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On the pathway to net-zero in EU's top eco-innovation performers: the effectiveness of energy transition policies

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ABSTRACT

This study explores the impact of eco-innovation performance, green energy transition, energy transition, economic growth, and natural resources depletion on ecological footprint in a specific group of countries, the 'eco-innovation leaders', recently identified by the EU for their eco-innovation performances. Due to structural breaks and cross-sectional dependence, the study benefits from novel Fourier-PEGLS and Fourier-CS-ARDL methods with an extended period of 1990–2022. The empirical findings confirm long-run cointegrated relationships among eco-innovations, ENEF, the green energy transition, economic growth, and natural resource depletion in the eco-innovation leaders. The novel Fourier-CS-ARDL and Fourier-PEGLS models further indicate that eco-innovations, energy efficiency, and the green energy transition significantly reduce ecological footprint and, hence, environmental degradation. Convergence to the long-run equilibrium takes approximately 2.7 years, with 37.09% of the deviations from the long-run equilibrium corrected each year. The country-specific duration of convergence ranges from 1.78 to 9.9 years, with Finland experiencing the shortest convergence period and Denmark having the longest. Moreover, with robust methods, the study identifies bidirectional and unidirectional Granger causality between eco-innovation, ENEF, economic growth, natural resources depletion, and green energy transition with feedback effects for a large set of tested directions of causality, which have profound impacts. These findings provide a comprehensive analysis of how eco-innovation, green energy transition, and ENEF contribute to reversing environmental degradation, with implications for achieving carbon neutrality targets in the EU.

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1. Introduction

Nowadays, most countries deal with various environmental issues, including climate warming, natural resources depletion, habitat destruction, and loss of biodiversity. Considering that many researchers point out human-induced economic activities as the primary reason for these environmental issues (Intergovernmental Panel on Climate Change 2001; Trenberth 2018), economic growth that is environmentally friendly has become one of the primary goals of all nations (Holden et al. 2014; Sachs 2015).

The origins of global environmentalism are often traced back to the 1972 United Nations (UN) Conference on the Human Environment held in Stockholm. This conference inspired subsequent initiatives such as the foundation of the UN Environment Programme (UNEP). However, the discourse pertaining to sustainable development––combining both innovation and economic development––often referred to as green innovation or eco-innovation (EI) has become increasingly important after the UN Conference held in Rio in 1992 (Colombo et al. 2019; Ravenhill 2020). The Kyoto Protocol, the first binding agreement to cut carbon emissions, was an outcome of the UN Climate Change Conference, or Conference of the Parties (COP), in 1997. Throughout the years, the COP has become an important part of global climate action by gathering countries together to determine the agenda to reduce emissions and foster sustainable development all over the world (United Nations Framework Convention on Climate Change 2024).

In 2015, UN members agreed on the 2030 Agenda for Sustainable Development, concerning an urgent call to action of all nations within the context of 17 Sustainable Development Goals (SDGs) emphasizing global cooperation (United Nations 2024). These goals covered the economic, social, and environmental aspects of sustainable development (Sipos and Ionescu 2024). Another important deal was the COP21 held in Paris in 2015, where around 196 parties signed an agreement declaring their commitment to limiting global warming to less than 2 degrees Celsius (United Nations 2024). Besides, COP21 is also considered to strengthen the ability of these nations to

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mitigate the impacts of climate change by using a set of policies focusing on the necessary financing, technologies, and an improved capacity-building framework (United Nations 2024).

The European Union (EU) and its member states are committed to achieving climate neutrality by 2050 (European Commission, 2024). In this regard, the European Commission (EC) launched the European Green Deal (EGD) in 2019, setting out policy measures (Eckert and Kovalevska 2021). In 2023, the EU marked a significant step towards the 2030 climate target, and total net greenhouse gas (GHG) emissions of the EU reduced to 37% below 1990 levels in comparison with a 31% decrease in the previous year (European Environment Agency 2024a). Nevertheless, when examined on a country basis, one cannot ignore the fact that some countries stand out more in reducing their environmental impact (EEA 2024b). The environmental pollution proxied with the CO_2 emissions, along with the EU's various targets discussed above, is depicted in Figure 1 for the post-1990 period. Accordingly, the 2020 target had been achieved, and even surpassed by the EU, indicating a significant success in reducing CO_2 emissions by 2020.

The EU classifies its 27 member states as top, average, or low EI performers. This classification is dependent on how countries translate climate targets into real-world impact, as measured by factors such as investments in R&D, governmental support to develop and adopt ecological technologies, and their outputs in green technology patents. Other metrics include energy efficiency (ENEF) and resource efficiency, which measure not only how effectively each EU member state achieves its national energy consumption targets, but also how natural resources are efficiently utilized. Consequently, most countries, including EU members, have deeply engaged in promoting EI in order to achieve environmentally friendly innovations without jeopardizing economic growth (Y) (Stosic et al. 2016; Gente and Pattanaro 2019; Lesakova and Laco 2020).

In addition to the development of EI, an improved ENEF is another factor reducing the ecological footprint (EF) (see Akpanke et al. 2024; Altın 2024; Luo and Sun 2024). In the European context, the EGD is one of the most comprehensive strategies initiated by the European Union in 2019 to stimulate the green transition in the region. As earlier mentioned, the EGD target aiming to achieve net-zero emissions by 2050 is to replace the traditional linear economy with a circular one by strengthening the use of cross-border adjustment (European Commission 2021).

The EU countries have made significant progress in reducing GHG emissions, particularly by accelerating the decarbonisation of their economies through the rapid development of renewable energy (RE) since 1990 (EU 2012). Thus, the share of RE had risen from 10.2% in 2005 to approximately 24% of the EU's gross total energy consumption by 2023. Moreover, primary energy utilization and final energy consumption of the EU have fallen by 19% and 11%, respectively, since 2005 (European Environment Agency, 2024c). Despite this progress, the EU members could not reach their targets pertaining to ENEF. In 2023, the European Union's energy consumption reached a record low of 1,211 Mtoe, which is 22% above the 2020 target. The EU's final energy consumption was 894 Mtoe, which is about 17.2% above the 2030 target. These statistics indicate that while progress has been made since 2020, further efforts are necessary to meet the 2030 ENEF objectives (Eurostat 2025).

Another important issue about the discourse of environmentalism is the nexus between the natural resource depletion (NRD) and EF, since sustainable development necessitates a healthy natural system with continuous and timely growth. As human beings, we all depend on natural resources for our basic needs and economic activities. However, the over-exploration of natural resources may result in ecological degradation (Shittu et al. 2021; Zia et al. 2021; Luo and Mabrouk 2022). According to the 2024 Global

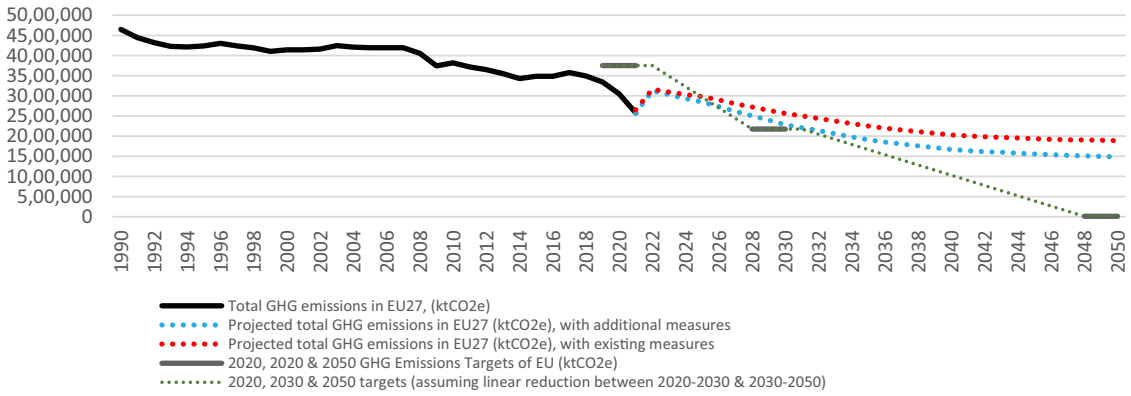


Figure 1. Total greenhouse gas emissions in EU27, targets of 2020, 2030 & 2050, and projections under two scenarios: with existing measures vs. with additional measures. Source: EEA, Anthropogenic greenhouse gas emission projections data, 2021–2050. Governance Regulation Act 2018/1999. Available at: https://www.eea.europa.eu/en/analysis/indicators/total-greenhouse-gas-emission-trends (Accessed on 12 February 2025).

Resources Outlook of the UN Environment Programme, without concerted interventions, resource extraction could rise by 60% compared to 2020 levels. This means that an estimated 60% growth in resource utilization by 2060 could disrupt efforts to accomplish not only the environmental targets but also economic welfare. At this point, the UN report warns all stakeholders and public policymakers about the need to take urgent measures (United Nations Environment Programme 2024). However, transition to RE sources such as solar, wind, and hydroelectric could reduce the harmful impact of GHG emissions (Ahmad et al. 2024). Associated with the 2030 climate targets aiming to cut GHG emissions, several European countries have focused on developing green economic policies and strategies towards a more environmentally sustainable future (Ma et al. 2024; Zhang et al. 2024).

Given this background, our study seeks to address the following research questions:

Research Question 1: How do the RET, EI, and ENEF affect the EF of EU countries with high EI performance?

Research Question 2: What impact does NRD have on the environmental performance of EU countries with high EI performances?

Research Question 3: Are EI, ENEF, and RET helpful tools for managing existing natural resources more efficiently and contributing to a sustainable environment?

While empirical studies on the effects of RET on environmental sustainability have burgeoned or gained currency in the literature, there are only a few such studies that consider how the depletion of natural resources can undermine the effectiveness of these policies. In light of the fact that policymakers in the EU have grappled with the question of environmental sustainability amidst resources depletion over the years, this study explores the effect of EI performance, RET, ENEF, Y, and NRD on EF in a specific group of countries recently identified by the EU as 'EI leaders' due to their EI performances.

Therefore, our study contributes to the existing literature in several ways: first, we examine the effectiveness of not only energy transition policies––EI, renewable energy transition (RET), and ENEF ––but also how NRD could undermine the efficacy of these policies. Secondly, we deviated from the existing literature by employing NRD instead of NRR. Intuitively, these two measures––NRD and NRR––are closely related; however, they have critical differences as they measure different aspects of natural resource use in the economy. Third, our study is the first to assess the effectiveness of energy transition policies amidst NRD in the EU's EI leading countries. Fourth, while the PEGLS and CS-PARDL models are well-known in controlling cross-sectional dependence (CSD), our study further extends these models with Fourier terms in order to account for structural breaks (SBs) with uncertain timing and form. The proposed models are known as Fourier-PEGLS and Fourier-CS-ARDL models in this study. Further, given data availability on EI, and the nature of the EF, employment of threshold-based nonlinear models such as the nonlinear NARDL (Shin et al. 2014) is not feasible. As threshold models require sudden shifts, the nature of EF, similar to CO_2 emissions, is characterized by smooth changes in the long run for a set of reasons documented. These include the slow-moving and accumulated nature of EF, which occurs due to smooth transition to technological change, technology adaptation in economies, long-run changes in population sizes (Wackernagel et al. 2002), socio-economic factors (Dietz et al. 2007), inertia in environmental variables (Stern 2004), and carbon lock-in (Unruh 2000). Further, as put forth by endogenous growth theories, technological change is a long-run driver of Y (Romer 1990). However, the relationship between innovations and Y is nonlinear (Ersin et al. 2022). Similarly, changes in EI affect EF, especially in the long run. In the short term, there are smooth structural changes due to incapabilities in adapting to technology, resulting from technological lags due to intellectual property rights (Ustabas and Ersin 2016). As a result, Fourier-CS-ARDL and Fourier-PEGLS are feasible options in addition to the time dimension length of available data of EI.[1]

The rest of this paper is structured as follows: the literature review is given in Section 2. Section 3 presents the novel Fourier-augmented methods used in this study. Empirical results and discussion are provided in Section 4, while Section 5 concludes the paper.

2. Literature review

The determinants of environmental quality in European and other countries have been widely studied by previous studies (see Shittu et al. 2021; Oyebanji et al. 2022; Altın 2024; Nuta et al. 2024; Bildirici et al. 2025) with particular focus on a set of factors we consider in this study. These are the renewable energy transition (RET), energy efficiency (ENEF), eco-innovation (EI), natural resource depletion (NRD), and economic growth (Y). Further, the selection of ENEF, RET, EI, and NRD is due to their key roles in the calculation of the EI performance index of EU, as factors that contribute to ecological performance. The literature review section also showed that the employment of RET in analyses is limited, as the depletion variable appeared as a new variable; however, as a related variable, natural resource rents (NRR) have found significant applications. Furthermore, in the context of panel econometrics, as studies employed methods that aimed at controlling CSD and heterogeneity, a limited set of studies employed methods incorporating

nonlinearity and SBs. Despite the richness of related literature, studies measuring the combined effects of CSD, SBs, and heterogeneity are limited, especially for the focus group of this study and the variables examined in a panel context.

Table 1 provides a regionally organized overview of the relevant literature and summarizes the effects of multiple determinants on ecological performance across different economies, including the European Union.

Table 1. Review of literature.

