y ⟶ ETD	16.026 *** [0.00]	13.830 *** [0.00]	Unidirectional [2] Y ⟶ ETD
ETD ⟶ Y	2.452 ** [0.014]	1.888 * [0.059]	
RET ⟶ CCM	10.497 *** [0.00]	8.966 *** [0.00]	Bidirectional RET ↔ CCM
CCM ⟶ RET	13.357 *** [0.00]	11.482 *** [0.00]	
Y⟶ CCM	25.611 *** [0.00]	22.262 *** [0.00]	Unidirectional Y ⟶ CCM
CCM ⟶ Y	1.146 [0.252]	0.7397 [0.46]	
Y ⟶ RET	12.912 *** [0.00]	11.090 *** [0.00]	Unidirectional Y ⟶ RET
RET ⟶ Y	1.120 [0.26]	1.254 [0.21]	

[1] H0: non-Granger-causality homogenously; H1: Granger-causality. The test is robust to SBs, CSD, and heterogeneity. ⟶ and ↔ indicate unidirectional and bidirectional causality. *, ** and *** represent significance at 10%, 5% and 1%. *p*-values are in brackets. The decision column summarizes the test result at $\alpha = 0.05$ and $\alpha = 0.01$. Results obtained with bootstrapping replications equal to one thousand. [2] For this specific case, causality is unidirectional at $\alpha = 0.05$. However, at $\alpha = 0.10$, the result is bidirectional causality.

5.7. Discussion and Policy Implications

These findings suggest the importance of shifting to policies targeting clean production, transitioning to clean energy more effectively, the necessity of investments to generate EIs in all OECD members to reverse environmental degradation, and achieving successful decoupling. These results point to the importance of advancing mechanisms to achieve successful energy transition and eco-innovations to support CO_2e mitigation in OECD. CCM and ETD also have dynamic feedback with RET, making different EIs and RET vital to reverse CO_2e. Negative effects of economic activity indicate the importance of clean production policies. Further, given heterogeneity, we suggest that the countries with low commitment to RET and EI should apply policies targeting green technology development or adaptation. Tax incentives and subsidy policies could also generalize decoupling to all OECD members. These findings support the encouragement of green innovation [59], environmental regulations, the fostering of EIs [43], the importance of different EIs [10], and the importance of clean energy innovations [85].

Furthermore, policymakers can leverage the feedback loops between RET and CO_2e by encouraging energy transition in industries by introducing a set of carbon allowances and carbon taxes for the endogenization of CO_2e by industries and producers. Furthermore, policymakers could also generate incentives for developing zero-carbon biofuels and provide subsidies aiming at carbon-capture facilities. In addition, policymakers could also

leverage the loops between RET and both EIs, in addition to the loop between RET and CO_2e, by improving R&D supports on green technologies. Last but not least, OECD, as an important group in global economic production, could aim at synchronizing energy transition policies by establishing international cooperation mechanisms, which also include EI technology transfer policies among its members to achieve a unified combat of climate change by cleaner production, green technology adaptation and significantly improving energy transition for countries with low-to-moderate renewables in total energy mixes.

6. Conclusions

The study investigates the roles of clean energy transition and different EIs in the context of decoupling and, if it exists, distinguishes between the types of decoupling, relative or absolute, for OECD. The examined group is subject to a diverse set of countries in terms of their commitment to energy transition, environmental policy adaptation, and economic policy shifts. The examination of the group is critical, given the share of CO_2e emitted from OECD as well as the importance of the ecological policies adopted by OECD towards the global combat against climate change.

By employing a large panel for thirty-four countries for 1990–2023, preliminary tests suggested that the dataset, including EIs, CO_2e, RET, and Y, is subject to SBs in addition to heterogeneity and CSD. In case of heterogeneity and CSD, the recent CS-ARDL model and the commonly applied DH causality test are among viable options; however, both require the establishment of no SBs and linearity, which is not the case for many datasets. Therefore, the study suggested a simple generalization of these methods to three novel methods: the Fourier-CS-ARDL and Fourier-AMG models, followed by the FDH causality test. These approaches aim at controlling CSD and SBs simultaneously in heterogeneous panels. Results showed robustness to SBs and CSD and helped in identifying the effects of Y, RET, and different EIs. After establishing estimates for long-run elasticities and causality relations robust to these factors, comparative results showed significant biases with PMG estimators and Panel ARDL models, especially for parameter estimators and their standard errors. Thereby, robust parameter estimates and controlling type 1 and 2 errors require the application of the suggested methods, which helped in generating policy suggestions for environmental and climate action objectives.