Authors	Region/Period	Method	Env. Var.	Results
Altın (2024)	G7 nations, 1971–2023	PVAR	CO_2	↑ ENEF ↓ CO_2 ↑ REC ↑ CO_2
Degirmenci et al. (2024)	G7 nations, 1990–2020	CCEMG and AMG long run estimators	Biocapacity/EF	↑ GET results in ↑ in environ. Sustainability
Guan et al. (2022)	G10 nations, 1995–2019	ARDL	EF	↑ EI ↓ EF
Luo and Sun (2024)	G20 nations, 1990–2021	Panel threshold, nonlinearity	EF	↑ ENEF ↓ EF
Rout et al. (2022)	BRICS economies, 1990–2018	ARDL	EF per capita	↑ EI ↓ EF
Akpanke et al. (2024)	OECD countries, 1990–2020	CS-PARDL, DCCEMG and AMG	EF	↑ REC ↓ EF ↑ Y ↑ EF ↑ ENEF ↓ CO_2
Adedoyin et al. (2020)	CEE, CIS & NMS, 1992–2014	Generalized Method of Moment	CO2 emissions	↑ REC ↑ CO2 emissions
Raghutla et al. (2022)	9 selected N11 countries, 1990–2018	Panel quantile regression	EF	↑ REC ↑ Y ↑ EF
Beltrán-Esteve and Picazo-Tadeo (2015)	38 selected countries, 1995–2009	DEA, directional distance functions	8 air pollutants	↑ EI ↑ EP in the transport industry
Abid et al. (2022)	S. Arabia, 1980–2017	Bootstrap ARDL, Granger causality	EF	↑ REC ↑ GDP ↓ EF
Ulucak and Lin (2017)	USA, 1961–2013	Fourier	EF	↑ NRD ↑ EF
He et al. (2024)	China, India and the USA, 1973–2019	CSD	EF	↑ NRD ↑ EF
Xue et al. (2021)	Bang., Ind., Pak. & Sri Lanka, 1990–2016	CSD, slope heterogeneity	EF	↑ REC ↓ EF
Sharma et al. (2021)	Selected 8 countries of South & Southeast Asia, 1990–2015	CS-PARDL	EF	↑ REC ↓ EF
Shittu et al. (2021)	45 Res.-rich Asian countries, 1990–2018	Panel	EF	↑ NRR ↓ EF
Luo and Mabrouk (2022)	Res.-rich economies, 1990–2018	CS-PARDL	EF	↑ NRR ↑ EF
Ma et al. (2024)	Top & least green growth economies, 1990–2021	Westerlund's cointegration, CS-PARDL	EF per person	↑ NRR ↓ EF in the least green economies
Zia et al. (2021)	China, 1985–2018	ARDL	EF	↑ NRD ↑ EF
Oyebanji et al. (2022)	Spain, 1990–2018	CS-PARDL	CO2e	↑ EI ↓ EF
Peyravi et al. (2023)	Lithuania, 2010–2018	DEMATEL	EPI	↑ EI ↑ EPI
Lesakova and Laco (2020)	Slovakia, 2016–2018	Causal analysis, deduction, abstraction, comparison, and synthesis	EPI	All stakeholders must cooperate to improve EI.
Bildirici, et al. (2025)	EU15 in time series context 1990–2022	Fourier ARDL and Granger causality, structural breaks	CL	↑ CPU ↓ CL ↑ EI ↓ CL ↑ EPS ↑ CL ↑ Y ↑ CL
Mačiulytė-Šniukienė and Sekhniashvili (2021)	EU members, 2010–2020	Random effect regression	EPI	↑ EI ↑ EPI
Sipos and Ionescu (2024)	EU 27, 1995–2009	SEM	EPI	EI index dimensions contribute to achieving 11 of 17 SDGs.
Beltrán-Esteve and Picazo-Tadeo (2017)	EU 28, 2001–2013	DEA, directional distance functions	GHGs, particulate matter (PM10)	↑ EI ↑ Environmental performance
Sobczac et al. (2022)	EU 28 2013–2019	Multivariate statistical analysis	EPI	Swe., Lux., Ger. Fin., & Den. are leaders in both innovation and EI.

EPI: Environmental Performance Index, EPI: Eco-innovation performance index, CSD: Cross Section Dependence, ARDL: Autoregressive distributed lag, CS-PARDL: Cross-sectional-panel ARDL, Y: Economic Growth, EF: Ecological footprints, CL: Carbon leakage, Y: Economic growth, NRD: Natural resource depletion, DEMATEL: Decision-Making Trial and Evaluation Laboratory, PVAR: Panel vector-autoregressive, ENEF: ENEF, DEA: Data Envelopment Analysis, NRR: Natural Resource Rent, GHGs: Greenhouse gases, EI: Eco-innovation, SEM: Structural Equation Model, CIS: Commonwealth of Independent States, CEE: Central and Eastern Europe, NMS: New Member States, REC: Renewable energy consumption, GET: Green energy transition (indicating renewable energy transition).

The overlook to Table 1 suggests that a substantial body of research recognized EI as a critical determinant of environmental improvement, bringing EI to the centre of examination for its effects on the environment (Guan et al. 2022; Oyebanji et al. 2022; Rout et al. 2022). Among these studies, Beltrán-Esteve and Picazo-Tadeo (2015) examined 38 countries with the DEA method over 1995–2009, and findings indicated a significant positive influence of EI on ecological performance (EP). By employing the Luenberger productivity index, directional distance functions, and DEA, Beltrán-Esteve and Picazo-Tadeo (2017) further demonstrated the positive impacts of EI on four EP measures: particulate matter, acidification, tropospheric ozone production, and global warming. By focusing directly on EU countries, EI has been identified as a key driver of environmental enhancement in Europe through cleaner production techniques and green patents (Popp 2006; Albino et al. 2014; Mačiulytė-Šniukienė and Sekhniashvili 2021; Peyravi et al. 2023).

Other strands of the literature indicate that a rising RE in the form of consumption or production (REC and REP), as well as RET, significantly mitigates EF by reducing dependence on fossil fuels and alleviating environmental pressures in developed economies (Apergis and Payne 2014; Destek and Aslan 2017). Raghutla et al. (2022) analyzed N-11 countries for the period 1990–2018 for the influence of REC and per capita income, and their findings showed the significant positive impacts of these variables on EF. Likewise, many of the researchers (Sharma et al. 2021; Xue et al. 2021; Abid et al. 2022; Degirmenci et al. 2024), with methods detailed in Table 1, showed that rising RE in total energy mixes significantly reduces environmental pollution in different economies, as a set of studies further confirms the varying effects of RE on environmental quality (Adedoyin et al. 2020).

Advancements in ENEF have also been increasingly recognized as a critical driver to promote sustainable development, as they help decouple economic expansion from environmental degradation. Altın (2024), by employing panel econometrics methods, demonstrated improvements in ENEF and adoption of more efficient technologies contributing to the reduction of CO2e in G7 for the period of 1971–2023. Further, by employing CS-PARDL, DCCEMG, and AMG, Akpanke et al. (2024) reported that ENEF contributes to the reduction of CO2e in OECD for a sample covering 1990 to 2020; however, these effects on CO2e has not been found to be significant on EF. Moreover, ENEF is often linked with the utilization of RE sources and infrastructure modernization, arguing that ENEF policies not only improve resource utilization but also support broader ecological objectives. By focusing on methods that allow nonlinearity with their panel threshold analysis of G20 economies covering the 1990–2021 period based on the Environmental Kuznets Curve (EKC), Luo and Sun (2024) indicated that ENEF reduces EF contributions to the Inverted-U concept of EKC under different regimes with varying effects. By focusing on EU15 and by employing Fourier-ARDL and Fourier-causality methods, Bildirici et al. (2025) found that climate policy uncertainty and EI contribute negatively, as Y and environmental policy stringency contribute positively to environmental pollution in the form of carbon leakage in the EU15.

Studies focusing on NRD generally find that greater depletion of natural resources is positively associated with the EF, reflecting direct environmental pressure arising from unsustainable extraction and resource use (Ulucak and Lin 2017; Zia et al. 2021; He et al. 2024). In contrast, research examining NRR reports more heterogeneous effects. While NRR is often associated with higher EF in economies characterized by resource-dependent growth and weak environmental governance (Shittu et al. 2021), some studies have argued that the adverse impact of natural resource depletion can be substantially mitigated through the incorporation of green technologies into economic activities (Luo and Mabrouk 2022).

By employing NRR other than NRD, Ma et al. (2024), applied Westerlund cointegration tests and CS-PARDL under CSD and heterogeneity, and concluded that NRR is inversely related to ecological sustainability measured with EF per person in the least green economies, emphasizing that these economies have not sufficiently adopted effective environmental protection policies and advanced green innovations to reduce pressure on natural resources. Correspondingly, empirical research of Shittu et al. (2021) based on panel data for 45 resource-rich Asian countries over the period from 1990 to 2018, and by centering on NRR, their findings showed the positive association of NRR with EF. Furthermore, Zia et al. (2021), via adopting the ARDL approach, indicated that an increase in natural resource exploitation between 1985 and 2018 contributed to the expansion of China's EF. Alternatively, Ahmad et al. (2024) examined energy transition and EF in the EU for 1990–2020, with particular focus on FinTech for its moderating effects by employing CSD-robust methods and FMOLS estimator for robustness, and findings demonstrated the negative impacts of NRR by worsening RET and EF.

Overall, the literature emphasizes that while pressures on natural resources intensify ecological sustainability concerns, strategic and coordinated improvements in EI, ENEF, and RET can significantly reduce EF, contributing to sustainable development. However, studies examining all these determinants simultaneously in the context of the EU and their EI performances are relatively scarce. As stated previously, our study aims to fill this gap in the existing literature by demonstrating the joint impact of the above-mentioned variables among European high-performing countries in environmental innovation, considering both short-run and long-run dynamics within a

framework that allows the incorporation of heterogeneity, CSD, and SBs in the panel of top EI performers of the EU.

3. Model, data, and methodology

3.1. Model of the study

As stated in Section 1, within the EGD strategy, the EU takes EI as the utmost importance in achieving sustainable development and in reversing the adverse effects of climate change. Though the name refers to EI performance, the EI performance program of the EU covers a set of indicators including not only EI but also natural resource, energy, and material efficiencies within the energy transition goals as legislated by the EU. With this motivation, the model of this study is:

$$EF_{it} = \delta_0 + \delta_1 EI_{it} + \delta_2 RET_{it} + \delta_3 NRD_{it} + \delta_4 ENEF_{it} + \delta_5 Y_{it} + u_{it} \quad (1)$$

where, EF_{it} represents the ecological footprint at the i^{th} EU country at year t, RET_{it} represents the clean energy transition, NRD_{it} is the natural resource depletion, and $ENEF_{it}$ denotes energy efficiency. Variable details are discussed in the data below. These variables are key indicators in the formation of the ecological performance pillars in the EU. Lastly, Y_{it} is the real GDP as a control variable for economic growth[2].

3.2. Data

As noted in the Introduction, the EU's EI performance index is published for the 2013–2022 period, and due to the short length of the time series dimension, it is not possible to employ the index in a panel data set that focuses on methods to capture dynamic long-run relations. To overcome the short length of the yearly dimension, we employed the environment-related technology innovations per person data of the OECD to measure EI. Further, NRD, RET, and ENEF variables are obtained from EUROSTAT and the World Bank, and these indicators are selected to achieve a dataset in accordance with the pillars of the EI performance indicator of the EU. As a result, the sample covers 1990–2022. Table 2 summarizes the variables, definitions, and their sources.

As noted in Section 1, the EU collects EU members in three groups for their EI performance, and the examination of the top performers is of crucial importance. The countries and their position in the EI performance are depicted in Figure 2. Accordingly, the EU average of EI performance index is 115.6 in 2022, the last available data in the conduct of this study, and the EU distinguishes its members into three distinct groups in terms of their EI performances as presented in Figure 2. These are the catching-up, the average performers, and 'the EI leaders', to which the study centers its focus group. This study, therefore, focuses on top EI performers in the EU, with the objective of empirically evaluating whether the EI performance has translated into measurable reductions in ecological footprints (EFs) and consequently mitigating global warming within the EU context. Accordingly, the countries included in the analysis are Austria, Denmark, Finland, France, Germany, Italy, Luxembourg, the Netherlands, and Sweden.[3]

3.3. Econometric methodology

3.3.1. Fourier-panel-ARDL model

A pooled mean group (PMG) estimator is proposed as a generalization of the infamous autoregressive distributed lag (ARDL) model to dynamic panels with the panel ARDL (PARDL) model (Pesaran et al. 1999). The PARDL had found significant applications in the literature; however, while capturing slope heterogeneity, the model and the estimator are not robust to SBs. In

Table 2. Variables and sources.

Anno.	Variable	Definition/Unit	Source
EF	Ecological footprint	Ecological footprint, total, in global hectares (GHA)	GFN (https://www.footprintnetwork.org/)
EI	Eco-innovation	Patents on ecofriendly technology innovations, per person	OECD (https://www.oecd.org/en/data.html)
ENEF	ENEF	ENEF represents GDP (in constant 2021 PPP $) per unit of energy consumption (primary energy consumption, oil equivalent). World Bank World Development Indicators (WDI) defines ENEF as the ratio of real production to energy use, and GDP is converted to constant 2021 international $ and PPP to obtain a consistent and comparable measure. WDI obtains ENEF from International Energy Agency (IEA).	WDI, IEA (https://www.iea.org/data-and-statistics) and (https://databank.worldbank.org/source/world-development-indicators#)
RET	Clean energy transition	% of renewable energy in total energy consumption	EUROSTAT (https://ec.europa.eu/eurostat)
NRD	Natural resource depletion	Natural resource depletion, % in gross national income, and the natural resource depletions included in the calculation by World Bank are the sum of net mineral, energy and forest depletions.	WDI (https://databank.worldbank.org/source/world-development-indicators#
Y	Economic growth	Real gross domestic product, constant, 2015 U.S. dollars	WDI (https://databank.worldbank.org/source/world-development-indicators#

GFN is Global Footprint Network, OECD is Organization of Economic Corporation and Development, WDI is World Bank's World Development Indicators, IEA is International Energy Agency, EUROSTAT is European Commission Statistics databases.