Under model results, the study obtained a better examination of decoupling. As shown in empirical results, in addition to traditional PMG and Panel ARDL, the Fourier-ARDL model also led to biases due to omitting CSD. After combining findings from Fourier-CS-ARDL and Fourier-AMG with FDH causality tests, empirical findings led to the identification of long/short-run relations as well as complex causality relations among RET, EIs, CO_2e, and Y. These findings favor rejection of "absolute" decoupling and acceptance of "relative" decoupling due to a set of results. First, the sign and size of long-run and short-run elasticities of CO_2e to Y are strictly positive; however, they are also highly inelastic, confirming the existence of a "relative" form of decoupling. Second, we estimated positive elasticities for Y. However, the negative elasticities for RET, CCM and ETD indicate effective CO_2e mitigation from these three factors. In fact, the elasticity of CO_2e to RET is close to that obtained for Y in absolute terms, specifically in the long run, however, it is lower in the short run. As a result, among the three CO_2e-mitigating factors, RET's effect significantly reduces the effect of Y. Further, though Y in OECD is not in the form of a "clean growth" in terms of its elasticities, Y is a significant Granger-cause of CO_2e, and indirectly, Y contributes to CO_2e mitigation. A similar relation also holds for CCM- and ETD-type EIs. For both, the long-run elasticity of CO_2e is less but significant, indicating the role of environmental technologies on climate change and environmental technology development, in terms of effectively reducing CO_2e in OECD. Among the two,

CCM's effect is greater than that obtained for ETD in the long run. Further, CCM is also an important EI that reduces CO_2e in the short run.

Thirdly, not only RET, but also CCM and ET, i.e., all factors that mitigate CO_2e, are Granger caused by Y. In addition, findings identify feedback loops among RET and CO_2e, as well as among both EIs and RET, indicating an opportunity for policymakers to benefit from these cyclical relations to combat climate change and to achieve absolute decoupling. As a result, policies should focus on improving R&D targeting clean energy, CCM, and ETD innovations with subsidy and tax policies. Further, policymakers should consider carbon-capture investments on the public side, or subsidies to establish public–private cooperations to substitute fossil fuels with net-zero biofuels. Further, establishing effective carbon markets is also a viable option to generate the endogenization of environmental emissions. In addition, these findings also point to the limited effects of efforts towards CO_2e mitigation and decoupling, given the size effect of Y outweighing those from the remaining factors. The heterogeneity of OECD has a significant role in these results, and policymakers in OECD should generate international policy coordination mechanisms and technology transfer and adaptation incentives to achieve a more powerful transition to clean energies with eco-innovations.

To support study findings and to examine sensitivity to omitting CSD and SBs, the study examined findings with comparative analyses after establishing various models, including Panel ARDL and Fourier-ARDL. Results showed that the PMG estimator tended to inflate the effects of Y on CO_2e, with long-run elasticity approaching 0.95 and 0.83, respectively; the latter is after controlling for SBs with Fourier-ARDL. If SBs, CSD, and heterogeneity are left uncontrolled, these findings would significantly hinder the identification of the effects of variables on CO_2e, thereby leading to falsely measuring decoupling in OECD. RET, Panel ARDL and Fourier-ARDL models produced LREs that were lower than those obtained with Fourier-AMG and Fourier-CS-ARDL. In terms of CCM and ETD, the deviation is ignorable, given the close estimates achieved with different methods, including Fourier-ARDL and Panel-ARDL. These results showed the significant bias that especially occurs for economic growth, CO_2e, and the energy transition variables employed. Therefore, these results could point to SBs and CSD affecting elasticity estimates differently, and data on EIs show less cross-sectional correlation, indicating lower sensitivity of EI among different nations.

Furthermore, when we compare the results with the literature, we identified the effect of EIs to be less pronounced in our large panel covering thirty-four countries in OECD for 1990–2023. These effects could significantly vary between the best and the low EI performers. If a panel excluded the low performers, the overall effect of EIs could result in larger elasticity coefficients. However, this would create a selection bias. Further, the suggested methods require moderate N and T in the panel for effective estimation. Therefore, by employing a large and heterogeneous panel with methods robust to SBs, CSD and heterogeneity, the findings confirmed the importance of RET and EIs in OECD.

Moreover, novel FDH causality results further identified a complex structure in the relationships studied. We identified bidirectional feedback between CO_2e and both EIs, between RET and CO_2e, and between RET and EIs. These findings point to cyclical loops between both EIs and between energy transition and CO_2e. As noted above, though Y contributes significantly to CO_2e, with an inelastic relation that lessens the translation of Y into CO_2e, it also acts indirectly through RET, CCM, and ETD in reversing part of these effects. Further, both EIs are effective Granger-causes of RET, in addition to CO_2e. As a result, though elasticities of CCM followed by ETD were highly inelastic, they contribute to CO_2e mitigation through energy transition. The unidirectional effects of Y on RET, EIs, and CO_2e further influence these cyclical loops between CO_2e and the CO_2e-mitigating

factors. Therefore, these findings point to "relative" decoupling, but also to the importance of Y given its influence on RET and both EI types. Therefore, though negative effects of Y on environmental degradation are clear, if supported with clean growth policies, Y could boost energy transition and environment-friendly technologies. These issues have become even more pronounced today after the recent energy crisis. As a result, findings point to the necessity of policies to achieve clean production and a more effective energy transition with EIs.