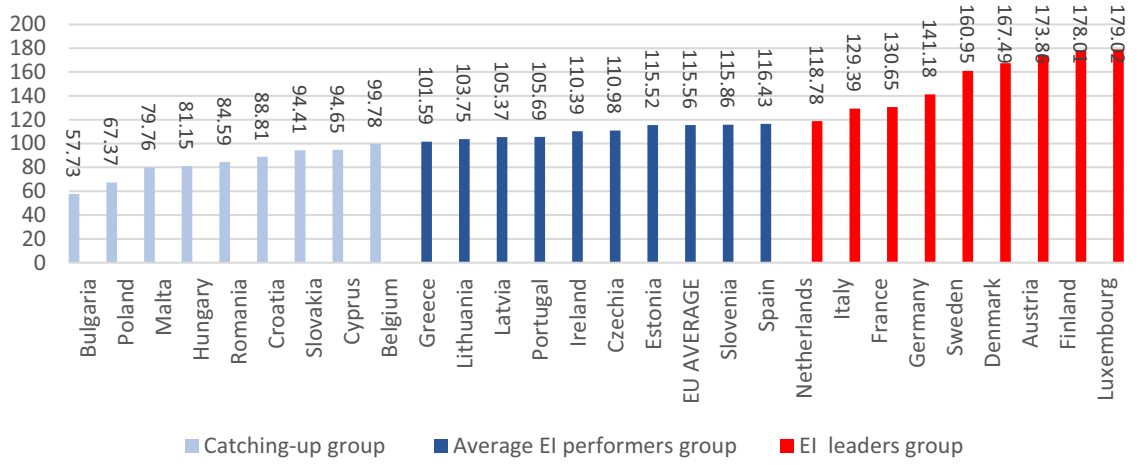


Figure 2. EI performance index values for EU27. Source: European Commission, "Eco-innovation at the Heart of Green Business", available at https://green-business.ec.europa.eu/eco-innovation_en (accessed on 28 January 2025).

another strand, for unit root testing, Enders and Lee (2012) proposed the use of flexible Fourier terms to account for SBs with uncertain timing and form. The ARDL and PARDL models were afterwards expanded to Fourier-Panel-ARDL (FPARDL) by seminal studies (Banerjee et al. 2017; Bildirici and Ersin 2023). It has been recently demonstrated that SBs affect EF and EI variables due to factors such as shifts in environmental policies and disputes such as the Russia-Ukraine War (Ersin et al. 2024).

A bivariate FPARDL model for variables Y and X with an unrestricted form is presented for simplicity as,

$$\Delta Y_{it} = \underbrace{\theta_0 + \theta_1 Y_{it-1} + \theta_2 X_{it}}_{long-run} + \underbrace{\sum_{p=1}^{p} \vartheta_{ip} \Delta Y_{it-p} + \sum_{q=0}^{q} \sigma_{ip} \Delta X_{it-q}}_{short-run} + \underbrace{f_k(\lambda_{0,k}, \lambda_{1,k})}_{Fourier-functions} + \varepsilon_{it} \quad (2)$$

Eq. (2) consists of three parts, the first two capture the long- and the short-run dynamics with heterogeneous structure for panels. The third part of Eq. (2) captures SBs using a flexible Fourier function,

$$f_k(\lambda_{0,k}, \lambda_{1,k}) = \sum_{k=1}^{k} \lambda_{i0,k} \sin(2\pi k \times t/T) + \sum_{k=1}^{k} \lambda_{i1,k} \cos(2\pi k \times t/T) \quad (3)$$

and the FPARDL model (Banerjee et al. 2017; Bildirici and Ersin 2023) not only provides long and short-run dynamics, but is robust to SBs in heterogeneous panels (Ersin et al. 2024).

3.3.2. Fourier-CS-PARDL model

For PARDL models, an augmentation is achieved by including cross-sectional (CS) terms to control for CSD with the CS-PARDL model of Chudik and Pesaran (2015a). However, application of CS-PARDL requires linearity and the existence of no SBs in the panel (Chudik and Pesaran 2015a). In this study, CS-PARDL is extended further with Fourier terms. The proposed Fourier-CS-PARDL model is,

$$\Delta Y_{it} = \theta_0 + \theta_1 Y_{it-1} + \theta_2 X_{it} + \sum_{p=1}^{p} \vartheta_{ip} \Delta Y_{it-p} + \sum_{q=0}^{q} \sigma_{iq} \Delta X_{it-q} + \sum_{r=0}^{r} \tau_{ir} \bar{Z}_{it-r} + f_k(\lambda_{0,k}, \lambda_{1,k}) + \varepsilon_{it}. \quad (4)$$

where $f_k(\lambda_{0,k}, \lambda_{1,k})$ is defined as in Eq. (3). After substituting the variables of this study, the model is,

$$\begin{aligned} \Delta EF_{it} = {} & \varsigma_0 + \varsigma_1 EI_{it} + \varsigma_2 RET_{it} + \varsigma_3 NRD_{it} + \varsigma_4 ENEF_{it} + \varsigma_5 Y_{it} \\ & + \sum_{p=1}^{p} \vartheta_{ip} \Delta EF_{it-p} + \sum_{h=0}^{h} \vartheta_{ip} \Delta EI_{it-p} + \sum_{q=0}^{q} \sigma_{iq} \Delta RET_{it-q} \\ & + \sum_{l=0}^{l} \kappa_{il} \Delta NRD_{it-l} + \sum_{m=0}^{m} v_{im} \Delta ENEF_{it-m} + \sum_{s=0}^{s} \eta_{is} \Delta Y_{it-s} \\ & + f_k(\lambda_{0,k}, \lambda_{1,k}) + \sum_{r=0}^{r} \tau_{ir} \bar{Z}_{it-r} + \varepsilon_{it} \end{aligned} \quad (5)$$

In Fourier-CS-PARDL in Eq. (7), we adopted a discrete Fourier function order k (Phillips 1999). In the estimation, we suggest a single-stage estimation (Ludlow and Enders 2000). Fourier-CS-PARDL could be estimated with the common-correlated-effects (CCE) estimator (Pesaran 2006), similar to the CS-PARDL (Chudik and Pesaran 2015b). Optimum k is determined from candidate orders $k = 1,2, \ldots ,5$ for relatively large samples in T and N dimensions (Enders and Lee 2012). After estimation, the testing of the significance of Fourier terms is necessary for $k = 1,2, \ldots m$, where m is the largest order. The restricted model is:

$$\begin{aligned}&\Delta \mathrm{EF}_{\mathrm{it}}\\&= \varsigma_0 + \varsigma_1 EI_{it} + \varsigma_2 RET_{it} + \varsigma_3 NRD_{it} + \varsigma_4 ENEF_{it} + \varsigma_5 Y_{it}\\&\quad + \sum_{p=1}^{p} \vartheta_{ip} \Delta \mathrm{EF}_{\mathrm{it-p}} + \sum_{h=0}^{h} \vartheta_{ip} \Delta \mathrm{EI}_{\mathrm{it-h}} + \sum_{q=0}^{q} \sigma_{iq} \Delta \mathrm{RET}_{\mathrm{it-q}}\\&\quad + \sum_{l=0}^{l} \kappa_{il} \Delta \mathrm{NRD}_{\mathrm{it-l}} + \sum_{m=0}^{m} \nu_{im} \Delta \mathrm{ENEF}_{\mathrm{it-m}} + \sum_{s=0}^{s} \eta_{is} \Delta \mathrm{Y}_{\mathrm{it-s}}\\&\quad + \sum_{r=0}^{r} \tau_{ir} \bar{Z}_{it-r} + \varepsilon_{it}\end{aligned} \tag{6}$$

which is to be used to calculate an F statistic:

$$F = \frac{(SSR_R - SSR_{UR})/2k}{SSR_{UR}/(N - 2k - 1)} \tag{7}$$

where $N = t \times i$, SSR_R, SSR_{UR} are the sum of squared residuals of the restricted and unrestricted models, $2k$ is the number of restrictions under H_0:$\lambda_{i0,k} = 0, \lambda_{i1,k} = 0$. The F statistic follows an F distribution with $2k$ and $N - 2k - 1$ degrees of freedom. The testing of Fourier terms also represents a test of linearity against SBs (Ersin et al. 2024). Due to the sample size, as well as after examining the candidate models with Schwarz information criterion (SIC), we assumed $m = 2$ for parsimony and for the given size of time dimension (Ersin et al. 2024).

3.3.3. Fourier-CS-PARDL & bounds test

The existence of a single cointegrated vector is a requirement for ARDL (Narayan 2014), and its various extensions (Bildirici and Ersin 2023; Bildirici et al. 2023), and the same holds for the Fourier-CS-PARDL model. Once cointegration is established, a restricted form for Fourier-CS-PARDL is estimated,

$$\begin{aligned}&\Delta \mathrm{EF}_{\mathrm{it}}\\&= \upsilon_0 + \rho(EI_{it-1} + \upsilon_2 RET_{it} + \upsilon_3 NRD_{it} + \upsilon_4 ENEF_{it} + \upsilon_5 Y_{it})\\&\quad + f_k(\lambda_{0,k}, \lambda_{1,k}) + \sum_{p=1}^{p} \vartheta_{ip} \Delta \mathrm{EF}_{\mathrm{it-p}} + \sum_{h=0}^{h} \vartheta_{ip} \Delta \mathrm{EI}_{\mathrm{it-h}}\\&\quad + \sum_{q=0}^{q} \sigma_{iq} \Delta \mathrm{RET}_{\mathrm{it-q}} + \sum_{l=0}^{l} \kappa_{il} \Delta \mathrm{NRD}_{\mathrm{it-l}} + \sum_{m=0}^{m} \nu_{im} \Delta \mathrm{ENEF}_{\mathrm{it-m}}\\&\quad + \sum_{s=0}^{s} \eta_{is} \Delta \mathrm{Y}_{\mathrm{it-s}} + \sum_{r=0}^{r} \tau_{ir} \bar{Z}_{it-r} + \varepsilon_{it}\end{aligned} \tag{8}$$

and the error-correction representation is,

$$\begin{aligned}&\Delta \mathrm{EF}_{\mathrm{it}}\\&= \upsilon_0 + \psi ECM_{it-1} + f_k(\lambda_{0,k}, \lambda_{1,k}) + \sum_{p=1}^{p} \vartheta_{ip} \Delta \mathrm{EF}_{\mathrm{it-p}}\\&\quad + \sum_{h=0}^{h} \vartheta_{ip} \Delta \mathrm{EI}_{\mathrm{it-h}} + \sum_{q=0}^{q} \sigma_{iq} \Delta \mathrm{RET}_{\mathrm{it-q}} + \sum_{l=0}^{l} \kappa_{il} \Delta \mathrm{NRD}_{\mathrm{it-l}}\\&\quad + \sum_{m=0}^{m} \nu_{im} \Delta \mathrm{ENEF}_{\mathrm{it-m}} + \sum_{s=0}^{s} \eta_{is} \Delta \mathrm{Y}_{\mathrm{it-s}} + \sum_{r=0}^{r} \tau_{ir} \bar{Z}_{it-r} + \varepsilon_{it}.\end{aligned} \tag{9}$$

where ψ should be tested for statistical significance, and $-1 < \psi < 0$, which leads to calculation of $|1/\psi|$ to evaluate the speed of convergence towards the long-run equilibrium (Banerjee et al. 2017; Bildirici and Ersin 2023).

3.3.4. Fourier-CS-PEGLS model

For small samples with $T > \mathrm{N}$, the model is generalized with the EGLS (Hansen 2007) estimator; hence, to distinguish it, we call the EGS-variant of the Fourier-CS-PARDL, the Fourier-CS-PEGLS, which is suggested for parsimony. The model is also an alternative in case of statistical non-rejection of slope homogeneity. The Fourier-CS-PEGLS model is,

$$\begin{aligned}\Delta \mathrm{Y}_{\mathrm{it}} &= \theta_0 + \theta_1 \mathrm{Y}_{\mathrm{it-1}} + \theta_2 \mathrm{X}_{\mathrm{it}} + \sum_{\mathrm{p}=1}^{\mathrm{p}} \vartheta_{\mathrm{p}} \Delta \mathrm{Y}_{\mathrm{it-p}} + \sum_{\mathrm{q}=0}^{\mathrm{q}} \sigma_{\mathrm{q}} \Delta \mathrm{X}_{\mathrm{it-q}}\\&\quad + \mathrm{f}_{\mathrm{k}}(\lambda_{0,\mathrm{k}}, \lambda_{1,\mathrm{k}}) + \varepsilon_{\mathrm{it}}\end{aligned} \tag{10}$$

which includes additional Fourier terms defined in Eq. (3) to control for SBs, and the Panel EGLS estimator is robust to cross-sectional correlations and heteroskedasticity (Hansen 2007).

3.4. Panel Granger-causality test with Fourier terms

The study generalizes the panel Granger-causality (PGC) test of Juodis et al. (2021) to the Fourier-CSD-PGC test for panels with SBs, CSD, and heterogeneity. Juodis et al.'s method is shown to have robustness to heterogeneity and cross-sectional heteroskedasticity (Juodis et al. 2021) and provides a basis. Other contributions to generalize PGC to Fourier include Nazlioglu et al. (2019) and to Bildirici and Ersin (2023). The generalization here also includes the incorporation of error-correction terms and Toda-Yamamoto (TY) correction (Toda and Yamamoto 1995) as done by Bildirici and Ersin (2023). TY correction aims at controlling uncertainty in the integration orders of variables. A similar generalization had been conducted by Ersin et al. (2024) for panels with SBs.

Bivariate Fourier panel VAR is,

$$\begin{aligned}Y_{it} &= \varphi_{0i} + \sum_{p=1}^{p} \varphi_{ip} Y_{it-p} + \sum_{p=1}^{p} \gamma_{ip} X_{it-p} + \mu_1 Y_{it-(p+\mathrm{dmax})}\\&\quad + \mu_2 X_{it-(p+\mathrm{dmax})} + \sum_{r=0}^{r} \tau_{ir} \bar{Z}_{it-r} + \psi_{1i} ECM_{it-1}\\&\quad + f_k(\lambda_{0,i,k}, \lambda_{1,i,k}) + \varepsilon_{it}\end{aligned} \tag{11}$$

$$\begin{aligned}X_{it} &= \phi_{0i} + \sum_{p=1}^{p} \varphi_{ip} X_{it-p} + \sum_{p=1}^{p} \eta_{ip} Y_{it-p} + \sigma_1 X_{it-(p+\mathrm{dmax})}\\&\quad + \sigma_2 Y_{it-(p+\mathrm{dmax})} + \psi_{2i} ECM_{it-1}\\&\quad + \sum_{r=0}^{r} \upsilon_{ir} \bar{Z}_{it-r} + f_k(\lambda_{0,i,k}, \lambda_{1,i,k}) + \varepsilon_{it}\end{aligned} \tag{12}$$

here, *dmax* represents the maximum order of integration for $X_{it-(p+\mathrm{dmax})}$,$Y_{it-(p+\mathrm{dmax})}$ for TY correction,$\bar{Z}_{it}$ is cross-sectional averages, p is the optimum lag length determined by SIC. In Eq. (12), non-Granger-causality from X to Y is tested under the null, and the alternative is Granger-causality with heterogeneity from X to Y,

$$H_0 : \gamma_{ip},\ for\ all\ p\ and\ i.$$
$$H_1 : \gamma_{ip} \neq 0,\ for\ all\ p\ and\ i;\ or,\ at\ least,\ for\ some\ i\ and\ p. \quad (13)$$

In Eq. (13), the Granger-non-causality under the null followed by its alternative becomes,

$$H_0 : \eta_{ip},\ for\ all\ i\ and\ p.$$
$$H_1 : \eta_{ip} \neq 0 for\ all\ i\ and\ p;\ or,\ at\ least\ ,\ for\ some\ i\ and\ p. \quad (14)$$

The generalized Fourier-CSD-PGC test here provides robustness against SBs, CSD, and integration uncertainty as in selected recent tests (Bildirici and Ersin 2023; Ersin et al. 2024).

The flow chart of the empirical research framework is presented in Figure 3.

4. Empirical results

4.1. Descriptive statistics

To help in achieving desired statistical properties, all variables in levels are subject to natural logarithms, such as controlling outliers and skewness, and achieving better distributional qualities. Table 3 reports the descriptive statistics of the variables at levels and first differences.[4]

The mean of the levels variables is positive across the variables apart from NRD since NRD is a percentage variable that takes negative values after logarithms. At first differences, EF and NRD have a negative mean value while the remaining variables have a positive value. From the standard deviation, we observe that the data are clustered closely around the mean for differenced variables. This suggests that the level variables are more volatile compared to the first difference variables. Moreover, the variables are positively and negatively skewed, with their values close to zero, except for the first difference of RET. The levels and first difference variables exhibit a positive kurtosis with evidence of leptokurtic distribution in the first difference variables. Consequently, the null hypothesis of normal distribution is rejected as shown by the probability values of JB statistics at levels and first difference variables for all variables, and the only exception is ENEF in first differences.

4.2. Results of the correlation test

Table 4 divulges the correlation results. As we can see from the said Table, EF has a negative correlation with

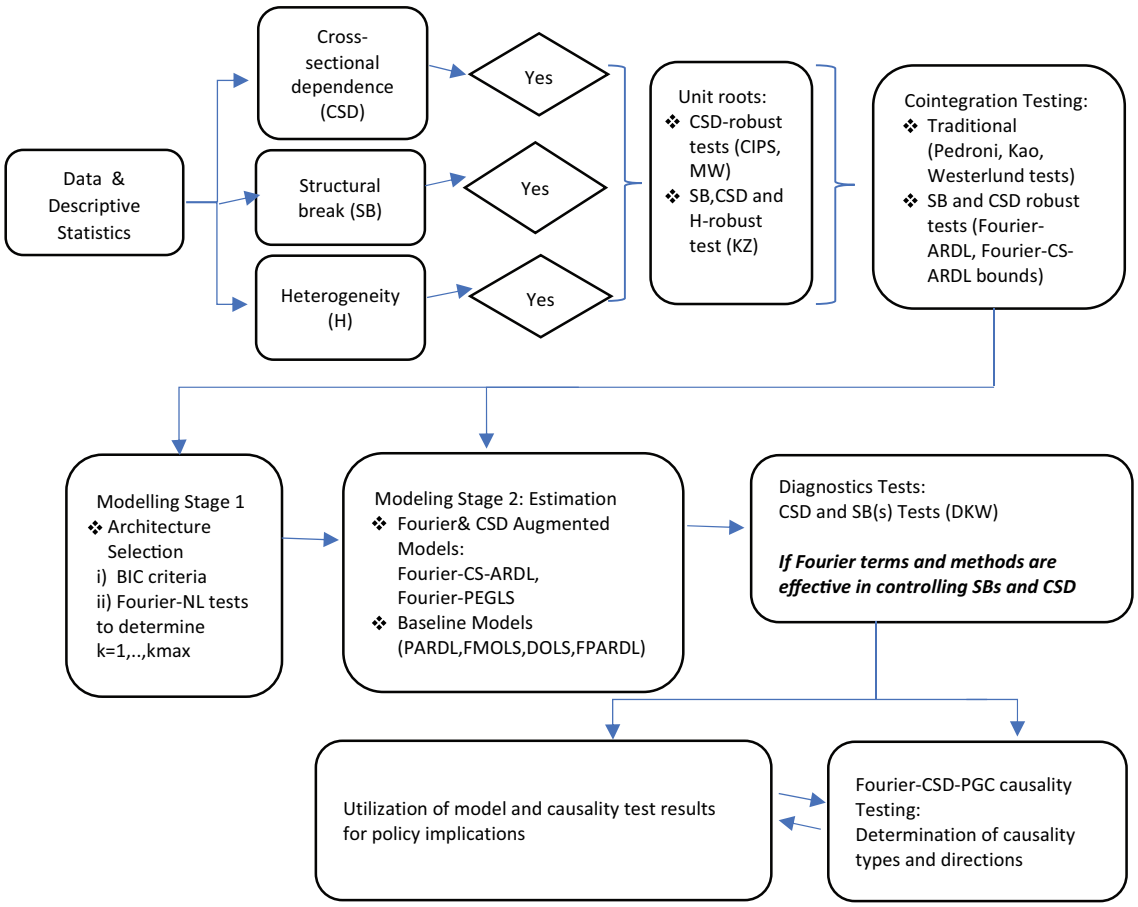


Figure 3. Flowchart of empirical stages.

Table 3. Descriptive statistics.

	Level variables					
	EF	EI	NRD	RET	ENEF	Y
Mean	18.191	3.082	−2.716	2.479	2.551	26.968
Max.	20.100	4.520	0.610	4.059	3.231	28.911
Min.	15.486	0.256	−8.805	0.095	1.788	23.951
Sd.	1.272	0.734	1.379	1.030	0.309	1.271
Skew.	−0.305	−0.692	0.037	−0.528	−0.368	−0.326
Kur.	2.327	3.549	3.652	2.288	2.603	2.416
JB	9.907***	26.626***	5.167*	19.448***	8.399**	9.196**
p, JB	0.007	0.000	0.075	0.000	0.014	0.010
	Variables in first differences					
Mean	−0.002	0.033	−0.004	0.044	0.016	0.018
Max.	0.311	2.184	3.911	0.539	0.138	0.083
Min.	−0.452	−1.805	−4.500	−0.961	−0.095	−0.094
Sd.	0.072	0.239	0.638	0.119	0.038	0.026
Skew.	−0.541	0.968	−0.265	−2.285	0.198	−1.063
Kur.	10.218	38.127	16.367	26.534	3.474	6.206
JB	619.2***	14387.7***	2080.4***	6681.1***	4.431	172.05***
p, JB	0.000	0.000	0.000	0.000	0.109	0.000

*** denotes 1% level of statistical significance. JB is the Jarque-Berra test statistic and p, JB is probability of the null hypothesis of normality. Sd., Skew., and Kur. are standard deviation, skewness and kurtosis, respectively.

Table 4. Correlation results.

	EF	EI	NRD	RET	ENEF	Y
EF	1					
EI	−0.0678**	1				
	(−2.13)					
NRD	0.0761**	−0.0267	1			
	(2.27)	(−0.044)				
RET	−0.1008*	0.1734***	0.026	1		
	(−1.69)	(2.94)	(0.434)			
ENEF	−0.0534*	0.0504*	−0.0205	0.4672***	1	
	(−1.89)	(1.84)	(−0.0342)	(8.81)		
Y	0.3412***	−0.0227	0.1402**	0.1879***	0.3959***	1
	(6.05)	(−0.38)	(2.36)	(3.19)	(7.188)	

Pearson correlation statistics (centered) are reported; t statistics are in parentheses. ***,**,* indicate significance at 1%, 5% and 10%, respectively.

EI, RET, and ENEF, while the correlation of EF with NRD and Y is positive. We also find that EI has a negative correlation with NRD and Y, and a positive correlation with RET and ENEF. Further, Y has a significant positive correlation with EF, NRD, RET, and ENEF.

Furthermore, while NRD is positively correlated with RET, ENEF, and Y, it is also evident that RET is positively correlated with ENEF and negatively correlated with Y. Finally, we find that ENEF is positively correlated with Y.

4.3. Results of cross-sectional dependence, structural breaks, and unit root tests

A battery of CSD tests using levels variables and first difference variables was examined and reported in Table 5. Findings designated the rejection of H_0 of no CSD at 1% level for both levels and first difference variables.

Afterward, Table 6 divulges the outcomes of the sequential test for SBs with unknown breakpoints proposed by Ditzen et al. (2025). This test assumes CSD and heteroskedasticity with the H_0 of no break and alternative hypothesis of a single break at the first stage, followed by sequentially testing a higher number of breaks. The outcomes of the sequential testing for SBs pointed to the non-rejection of 3 breaks in the long-run, and 2 breaks in the short-run relations. Further, the test identifies 1997, 2000, 2008, 2009, and 2010 as the SB dates.

Having identified CSD and SBs in data, it becomes imperative to apply 2nd generation unit root tests, and we apply MW (Maddala and Wu, 1999) and CIPS test (Pesaran, 2007). Due to the identification of SBs, MW and CIPS tests are followed by the Karavias and Tzavalis (2014) test (KZ). While MW and CIPS allow controls for CSD, KZ incorporates SBs, non-normality, CSD, and heteroskedasticity.

In Table 7, MW and CIPS tests reveal that all the variables are non-stationary in their levels forms; however, in their first differences, we find evidence of stationarity at the conventional 5% level for statistical significance. With KZ test, EI and NRD are weakly stationary at 10% level for level variables when both CSD and SBs are controlled for. However, at first differences, and at the conventional 5% level, we find that all the variables become stationary. If the identified break dates in Tables 6 and 7 were examined, the 1997 breakpoint that occurred for EF, NRD, and ENEF captured the Kyoto Protocol and also the excessive growth period before the Asian financial crisis, whereas 2008,

Table 5. Cross-sectional dependence tests.

	EF	EI	NRD	RET	ENEF	Y
Variables in levels						
BP-LM	313.27***	882.07***	304.12***	867.32***	1022.54***	1038.25***
PS-LM	32.68***	99.71***	31.60***	97.97***	116.265***	118.12***
BCS-LM	32.53***	99.57***	31.45***	97.83***	116.119***	117.97***
P-CD	11.95***	29.19***	10.67***	29.21***	31.936***	32.14***
Variables in first-differences						
BP	216.05***	149.16***	222.70***	110.15***	243.496***	611.19***
PS	21.22***	13.34***	22.00***	8.74***	24.454***	67.79***
BCS	21.07***	13.19***	21.85***	8.59***	24.30***	67.64***
PCD	13.80***	9.50***	11.12***	6.73***	13.506***	24.40***

BP-LM: Breusch-Pagan Lagrange multiplier (LM) test, PS-LM: Pesaran's scaled LM test, BCS-LM: Bias-corrected scaled LM test, P-CD: Pesaran's CSD test. *** indicates rejection of the null hypothesis of no CSD at 1% level of statistical significance.

Table 6. Sequential tests for structural breaks.

Sequential Hypotheses:	Long-run regression	Short-run regression	Bai & Perron Critical Values		
H_1:	Test stat.	Test stat.	1% CV	5% CV	10% CV
F(1|0)	8.96***	6.18***	4.35	3.53	3.10
F(2|1)	6.26***	4.74**	4.73	3.90	3.52
F(3|2)	4.49**	3.20	4.92	4.13	3.75
F(4|3)	3.91*	3.03	5.04	4.28	3.89
No. of breaks at 5% significance:	3	2			
Break date(s), at 5% significance:	1997	2008			
	2000	2010			
	2009				

F is the sequential multiple breakpoint test of Ditzen, Karavias & Westerlund (DKW, 2021). F(1|0) is the test statistic for testing H_0: no break, against H_1: single break. If the null is rejected, the test is maintained sequentially with F(2|1) and F(3|2) test statistics for testing 1 vs 2 and 2 vs. 3 breaks sequentially by assuming cross-sectional correlation and heteroskedasticity. Default trimming of 0.1 (10% from the first and last observations in time dimension) is applied. Maximum of 3 breaks (against 4) is tested. ***/**/* denote statistical significance at 1%/5%/10% for which CV represents Bai & Perron critical values taken from Ditzen et al. (2025).