Furthermore, effective CO_2e mitigation in OECD requires a more homogeneous response with policies targeting the decoupling of CO_2e from Y in all OECD countries. These results are in line with the heterogeneous structure of OECD and the members' varying levels of fossil fuel dependence will contribute to the success or failure of decoupling in the whole OECD. The commitment to EIs and RET clearly helps nations to achieve these goals in the long run, in addition to the short-run effects of RET and CCM. The CO_2e acceleration effects of Y should be lessened in the long and short run by providing technology transfer supports and incentives to the low- and moderate-performing OECD in terms of energy transition, eco-innovation development, and adaptation.

Overall, to achieve a "clean production" state, i.e., reversing CO_2e acceleration effects from Y further with EIs and RET, policymakers should take the important steps outlined above. In addition, to achieve a homogeneous increase in clean energy transition among OECD members, policymakers in OECD should focus on generating international coordination mechanisms and green energy transition and innovation targets to establish clean and green economic growth in the whole OECD to achieve absolute decoupling.

These outcomes are critically important in the context of SDGs, specifically, SDG7, SDG9, and SDG13 on green production, green growth, and clean energy [86]. The findings of this study also highlighted the necessity of international mechanisms (SDG17) in achieving sustainability, preferably with absolute decoupling, more eco-innovation, and stronger energy transition. Lastly, we believe that the contributions of this study restate the importance of two critical goals of the Kyoto Protocol [2], namely "clean development" and "international collaboration", which are even more critical today. Under robust results, study findings confirm the requirement of a stronger and wider response in OECD members with green R&D projects, support for EIs, and increasing speed in energy transition.

Lastly, if we summarize the characteristics of innovations, theoretical foundations pointed to their long-run effects, which occur in a long period due to factors including technology lags, technological and structural change problems, effectiveness of intellectual property rights and variation in these laws on innovation and patents among different countries, contributing to varying levels in EIs and to the ineffectiveness of most EIs in the short run. Further, other factors include economic disincentives that result in appropriability problems by eliminating the incentives to innovate in developing nations, which are at various stages of economic development in the sense of Rostow; as a result, these nations would sacrifice environmental sustainability for economic growth. Therefore, incentives given to innovate EIs are influenced negatively. In addition, during these development stages, developing countries should combat social and economic factors, including poverty, which also reduces efforts to prioritize environmental sustainability, especially in resource-rich OECD economies. Thus, effective policies should be established to generate incentives for adopting green technologies and green technology spillovers, especially in the context of clean energy transition and climate change mitigation innovations.

Limitations and Future Directions

The study focused on a moderate panel for OECD due to concerns regarding the achievement of a long panel to examine long-run relations under CSD and SBs. General-

ization to other country groups, especially non-OECD, is strongly encouraged for future studies. One limitation we observe is data unavailability on different forms of EIs for long periods and for many countries as the employment of more EI types would significantly reduce the number of countries included in our panel, which would contradict the focus of this study on decoupling in OECD, given the importance of the group in global GDP and CO_2e. However, the methods and models of this study could easily be applied to analyses on single countries or other country groups in future research. Methods suggested in this study allow solutions for SBs, CSD, and heterogeneity, and Fourier-AMG, Fourier-CS-ARDL, and FDH causality test methods are effective in controlling these effects common in panels. These methods are theoretically robust to endogeneity, which also existed for the models we estimated with the study's dataset. For different data, in case of severe contemporaneous endogeneity, future studies should generalize the Fourier-CS-ARDL, Fourier-AMG, and Fourier-DH-causality methods in this study to different estimators such as the generalized method of moments.

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Abbreviations

CO_2e	Carbon dioxide emissions
GDP	Gross domestic product
EI	Eco-innovation
CCM	Climate change mitigation EI
ETD	Environmental technology development EI
RET	Renewable energy transition
OECD	Organization of Economic Cooperation and Development
UN	United Nations
CSD	Cross-sectional dependence
SB	Structural break
Fourier-CS-ARDL	Fourier-Cross-Sectional-Autoregressive Distributed Lag
Fourier-AMG	Fourier-Augmented Mean Group
Panel-ARDL	Panel-Autoregressive Distributed Lag
PMG	Pooled Mean Group
DH	Dumitrescu–Hurlin causality test
FDH	Fourier-DH-causality test

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