Table 7. Unit root tests under CSD and SBs.

			Variables in Levels:			
Test/Variable:	EF	EI	NRD	RET	ENEF	Y
MW:	19.104	20.185	23.776	15.755	1.506	13.144
p:	[0.39]	[0.32]	[0.16]	[0.61]	[0.99]	[0.78]
CIPS:	1.960	−1.234	−0.382	−0.711	−0.030	−0.608
p:	[0.98]	[0.11]	[0.35]	[0.24]	[0.488]	[0.271]
KZ test:						
MinZ:	−0.0882	−1.1344*	−1.5391*	−0.0566	−0.1451*	−0.0408
Bootstrap p	0.4649	0.1000	0.0619	0.4774	0.0704	0.4837
No.of breaks:	2	2	2	2	1	1
Break date(s):	1997, 2008	2008	1997, 2009	2009, 2016	2003	2020
			Variables in fist-differences:			
	ΔEF	ΔEI	ΔNRD	ΔRET	ΔENEF	ΔY
MW:	224.549***	92.241***	152.354***	66.873***	118.145***	102.851***
p:	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
CIPS:	−13.772***	11.098***	−4.789***	−4.428***	−8.280***	−5.658***
p:	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
KZ test:						
MinZ:	−19.1920***	−2.7548***	−6.4027***	−10.2028***	−15.6783***	−2.227**
Bootstrap p	0.0000	0.0029	0.0000	0.0000	0.0000	0.05090
No. of breaks:	2	1	2	2	2	1
Break date(s):	1997, 2008	2008	1998, 2008	2018, 2019	1997, 2017	2009

***, ** and * are significance at 1%, 5% and 10% levels. MW and CIPS are Maddala and Wu (1999), Pesaran (2007)'s CIPS tests, both are robust to CSD. KZ is Karavias and Tzavalis (2014) panel breakpoint unit root test, for which MinZ is the min. Z test statistic with bootstrapped *p*-values. By assuming non-normality, CSD and heteroskedasticity, test is conducted with bootstrapping, where bootstrap p val. represents the p value. Similar to DKW test, KZ test is applied with the default trimming rate (10%).

2009, and 2010 correspond to the global financial crisis and great moderation. 2017 is the expansionary period after 2016, which has been subject to a set of events including withdrawal of the UK from the EU, and 2018 and 2019 are traceable to the economic slowdown in the identified years. As the

Table 8. Slope heterogeneity tests.

	BW[a]	BW[b]	PY
Delta:	−5.59***	−5.195***	2.186**
	[0.000]	[0.000]	[0.029]
Adj. Delta:	−6.301***	−5.970***	2.650***
	[0.000]	[0.000]	[0.007]

*** and ** denote 1% and 5% statistical significance. BW[a] and BW[b] are Blomquist & Westerlund (2013) tests, former tests slope heterogeneity under CSD and the latter under serial correlation in addition to CSD. PY is the Pesaran & Yamagata (2008) test of slope homogeneity and the test is autocorrelation-adjusted in panels. Both BW and PY test H_0 of homogeneous slopes against H_1 of slope heterogeneity.

test involves trimming data, the recent energy crisis cannot be captured as expected.

4.4. Results of slope heterogeneity tests

To provide insight into the heterogeneous slope pattern across the model for this study, we employ Blomquist and Westerlund (BW) (2013) and Pesaran and Yamagata (PY) (2008) slope heterogeneity tests. The results are presented in Table 8.

By employing the CSD and autocorrelation robust methods, both BW and PY tests suggested that the H_0 of slope homogeneity cannot be accepted at 1% significance levels, confirming the heterogeneous slope coefficients.

4.5. Results of cointegration tests

Having identified stationarity of the variables in the presence of SBs, CSD, and heteroskedasticity, several cointegration tests were applied. Results are presented in Table 9.

In the first section of Table 8, the traditional cointegration tests were reported. These are Pedroni and Kao followed by two Westerlund cointegration tests via bootstrapping as robust options to CSD. In all tests, the H_0 of no cointegration is rejected both in traditional and tests robust to CSD. At the second stage, bounds tests were examined. The two are traditional PARDL tests without and with dummy variables for break dates, followed by Fourier-augmented FPARDL and Fourier-CS-ARDL bounds tests. The results indicated cointegration between the variables after controlling for CSD and SBs simultaneously at 5% and 1% levels.

4.6. Model architecture and Fourier order selection

At this stage, the model architecture and the optimum Fourier order *k* are examined. The results are presented in Table A1 and Figure A1 in the APPENDIX. SIC criterion was employed for parsimony, and the optimum model structure was determined as (1,0,0,0,0,0); i.e., first lag of EF, followed by lag orders equal to 0 for the remaining variables. Optimum order k of the Fourier terms was determined through Fourier nonlinearity tests by altering $k = 1.,k_{max}$ with $k_{max} = 3$, and critical values are taken from King (2022). For all the Fourier-augmented models (FPARDL, Fourier-PEGLS, and Fourier-CS-ARDL), the highest rejection of H_0 and acceptance of the alternative of the Fourier-type nonlinearity are achieved with $k = 2$ and $k = 1$ for sinus and cosinus terms, respectively, with F statistics surpassing the critical value at 1% level of significance.

In addition to optimum model structures determined, we estimated and reported two additional

Table 9. Cointegration tests.

Pedroni[1]:		Kao[2]:	Westerlund (2005)[3]:		Westerlund (2007)[4]:	
Modified PP-t:	Modified DF-t:	Unadj. mod. DF-t:	VR[a]:		Gt:	Pt:
2.2209**	-2.3335***	-16.301***	-2.4002***		-2.890***	-8.198**
[0.0132]	[0.0098]	[0.0000]	[0.0082]		[0.000]	[0.020]
PP-t:	DF-t:	Unadj. DF-t:	VR[b]:		Ga:	Pa:
−7.3549***	−3.8199***	−8.9929***	−2.1534**		−9.704**	−8.714**
[0.0000]	[0.0001]	[0.0000]	[0.0156]		[0.020]	[0.010]
ADF-t:						
−6.8484***						
[0.0000]						
Traditional and Fourier-augmented bounds tests						
PARDL:		FPARDL:			Fourier-CS-ARDL:	
F, a:	F, b:	F,k = 2,1:			F, k = 2,1:	
5.967*** [0.008]	5.0094**	7.5140***			13.58***	
	[0.04]	[0.006]			[0.001]	

*** and ** denote 1% and 5% statistical significance.[1] Perdoni test is conducted with quadratic-spectral Kernel with lag length selected as 1 by SIC. [2] Kao test is utilized with Bartlett Kernel, lags selected as 2.44 with Newey-West. [3] Westerlund (2005) test has two versions, VR[a] (VR[a]) tests cointegration at some (all) panels. [4] Westerlund (2007) is CSD robust test obtained with bootstraping with 1000 replications. p values are in brackets. F,a and F,b are PARDL bounds F statistics calculated without and with dummy variables for identified break dates. FPARDL is robust to heterogeneity and SBs, Fourier-CS-PARDL test is to CSD, SBs and heterogeneity. Table A1 in the Appendix reports Fourier order selection tests, which led to k = 2,1 for sinus and cosinus terms respectively.

models for Fourier-PARDL and Fourier-PEGLS with 'second-best' results for comparative purposes and to test sensitivity to k-selection. For Fourier-CS-ARDL, no second-best result existed, since the F statistics other than the optimum k's did not suggest implementing a second-best model.[5] shows that for FPARDL, the second-best result is $k = 1$, $k = 2$ at the 5% level of significance, for which the F statistic is close to the critical value at 1%. For Fourier-PEGLS, the selected orders at 1% are $k = 2$ and $k = 1$; however, a second-best model is for $k = 1$ and $k = 1$. As can be seen in the estimation results, estimating Fourier terms with the second-best orders will also lead to relatively lower model fit in the results. However, the findings will indicate comparative results. Therefore, the estimation of the second-best models was implemented to evaluate the sensitivity of the parameter estimates and the diagnostic tests to order k.[5]

4.7. Estimation results I: models without Fourier terms and a control for CSD

In this section, we begin by applying a battery of panel estimation techniques, and the results are presented in Table 10 for four baseline models that vary in terms of approaches followed. However, as all these methods ignore CSD and SBs, these models will also provide a comparative basis for the models in the next section.

Following the establishment of cointegration, the modelling problem is approached by 4 models reported in 4 columns in Table 10. Models 1 and 2 are Panel ARDL models estimated with the PMG method, which allows heterogeneity. Model 1 omits any form of control for SBs, as well as CSD. Model 2 is also PMG-based and omits CSD; however, we test whether the inclusion of any dummy variables would help in capturing the effects of identified SBs, and hence, their effects on the estimation results. Similar to Model 2, we added dummy variables to Models 3 and 4, which are models estimated under FMOLS and DOLS methods, i.e., fully modified and dynamic ordinary least squares. With this respect, we aimed at experimenting whether the SBs would be controlled with the inclusion of dummy variables under different estimators[6]. Simply put, both Models 1 and 2 utilize PMG, allow a form of heterogeneity, while Models 3 and 4 avoid it.

If an overlook is presented, the effect of EI on EF is consistently negative in all models with a range of estimated parameters between −0.034 and −0.0847, without drastic variations, confirming the negative effects of EI on EF under different estimation strategies. However, the standard errors and t statistics vary more, possibly due to the effects of CSD and SBs, hindering the efficiency of estimators. For NRD, the parameter estimates vary more; the variation is not drastically high, and the results consistently confirm the positive effect of NRD. Again, noting that CSD was ignored in all settings, the standard errors and the t statistics are affected. In fact, the level of significance reduces as we move from Model 1 to 4 for the parameters of NRD, possibly due to omitting CSD in all models. For RET, the

Table 10. Estimation results I: traditional models, no Fourier terms and CSD.

Models:	1. Panel ARDL (no dummy variables)		2. Panel ARDL (with dummy variables)		3. Panel FMOLS (with dummy variables)		4. Panel DOLS (with dummy variables)	
Method:	PMG		PMG		FMOLS		DOLS	
Heterogenous slopes:	Yes		Yes		No		No	
Dummies for Outliers/Breaks:	No		Yes		Yes		Yes	
	coef.	t	coef.	T	coef.	t	coef.	T
EI_{it}	−0.064***	−5.67	−0.0847***	−10.92	−0.0419***	−5.21	−0.0340*	−1.644
NRD_{it}	0.0366***	4.39	0.0332***	4.44	0.0936***	4.01	0.0217***	2.84
RET_{it}	−0.1649***	−9.98	−0.0840***	−7.42	−0.0592***	−7.43	−0.0322*	−1.68
$ENEF_{it}$	−0.1595***	−3.75	−0.2919***	−7.87	−0.5712***	−4.97	−0.289**	−2.37
Y_{it}	0.9038***	7.35	0.9597***	10.75	0.7709***	6.22	0.5935***	5.65
Constant	−4.9925***	−17.4	−6.359**	−2.49	–	–	–	–
ect_{it-1}	−0.3291***	−3.92	−0.3713***	−4.40	–		-	
D_1999_{it}	–		0.0423**	2.07	+		+	
D_2009_{it}	–		−0.0975***	−3.59	+		+	
D_2020_{it}	–		−0.0636***	−4.68	+		+	
D_2016_{it}	–		−0.0442***	−3.55	+		+	
D_2022_{it}	–		+0.0201*	1.652	+		+	
Diagnostic Tests:								
BP-LM:	142.71***[0.000]		89.31*** [0.000]		294.78*** [0.000]		47.96* [0.08]	
P-SLM:	12.56***[0.000]		6.29***[0.000]		30.55***[0.000]		1.42 [0.15]	
BC-SLM:	12.42***[0.000]		6.11***[0.000]		30.36***[0.000]		1.27 [0.22]	
P-CD:	10.89***[0.000]		7.39***[0.000]		7.35***[0.000]		0.13 [0.91]	
DKW:	7.51 ** [0.0302]		8.947*** [0.000]		17.809*** [0.001]		7.94** [0.027]	

***, **, * reflect significance at 1%, 5% and 10% levels of significance. For PMG models, model architecture is selected by Schwarz information criterion (SIC). PMG models assume heterogeneity in the short-run coefficients including that of ect_{it-1}, the error correction term. Model 1 is the baseline Panel ARDL model. In the estimation, the observed SBs in the breakpoint and structural break unit root tests presented in Tables 4 and 5 were added to Models 2, 3 and 4 indicated with + for FMOLS and DOLS models. Due to insignificance and to achieve parsimony, dummy variables included are for years 1999, 2009, 2020, and 2016. 1999 is the shift to Euro in the EU, 2009 is for Great Recession in 2009, 2020 coincides with Covid-19 and the economic shut-down in 2020. D_2022 is included to test and to include the effect of recent energy crisis in 2022. D_2016 is an additive dummy variable for 2016 and afterwards, which represents the "EGD" policy focusing on fostering eco-innovation performances put forth in 2016.

findings confirm its negative effect under all model settings. However, its coefficients vary more drastically, as well as the t statistics. The same result is also evident for ENEF and Y and their effects. Specifically, while the coefficients of ENEF are negative across all models, confirming their negative effects, the coefficients of Y consistently confirm their positive effects.

Though the signs are consistent, the size of parameter estimates, as well as changes in their significance, lead to under- or over-determination of the size of their effects on EF. We could argue that as we move towards Model 4, one could speculate that the models control SBs more effectively, and thereby, the parameter estimates are approaching unbiasedness. However, such conclusions are invalid without testing the models for their success in capturing the CSD and SBs. Lastly, the coefficients of the dummy variables, noting that they coincided with major fundamental factors such as the 2009 Global Economic Crisis, we observe negative and statistically significant effects, except for D_1999, which is positive and statistically significant. Furthermore, we included D_2022 to capture the effect of the recent energy crisis caused by the Russia-Ukraine war. The findings pointed to the positive effect of the energy crisis at 10% level. This implies that an energy crisis can impede the EU's net-zero targets. The critical point here is that the control of such factors could have helped in approaching unbiasedness in the estimators and the parameter estimates of Y, EI, NRD, RET, and ENEF, as well as that of the error-correction term in Models 2–4. Still, such conclusions require testing the models for CSD and SBs to test if they had been effectively filtering these factors at conventional statistical significance.

To this end, at the first step, models in Table 10 are tested with a set of CSD tests. These tests are BP-LM, P-SLM, BC-SLM, and P-CD tests, for which the test statistics are reported in the last section of Table 10. The overlook suggests the non-rejection of CSD in all PMG models, as well as in DOLS- and FMOLS-based variants at the conventional 5% level of significance. One exception could be Model 4, the model estimated with DOLS, for which CSD cannot be rejected at 10% level in the first test only, while the remaining 3 tests confirmed rejection of the remaining CSD. Hence, it is safe to conclude at 5% that all tests confirmed the effectiveness of controlling CSD by Model 4, and the results could hint that the parameters and their estimators were less severely affected by CSD for the Panel DOLS method for our dataset and sample.

In the second step, models are tested for SBs to examine whether the inclusion of dummy variables has been helpful in controlling SBs. To this end, Ditzen et al. (2025) test statistic (DKW) is reported, and the results confirm the failure of all models in capturing SBs with or without dummy variables for all models at the conventional 5% level of significance, thereby suggesting their ineffectiveness in controlling SBs with dummy variables. This time, Model 4 could not strike out at 5% significance level, as SBs cannot be rejected for their residuals at 5%, we safely reject the null of no SBs at 5% significance level, indicating ineffectiveness of the DOLS-based model in filtering SBs. Hence, the model results are observed to suffer from SBs for all models, as well as from CSD, though we can argue that CSD could be filtered out by DOLS to a certain degree only in Model 4. Though this is the case, similar to all remaining models in Table 10, the model cannot capture heterogeneity as well as SBs.

4.8. Estimation results II: Fourier-panel-ARDL model

After the strategy followed with models in Table 10, a second way to control SBs as well as allowing

Table 11. Estimation results ii: Fourier-panel ARDL (FPARDL) models.

Models:	5. FPARDL		6. FPARDL	
Method:	PMG		PMG	
Fourier terms:	Yes		Yes	
	coef.	T	coef.	t
EI_{it}	−0.0578***	−7.20	−0.0577***	−3.22
NRD_{it}	0.01993**	2.47	0.0795**	2.44
RET_{it}	−0.1714***	−13.9	−0.0508***	−6.08
$ENEF_{it}$	−0.0775**	−1.97	−0.2649***	−5.71
Y_{it}	0.8946***	9.26	0.9841***	16.92
Constant	−5.0045**	−2.40	−7.1361***	−3.39
ect_{it-1}	−0.4008***	−4.13	−0.3425***	−4.09
Fourier, sin	0.05403**	2.46	0.0438***	4.69
Fourier, cos	−0.0217***	−5.16	−0.0154*	−1.86
k:	2; 1		1; 2	
Diagnostics Tests:				
BP-LM:	119.39*** [0.000]		147.15*** [0.000]	
P-SLM:	9.83*** [0.000]		13.10*** [0.000]	
BC-SLM:	9.68*** [0.000]		12.95*** [0.000]	
P-CD:	9.65*** [0.000]		10.39*** [0.000]	
DKW:	5.96 [0.106]		4.27 [0.190]	

***, ** and * denote 1%, 5%, and 10% statistical significance. k is the optimum order of sinus and cosinus terms, tested k orders are 1,2,3.

heterogeneity, we estimated Fourier augmented FPARDL models, and the results are reported in Table 11.

To save space, the coefficient interpretations are not detailed in this section. However, it should be noted that, similar to the results in Table 10, we observed small but existent variations in the parameter estimates and their sizes. Further, the findings again consistently suggested the negative effects of EI, RET, and ENEF and the positive effects of NRD and Y on EF.

As noted before, Fourier order selection tests were presented in Table A1 in the APPENDIX, and the optimum rejection of the H_0 for Fourier terms in the Fourier nonlinearity test was achieved once $k = 2$ and $k = 1$ for the 1st and 2nd Fourier terms (sinus and cosinus, respectively) at 1% level of significance in FPARDL models, as well as Fourier-Panel EGLS and Fourier-CS-ARDL models in the next section. As explained in Estimation results I: models without Fourier terms, and a control for CSD, we estimated models with second-best results, and in the context of FBARDL, this model is named as Model 6 with $k = 1,2$ in respective Fourier terms, whereas Model 5 is the optimum model selected.

FPARDL bounds test results are reported in Table 8, which confirmed the existence of cointegration between the variables in an SB-robust setting. Further, similar to the PMG-based models in Table 10, the expected qualities for the parameter of ect_{it-1} are satisfied for both models estimated in Table 11. These coefficients for Model 5 and Model 6 are negative and significant, are estimated as −0.4008 and −0.3425, respectively, which suggest that the short-term deviations from the long-term equilibrium are corrected yearly with the adjustment speed of about 40.08% and 34.25%.

The reason for reporting a second-best model is for comparative purposes and to examine sensitivity to Fourier order selection among optimum and second-best model structures. The most important overall finding by focusing on the diagnostics is the effectiveness in controlling SBs as pointed out by DKW tests in the last section. As the optimum model structure was selected as 2;1, the second-best model, Model 6 with orders $k = 1; 2$, resulted in a 2nd Fourier term to be significant at 10% level. However, comparing Model 6 to 5 allowed us to test the sensitivity of parameter estimators to selected k in at a controlled level, since the optimum orders were selected at 1% level of significance, as the second-best model was achieved for significance at 5%. In both results, minimal and acceptable variation in parameter estimates existed for the size of parameter estimates, while their signs were always preserved. Most importantly, these results confirmed the importance of controlling SBs once compared to the estimation results presented in Table 10. Still, in both Models 5 and 6, the diagnostic tests pointed to CSD in the remainders.

4.9. Estimation results III: Fourier-CS-PARDL and Fourier-PEGLS models

The fact that the models reported in Tables 10 and 11 failed to capture the effects of CSD and SBs in simultaneity, and the qualities of the data in hand require models to incorporate both into their architectures. Under CSD and SBs simultaneously, this study incorporates Fourier and CS terms into the model architecture, and the first model proposed is the Fourier-CS-PARDL, which borrows the Fourier terms from the FPARDL and the CS terms from CS-PARDL. A second proposed model is Fourier-PEGLS that also incorporates Fourier terms to control SBs and is theoretically robust to CSD. The second model is an alternative to the first in the case of small to moderate sample sizes.[7] With this way, loss of degrees of freedom is significantly preserved, and the proposed models provided a parsimony solution under lower sample sizes.[8]

In Table 12, two Fourier-PEGLS models are reported in the first two columns, the optimum and the second-best, followed by the Fourier-CS-PARDL in the last column[9] in the APPENDIX. The optimum model architecture was selected as k = 2 and k = 1, and the model is presented as Model 8. For comparative reasons similar to the FPARDL models, a second-best model with k = 1 and k = 1 is also estimated, and is numbered as Model 7 to test the sensitivity of parameter estimates and the diagnostic tests afterward. The last column reports Fourier-CS-PARDL, named as Model 9, for this model. Fourier test results pointed to k = 2 and k = 1 with the highest rejection of the null at 1%. Estimation of a second-best model was not necessary for Fourier-CS-ARDL, since the calculated Fourier F test statistics for this model were significantly less for other Fourier orders.[9] Under all settings, results suggest that EI, ENEF, and RET have a negative impact on EF, while NRD and Y have a positive impact in the long run. Most importantly, unlike the previous results, the diagnostic tests showed that both SBs and CSD have been effectively controlled, as the null hypothesis for BP-LM, BC-SLM, and P-CD tests and DKW test cannot be rejected in all the proposed models reported in Table 12. Also, for the Fourier-CS-PARDL model, the F-statistic of the Fourier-CS-PARDL bounds test is 13.58, surpassing the critical bounds values. This suggests the presence of cointegrated long-run relation between the variables modelled. Further, the error correction parameter of the Fourier-CS-PARDL model is estimated as −0.3709, which satisfies the expected requirements. Accordingly, the duration of convergence to the long-

Table 12. Estimation results iii: Fourier-CS-PARDL and Fourier-PEGLS models.

Model:	7. Fourier-PEGLS		8. Fourier-PEGLS		9. Fourier CS-ARDL	
Method:	EGLS (Cross-Section SUR)		EGLS (Cross-Section SUR)		CCE	
Fourier terms:	Yes		Yes		Yes	
	coef.	T	coef.	t	coef.	t
EI	−0.0768***	−9.55	−0.1115***	−8.85	−0.0637***	−6.87
NRD	0.0306***	16.51	0.0268***	−4.83	0.0127**	1.97
RET	−0.0467***	−12.41	−0.0541***	−15.55	−0.0207**	−2.30
ENEF	−0.1601***	−9.73	−0.2118***	−12.40	−0.1036***	−2.92
Y	0.9869***	3.37	0.9818***	3.14	0.9934***	7.09
Constant	−7.5805***	−9.56	−7.1913***	−8.85	−7.8760***	−5.13
ECT_{it-1}	–	–	–	–	−0.3709***	−8.76
Fourier, sin	0.0801***	9.48	0.0157**	2.24	0.0245***	5.10
Fourier, cos	−0.0421**	−5.18	−0.0422***	−6.05	−0.0683***	−7.85
k:	1; 1		2; 1		2; 1	
Diagnostics Tests:						
BP-LM:	27.11 [0.85]		29.73 [0.76]		48.44 [0.08]	
P-SLM:	−1.05 [0.29]		−0.74 [0.46]		1.47 [0.14]	
BC-SLM:	–		–		1.31 [0.19]	
P-CD:	1.38 [0.17]		0.21 [0.83]		1.66 [0.15]	
DKW:	4.25 [0.20]		4.16 [0.18]		4.01 [0.21]	
Break detected?	No		No		No	

*** and ** denote 1% and 5% statistical significance. *p*-values are reported in brackets.

run equilibrium lasts approximately 2.7 years, and 37.09% of the deviations from the long-run equilibrium are corrected in each year.

Furthermore, as the sign of parameter estimates is maintained, a set of important changes is captured after controlling SBs, heterogeneity, and CSD. If the parameter estimates were investigated, we noted that the parameter estimate of Y has little or even almost no variation in all models estimated, 0.9869 in Model 7, 0.9818 in Model 8, and 0.9934 in Model 9, indicating that in the long-run, a 1% point increase in Y results in a 0.99% point increase in EF in the top EI performance group of the EU, indicating the significant size of the positive effect Y on the environmental pollution. However, compared to previous methods, especially to FMOLS and DOLS in Table 10, the size of the parameter of Y has been estimated to be more in accordance with Fourier-augmented models in Table 11.

The former factor is the ENEF, which is measured as GDP per unit of energy consumption (constant 2021 PPP $ per kg of oil equivalent). Ceteris paribus, upsurges in ENEF significantly reduce EF, which is also in line with theoretical expectations. To this extent, our findings suggest parameter estimates of ENEF to be – 0.1601 in Model 7, −0.2118 in Model 8, and is −0.1034 in Model 9, and findings demonstrate that a 1% point increase in ENEF results in 16.01%, 21.18% and 10.34% decrease in EF, and though variation exists, it is expected due to employing different estimators with different model structures. However, under all settings, findings confirm the positive effects of ENEF on EF of the top EI performance group examined for EU. Further, noting that these economies appear as top EI performers of the EU, their progress in terms of ENEF has been significant in reducing the EF, hence contributing to environmental sustainability. Furthermore, as the second critical energy variable, the findings for RET showed the important role of green energy transition in reversing the inclines in EF. The parameters of RET are statistically significant and are negative, with estimates of −0.0479 and −0.0541 in the Fourier-PEGLS models, both around −0.05, and after allowing heterogeneity, the estimate of RET is −0.0207 in the Fourier-CS-PARDL model, indicating the significant role of green energy transition in curbing down the EF.

Last but not least, EI performances have a distinguished effect in reversing the positive pressures on the environmental gradation in addition to green energy transition, compared to the negative effects of Y, NRD, and ENEF: The inclines in EI effectively reduce EF in the selected group of top EI performers in addition to such helpful effects of RET. The parameter estimates of EI in models 7, 8, and 9 are −0.0768, −0.1115, and −0.0637, all negative and significant, confirming this result. In the two Fourier-EGLS models, a 1% point increase in EI reduces EF by −0.0968% and by −0.1115%, and compared to these two models, the Fourier-CS-PARDL model confirms the result with a relatively close, but lower estimate (−0.0637), after allowing heterogeneity, in addition to confirming the negative effect of EI under robust to SBs and CSD settings. Consequently, a 1% point increase in EI reduces EF by 0.1115% in the top EI performers group, and as the increases in Y and NRD put upward pressure on EF and worsen environmental degradation, RET, ENEF, and EI help in the reversal of environmental degradation by declining EF. The negativity and the size of the parameter estimates indicate the confirmation of environmental sustainability effects of

policies that focus on a set of binding measures to reduce fossil fuels in the total energy mix, as well as increasing ENEF, which should also be backed by limiting or reversing NRD in the EU region.

Compared to traditional models, the suggested methods clearly help in robustness to SBs and CSD, which affect both the parameter estimators and standard errors. After correcting for possible bias due to these two factors, the results obtained with Fourier-augmented methods point to a partially higher effect of Y on EF, ceteris paribus, a 1% point incline in Y, resulting in an almost 1 to 1, i.e. unit elasticity of EF to Y, in the long run. This means that Y remains a major channel of environmental pollution in these countries. However, the environmental improvement effect of EIs may tend to mitigate the detrimental effect of Y, as the EI continues to grow. Furthermore, findings also confirmed such effects for NRD, and though the size of the effect is relatively minimal, if not controlled, NRD potentially could worsen ecological sustainability significantly. The findings for the three models above indicated that a 1% point rise in NRD increases EF by 0.03%, 0.02%, and 0.01% points in the long run. As NRD is a percentage variable, EF is a stock variable; hence, though the estimated coefficient size is small, they indicate the significant effects of NRD on EF, and shifting to a more natural resource dependent economy would lead to a significant worsening of the ecology. As a result, EF and the selected variables and their specifications would be kept in mind in the evaluation. Hence, it is evident that reducing NRD of the economy by policies focusing on reversing the dependence on natural resources through material efficiency and enhancing EI and RET would significantly reduce pressure of Y on the ecology.

4.9.1. Heterogeneity results

Relative to Models 7 and 8, Fourier-CS-ARDL in Model 9 allows modelling heterogeneity in country-specific error-correction terms, durations to convergence to long-run equilibrium in each country, as well as country-specific Fourier functions capturing variation in SBs in the dataset. The results are reported in Table 13.

Accordingly, the findings indicate that in all countries analysed, error correction mechanisms are evident with the expectations regarding the relevant ECMt-1 parameter estimates. Further, in the tested EU countries, the duration of convergence to the long-run equilibrium after external shocks takes place with a varying number of years. For Denmark, the duration is the longest at 9.9 years, and the size of ECT parameter, its sign and significance comply with the statistical expectations. The shortest duration occurs in Finland with 1.78 years, followed by Germany, the Netherlands, France, and Sweden, between 2.24 and 2.55 years, followed by Austria and Italy, with convergence to long-run equilibrium discussed in Table 12 to occur in 3.19 and 3.24 years. As a result, for the top EI-performers of the EU, the long-run relations are obtained with highly significant error-correction properties in the short-run. Lastly, the Fourier functions and their parameters are capable of capturing SBs and confirming country-specific heterogeneity.

4.10. Results of Fourier-CS-PGC Granger-causality tests

To further check the directional causal relationship between the variables, we tested PGC by the Fourier-augmented PGC test as a generalization of Juodis et al. (2021) following methods presented in Panel Granger-causality test with Fourier terms to achieve a Fourier-augmented test with TY correction. The results are displayed in Table 14.

From the results, the null hypothesis of no Granger causality is rejected in most cases. As we can see from the results, a bi-directional causal connection (feedback effect) exists between EI and EF, ENEF and EF, Y and NRD, ENEF and RET, Y and RET, as well as Y and ENEF. This implies that the previous values of these variables can predict each other. Also, we find a unidirectional causality running from ENEF to EI, NRD to EF, Y to EF, EI to RET, Y to EI, RET to NRD, and ENEF to NRD. However, we find evidence of causality from RET to EF at 10% level of significance, and bidirectional causality between NRD and EI again at 10%. Accepting 10% level of significance, these findings point to bidirectional causality between NRD and EI, i.e., indicating feedback effects between NRD and EI. Furthermore, at 5% level of significance, the unidirectional causality from NRD to EI indicates that NRD in these countries has been an important driver of EI. These findings further support the negative impacts of NRD and Y shown by Zia et al. (2021); Luo and Mabrouk (2022); Raghutla et al. (2022) and Akpanke

Table 13. Fourier-CS-PARDL and country-specific heterogeneity.

Country:	Austria	Denmark	Finland	France	Germany	Italy	Luxemb.	Nether.	Sweeden
ECT	−0.314[a]	−0.101[b]	−0.563[a]	−0.399[a]	−0.446[a]	−0.309[a]	−0.372[a]	−0.443[a]	−0.392[a]
Duration	3.19	9.92	1.78	2.50	2.24	3.24	2.69	2.25	2.55
Fourier1	0.013[c]	0.0013[c]	0.0466[b]	0.035[a]	0.041[a]	0.0126[c]	0.022[b]	0.025[b]	0.024[b]
Fourier2	−0.057[a]	−0.017[a]	−0.1149[a]	−0.078[a]	−0.085[a]	−0.063[a]	−0.061[a]	−0.066[a]	−0.072[c]

[a], [b] and [c] reflect 1%, 5% and 10% statistical significance.ECT is the error correction term. Duration in years. Fourier1 and 2 represent sinus and cosinus Fourier parameters.

Table 14. Fourier-CS-PGC Granger-causality test results.

H_1:	HPJ Wald	P	Decision
EI →EF	12.6392***	0.0018	Bidirectional
EF → EI	6.4343**	0.0401	between EI to EF
NRD → EF	24.7697***	0.0000	Unidirectional from NRD to EF
EF → NRD	5.5320*	0.0629	
RET → EF	6.3441*	0.0960	No-causality at 5%, unidirectional
EF → RET	0.1804	0.6710	from RET to EF at 10%
ENEF → EF	4.3696**	0.0366	Unidirectional
EF → ENEF	0.8535	0.3556	from ENEF to EF
Y → EF	20.1494***	0.0000	Unidirectional
EF → Y	2.4702	0.2908	from Y to EF
NRD → EI	6.2356**	0.0443	Unidirectional causality from NRD to EI at 5%. However,
EI → NRD	6.6752*	0.0830	bidirectional causality between EI and NRD at 10%.
RET → EI	3.5332	0.3165	Unidirectional
EI → RET	13.8122***	0.0032	from EI to RET
ENEF → EI	12.5891***	0.0018	Bidirectional
EI → ENEF	8.9884***	0.0027	between EI and ENEF
Y → EI	14.3876***	0.0008	Unidirectional
EI → Y	6.6258*	0.0848	from Y to EI
RET → NRD	9.2169**	0.0559	Unidirectional from
NRD → RET	2.3890	0.6646	RET and NRD
ENEF → NRD	14.4047***	0.0024	Bidirectional
NRD → ENEF	9.5582***	0.0020	between ENEF and NRD
Y → NRD	13.3236***	0.0098	Bidirectional
NRD → Y	10.6905**	0.0135	between Y and NRD
ENEF → RET	13.3947***	0.0003	Bidirectional
RET → ENEF	12.1648***	0.0068	between ENEF and RET
Y → RET	14.2025***	0.0026	Bidirectional
RET → Y	15.963***	0.0031	between Y and RET
Y → ENEF	10.0719***	0.0065	Bidirectional between
ENEF → Y	7.3296**	0.0256	Y and ENEF

***, ** and * denote 1%, 5% and 1% statistical significance. Direction of causality is shown with .→. Test is conducted with 1000 bootstrap replications in STATA 17. Test is robust to cross-sectional heteroskedasticity and correlation.

et al. (2024), in addition, findings identify important causality effects among NRD, EI, and EF. Further, both EI and RET are identified to have significant causality effects with Y, NRD, and EF in the top-EI performers of the EU.

5. Discussion of finding

The empirical findings of this study have important implications for the effects of RET, EI, ENEF, and Y in the context of the 'eco-innovation performance leaders' of the EU. Accordingly, RET, EI, and ENEF have important effects in reducing the overall EF in the selected EU economies. This implies that increases in RET, EI, and ENEF support environmental sustainability through a decline in EF. Specifically, in the context of ENEF, our findings confirmed the negative effects of ENEF on EF obtained in the related empirical literature. The implication of the result is that the EU has the prospect of achieving its environmental target of reducing GHGs by at least 55% (compared to 1990) and ENEF target of 27% energy savings, all by 2030. Therefore, the finding concurs with Akpanke et al. (2024), who found the coefficient of ENEF to be negative and statistically significant. This result confirms the finding recently documented by Usman et al. (2025) that ENEF at household and commercial levels is attributed to a fall in energy-related CO_2 emissions in the US. Moreover, the model findings and causality test results also confirm Bildirici and Ya (2025), who showed the role of ENEF on CO_2 emissions for G7 countries.

Furthermore, the environmental degradation reversal effect of EIs may be driven by improvements in resource efficiency. The countries in our sample have initiated a series of decarbonisation policies and reduced human-induced global warming and climate change. These initiatives are likely to create favourable conditions for achieving net-zero emissions targets and other ambitious environment- and climate-related objectives. Moreover, as top performers of EIs, countries under investigation have invested heavily in research and development to offer eco-friendly alternatives, aiming to accelerate the pace of transition to a regenerative economy, i.e., giving back to the planet more than it takes from the planet. Specifically, EIs can reduce EFs in several ways: The environmental-related technology innovations can help reduce the effect of anthropogenic emissions released into the atmosphere by promoting ENEF and green energy utilization to accelerate a sustainable environment (Wang et al. 2023). Such results under SBs had been confirmed recently (see Ersin et al. 2024). Furthermore, technology innovations related to the environment could help in encouraging greening of businesses to transition towards clean energy (Gao et al. 2025). In addition, various studies also suggest behavioural changes for humans to achieve a collective action to minimize waste and efficient energy (Kurniawan et al. 2023). Overall, the negative effect of EI on EF found in this

study is supported by Beltrán-Esteve and Picazo-Tadeo (2015) for a large set of countries, and similar to our study, for EU countries by Beltrán-Esteve and Picazo-Tadeo (2017), by Mačiulytė-Šniukienė and Sekhniashvili (2021) for selected EU members, and Guan et al. (2022), and Rout et al. (2022) for G10 and BRICS nations, respectively. Our findings further underline the importance of EI at country-level data for the top EI performers of the EU, which we believe is an important example in EI performance and EF reduction. Noting that the macro-level data is an aggregation of companies and industries at the micro-level, several implications could be drawn. Companies should invest in EI and, in return, reduce their costs of production, improve their production capacity for eco-friendly products, and contribute further to green growth and environmental sustainability at the macro-level. It should also be remembered that these aspects are possible and backed by the policies of the EU's Green Business Strategy and EGD, with an aim of continuing reduction in environmental pressure towards net-zero in the year 2050 in the EU.

Similarly, the significant causal relations between RET and EF imply the effectiveness of energy transition policies from fossil fuels to clean energy. It is well recognized that human-induced climatic changes have been increasing at a rate of 0.2°C per decade. Hence, putting effort into reversing this trend becomes imperative. This result is not surprising given that the countries sampled are top performers of EIs. They have significantly reduced their EFs caused by human activities through green energy deployment policies, such as carbon pricing and funding research and development in RE. Therefore, our results concur with Raghutla et al. (2022) where it was found that green energy consumption dampens EF for 9 selected N-11 nations. Also, the results are consistent with Sharma et al. (2021) for Bangladesh, India, Pakistan, and Sri Lanka, and Degirmenci et al. (2024) for G7 nations supporting the importance of commitments to RET on EF reduction.

If evaluated together in the light of the first research question, we argue that the results unveil that EI, ENEF, and RET policies had been implemented effectively as dampening tools for ecological pressure. This reduction in EF is possibly enhanced not only by the decline in energy consumption, but also by the pursuit of green and environmentally friendly economic growth policies in the region through the deployment of clean energy alternatives and the drastic elimination of fossil fuels in energy consumption. By this result, we argue that EU environmental policies effectively target the transition to green energy with a significant role of EI and ENEF.

The results pointed to positive effects of NRD and Y on EF, which imply that NRD and Y exert enormous pressure on greenhouse gases to those naturally occurring in the atmosphere, thereby causing global warming and climate change to rise. Particularly, NRD and Y undoubtedly hurt the environment through increases in coal, oil, gas, and other natural resources exploration. Also, cutting down forests, increasing livestock farming, the utilization of fertilizer containing nitrogen, and fluorinated gases are all emitting greenhouse gases.

Most studies employed natural resources rent (NRR) instead of NRD. Intuitively, these two measures––NRD and NRR––are closely related; however, they have critical differences as they measure different aspects of natural resource use in the economy. NRR focuses on economic gains, calculated as the difference between price and cost of natural resources––the sum of oil, coal, natural gas, forest, and mineral rents. NRD, in contrast, focuses on the depletion of natural resources instead of economic gains, where natural resources included are minerals, forests, and energy sources. Hence, NRD is a 'net' variable after calculating the replenishment rates of nature and nature's capacity. As NRR focuses on the share of income earned from natural resources, NRD focuses on the loss of natural capital assets. NRD is a key indicator taken into consideration for green accounting and sustainable development, while NRR indirectly is an indicator of sustainability. Due to its focus on depletion rather than economic gains, the correlation between NRR and NRD could vary from country to country. An additional but important difference is that, as NRR is calculated as a percentage of GDP, NRD is published as % to GNI. As a result, by definition, depending on the existence of the employment of domestic or national factors of production in economic activity could also lead to variation in the degree of association and especially the sign of correlation. In economies where heavy rents from natural resources are visible with high NRRs, such as resource-rich economies where economic gains reflected in GDP are high, a positive association between NRR and NRD could occur; however, this is not a general case. It is acceptable to obtain a negative association between NRR and NRD, depending on how the economic activity is conducted in terms of factors of production used, employment of domestic or national resources, or depending on the natural resource, and not to mention the existence of an informal economy in certain developing countries. The existence of multinational corporations operating in extraction activities could also influence how the association between NRR and NRD occurs, depending on the country or region analysed.

Therefore, our findings are in line with Luo and Mabrouk (2022), who, by employing NRR instead, showed a positive long-run association between EF and NRR in research-rich nations after controlling CSD with CS-ARDL, while ignoring SBs. A set of studies found the sign of association to be negative for a

specific set of countries between NRR and EF. Shittu et al. (2021), who examined 45 Asian economies, found that NRR reduces EF; however, we noted that the size of the coefficients under their results is in the range of −0.006 to −0.003, very close to zero, and the countries analysed are highly heterogeneous relative to estimators. Similar to our study, but by employing NRR instead, Ma et al. (2024) collected selected countries into two sets, low and high green growth, and their findings for both confirmed positive effects of NRR on EF. Also, our finding is consistent with Balcilar et al. (2023). However, they further observed that once NRR interacted with operational behaviours of MNCs through FDI, the effect became beneficial to Africa's environmental goal of reducing climate risks. Similarly, Zia et al. (2021) employed China's dataset from 1985 to 2018 with ARDL for the effects of NRD on EF, while SBs were not controlled; their findings indicated a positive long-run effect of NRD on EF. Therefore, in light of the second question, we argue that NRD is detrimental to environmental sustainability through the increase in EFs of the top-EI performers of the EU.

Furthermore, in response to the third research question, it was found that both RET and ENEF have significant Granger-causality effects on NRD. Granger causality between RET and EI also points to the significant roles of EIs, ENEF, and RET on NRD, as well as the effects of the aforementioned variables on EF of the examined EU nations. Moreover, from the empirical analysis, it must be noted that supporting EIs with RET and ENEF would reverse the negative effects of Y. Overall, these empirical results show that green transition policies such as EI, ENEF, and RET are helpful in managing existing natural resources, thereby leading to economic growth and the environment.

6. Conclusion and policy implications

Eco-innovations and green energy transition are necessary for achieving environmental and climate action objectives. In this study, we investigate the implications of EI, green energy transition, and NRD on EF in top EI performers in EU countries. Although the existing literature has examined the role of EI and other green policies in reducing atmospheric emissions, many studies ignore how CSD and SBs could affect their outcomes. To address these problems, the empirical analyses were conducted by employing several econometric methods. Having identified CSD and SBs in the variables, we first employ the panel ARDL with and without dummy variables, as well as panel FMOLS and panel DOLS with dummy variables. The empirical results provide that EI and RET exert downward pressure on EF while ENEF, NRD, and Y exert upward pressure on EF, although these models apparently fail to capture the CSD and SBs. Hence, the panel Fourier-ARDL models are estimated. However, while SBs are captured by Fourier terms, the issue of CSD still persisted. To this end, we incorporated Fourier terms into panel EGLS and CS-PARDL in order to capture SBs and CSD issues.

The empirical results suggest that EI, ENEF, and RET have negative and significant relationships with EF, whereas NRD and Y have positive relationships with EF. These results are robust to both CSD, and SBs associated with the variables. Furthermore, a bidirectional causality is established between EI and EF, ENEF and EF, Y and NRD, ENEF and RET, Y and RET as well as between Y and ENEF. Moreover, a bidirectional causality flows from NRD to EF, Y to EF, EI to RET, ENEF to EI, RET and NRD, and ENEF to NRD.

Although some tangible and ambitious actions and improvements have been made towards sustainable development, the performance of countries in reducing environmental impact is diverging within the EU. In order to achieve the 2040 and 2050 targets, concerted efforts must be accelerated. Thus, the main question appears to be how can energy transition policies be better designed to foster innovation for the environmental development of more innovative, proactive, and comprehensive policies and measures to reduce EF? On this note, the following policy recommendations based on the findings of this study are adroitly put forward:

- Improving energy efficiency

Given that ENEF has a negative effect on EF, and a unidirectional causality flows from ENEF to EF, environmental programmes and policies should mostly focus on the notion of eco-efficiency, established on the framework of dialectic between the public and private actors, while involvement of other social stakeholders, including NGOs, social enterprises, and cooperatives, should not be neglected (see Colombo et al. 2019). Recently, the rising discourse of the circular economy began to come to the fore by necessitating the cooperation of all stakeholders, including public and social enterprises, NGOs, and other community-based initiatives. Taking seriously, to promote ENEF that delivers multiple environmental benefits, a close monitoring of such policies is required.

- Promoting environmental innovations

Since environmental innovations through patents on eco-friendly technologies dampen EF, policymakers and environmental stakeholders should focus on promoting environmental technologies and innovations. This requires public participation through funding environmentally friendly production technologies to increase the share of public environmental R&D expenditures to GDP for macro-level deployment and development of EIs. Also, there is a need for~~rising~~ environmental awareness to influence not only

companies but also nations in order to stimulate their sustainability performance and efficiency. Eco-friendly projects––promising significant benefits in this respect––can foster the EU's competitiveness in many ways. They can attract public funding and international investors, as well as create high-value-added employment. However, since we found a bidirectional causality between EI and EF, environmental innovation policies should be carefully designed and implemented to avoid rebound effects that are detrimental to the environment.

- Promoting renewable energy transition policies

Dampening EFs require the need to promote RE transition policies such as cost reductions through subsidies, tax relief and credit, rebates, loans, and grants, price-setting and quantity-forcing, public investments and market facilitation activities, power grid access, etc. These policies deal with various environmental issues, including NRD, climate warming, habitat destruction, and loss of biodiversity. Moreover, environmentally friendly technologies that foster the transition to RE can provide EU firms with effective solutions by making efficient use of existing valuable resources and reducing the EF of economic activities. According to the IEA report in 2025, the projected RET target decreased by 5% worldwide. However, the EU continued to increase its RET despite the energy crisis, with an increase of 4% in 2025. Given the recent geopolitical shocks, it is of the utmost importance for top EI performers to maintain their commitment to the clean energy transition to encourage EIs in these economies.

- Proper and smart management of natural resources

Since depleting natural resources triggers an increase in EFs, properly and smartly managing all natural resources by gradually fostering the use of RE systems could ensure eco-friendly use of natural resources. This requires qualified human capital and EI within the framework of the circular economy to make overwhelming contributions towards achieving related sustainable goals and mitigating EFs.

6.1. Limitations and future directions

The findings of this study provide insight into the criticality of EI, ENEF, and RET in dampening EF with methods robust to SBs, heterogeneity, and CSD. However, empirical studies still depend on existing datasets and methodological approaches, and the study faces a set of limitations. These also lead to future directions.

As noted in the empirical section, data availability restricted us to examining catch-up and average performer groups within the panel context. The panel of countries could be extended to a larger EU sample after eliminating a large set of EU countries for which data is limited on EI for long periods. However, the data availability issue for long periods could also be tackled by single-country studies or by examining other country groups. Future studies are specifically encouraged to examine the models put forth in this study between examined variables in other country groups, including Africa and Asia. The tests applied pointed to no problems in terms of endogeneity with the methods applied. However, future studies could employ these models with different estimators (such as GMM) to control for endogeneity if tests point to endogeneity under different datasets. As the time dimension expands in the future, another direction we suggest is to test the effects of the recent energy crisis and its effects on the trajectories of ecological and environmental variables in the context of the proposed models.

Notes

1. Sample size limitation, especially for the time dimension, is a critical feature for the EI dataset. Threshold-based methods could effectively help examine asymmetric effects of variation between negative and positive changes, such as those that occur for economic policy variables. However, threshold models not only assume sudden changes, but also require splitting the regression space into sub-samples called regimes. Different than such methods, Fourier-augmented models are feasible options by capturing a form of nonlinearity resulting from smooth forms of SBs, and no splitting of the sample space is necessary.
2. As noted in the literature review, NRR and its effects have been widely examined. As a critical variable, we employed NRD, and the reason is that both material productivity and water productivity are among the factors considered in the formation of the EU's resource efficiency outcomes pillar of their eco-innovation performance indicator, in addition to including energy efficiency under the same pillar, where both material and water productivity are measured with a focus on NRDs. Further, the third factor under the pillar, energy efficiency, is also included as a separate variable in the model. As a result, the selection of NRD is based on the importance of resource productivity in achieving the EGD strategy in the EU. Furthermore, due to multicollinearity issues, the employment of NRD as a single variable instead of separate variables discussed above is not feasible.
3. It should also be noted that if the panel is to be extended to the average performer and the catching-up groups, the size of the time series dimension significantly reduces. Missing data and data availability issues are observed for average and catch-up groups, not only for the early periods of 1990, but also missing data exists for post 2000 or post-2010 periods for certain countries in the group. As a result, in addition to the central focus of this study on the top EI performers, data availability is a second reason not to test or

to extend the analysis to catch-up and average performers.

4. As shown in the Results of slope heterogeneity tests, series are integrated of order 1; therefore, first differencing is necessary to achieve stationarity in all series. As a result, the first-differenced results are reported. Also, due to log-first-differencing, once first-differenced, the variables will approximate yearly growth rates.
5. Table A1 shows that for FPARDL, the second-best result is $k = 1$, $k = 2$ at the 5% level of significance, for which the F statistic is close to the critical value at 1%. For Fourier-PEGLS, the selected orders at 1% are $k = 2$ and $k = 1$; however, a second-best model is for $k = 1$ and $k = 1$. As can be seen in the estimation results, estimating Fourier terms with the second-best orders will also lead to relatively lower model fit in the results. However, the findings will indicate comparative results. Therefore, the estimation of the second-best models was implemented to evaluate the sensitivity of the parameter estimates and the diagnostic tests to order k.
6. The parameter estimates cannot be reported with FMOLS and DOLS estimators; the exogenous factors are included in the estimation method instead of parameterized model results. Further, ect_{it-1} is the error correction term that could be reported for Models 1 and 2. For the conditions for error correction to exist, see Econometric methodology.
7. The PEGLS estimator is employed with cross-sectional SUR and cross-sectional weights, and the estimator is theoretically robust to CSD and heterogeneity.
8. For parsimony, we also restricted leads and lags to be 1 in all estimated models, which were adequate to control CSD after being tested with diagnostic tests. Fourier-PEGLS is also a viable option to overcome the difficulties experienced during estimation with sample sizes being small to moderate in the time and cross-section dimensions.
9. Following Table A1 in the APPENDIX, the optimum model architecture was selected as k = 2 and k = 1, and the model is presented as Model 8. For comparative reasons similar to the FPARDL models, a second-best model with k = 1 and k = 1 is also estimated, and is numbered as Model 7 to test the sensitivity of parameter estimates and the diagnostic tests afterward. The last column reports Fourier-CS-PARDL, named as Model 9. For this model, the Fourier test results pointed to k = 2 and k = 1 with the highest rejection of the null at 1%. Estimation of a second-best model was not necessary for Fourier-CS-ARDL, since the calculated Fourier F test statistics for this model were significantly less than for other Fourier orders.

Author contributions

CRediT: **Özgür Ömer Ersin:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing; **Ayfer Ustabaş:** Investigation, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing; **Ojonugwa Usman:** Investigation, Project administration, Resources, Validation, Visualization, Writing – original draft, Writing – review & editing.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Data availability statement

Data will be made available on request. Data is also publicly available from the databases as detailed in Table 2 in Results of the correlation test of this study.

Annotations

EF	Ecological footprint
EI	Eco-innovation
NRD	Natural resource depletion
ENEF	Energy efficiency
RET	Renewable energy transition
CSD	Cross-sectional dependence
SBs	Structural breaks
PARDL	Panel autoregressive distributed lag
PEGLS	Panel explained generalized least squares
Fourier-PEGLS	Fourier PEGLS
FPARDL	Fourier PARDL
Fourier-CS-PARDL	Fourier cross-sectional PARDL
Fourier-CS-PGC	Fourier-cross-sectional panel Granger causality
RE	Renewable energy
REP	Renewable energy production
REC	Renewable energy consumption
Y	Economic growth
GDP	Gross domestic product

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Appendix

Table A1. Fourier order selection in three Fourier-augmented model structures.

Fourier(k;k)	(1;0)	(0;1)	(1;1)	(2;1)	(1;2)	(2;2)	(3;2)	(2;3)	(3;3)
sin	1	0	1	2	1	2	3	2	3
cos	0	1	1	1	2	2	2	3	3
				Fourier-ARDL					
F stat.	9.317**	9.220**	9.153**	20.682***	11.104**	8.352*	5.291	3.559	1.905
				Fourier-CS-ARDL					
F stat.	9.462**	9.039**	9.267**	20.449***	9.376*	8.200*	5.283	2.794	1.587
				Fourier-Panel-EGLS					
F stat.	8.761*	8.836*	11.301**	22.238***	9.221**	8.916*	6.960	6.375	3.765

Notes. A total of 486 models were estimated with max. The lag length for dependent and independent variables were taken as 2. The lowest Schwarz information criterion is achieved for a Fourier-CS-ARDL(1,0,0,0,0,0). Similar results were obtained for the two other Fourier-augmented models, i.e. FPARDL and Fourier-PEGLS.

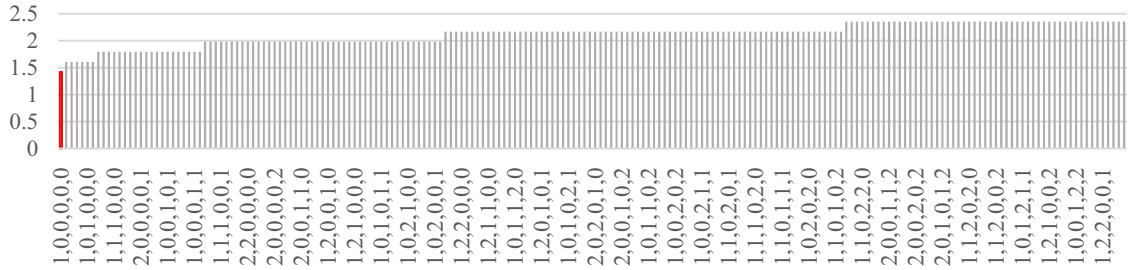


Figure A1. Model selection in Fourier-CS-ARDL.