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Policy Pathways for a Green Transition: Assessing the Interplay of Energy Diversification and Economic Complexity on the OECD's Load Capacity Curve

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Abstract

This study investigates policy-relevant pathways for achieving a green transition by examining the impact of energy diversification (ED) and economic complexity (EC) on load capacity factors (LCFs) across the Organization for Economic Co-operation and Development (OECD) countries from 1999 to 2021. To capture structural heterogeneity in environmental performance, this study develops a novel Energy Mix Concentration Index (EMCI), based on the Herfindahl–Hirschman Index, and employs Method of Moments Quantile Regression (MMQR), allowing for distribution-specific analysis beyond conventional mean-based estimators. The empirical framework integrates three distinct dimensions of ECI trade-based (ECI-Trade), technology-based (ECI-Technology), and research-based (ECI-Research) alongside GDP per capita and its squared term to test the validity of the load capacity curve (LCC) hypothesis. The findings of MMQR confirm the validity of the LCC hypothesis in OECD countries. ED is found to exert a statistically significant downward pressure on LCFs across all quantiles, with particularly strong adverse effects in environmentally constrained economies, highlighting the relevance of Jevons' paradox when diversification is not explicitly oriented toward low-carbon energy sources. Regarding EC, research-driven complexity positively affects LCFs, especially in lower LCF quantiles, by facilitating structural shifts toward cleaner, knowledge-intensive activities. In contrast, trade- and technology-based ECI reduce LCFs due to scale effects, supply-chain emissions, and rising energy demand, except in high-performing economies where strong institutions, stringent environmental regulations, and advanced renewable systems enable complexity-induced eco-innovation. These results underscore that innovation and diversification are not environmentally neutral and must be strategically directed. Overall, this study demonstrates that a successful green transition requires more than ED and economic upgrading alone. Effective policy pathways must combine targeted low-carbon energy strategies, mission-oriented research and development, and demand-side regulatory frameworks to ensure that EC reinforces, rather than undermines, environmental sustainability. The findings offer nuanced guidance for OECD policymakers seeking to align post-pandemic recovery strategies with long-term ecological resilience.

Keywords: green transition; energy diversification; economic complexity; load capacity curve

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1. Introduction

Air pollution and various weather and climate extremes have resulted from excessive reliance on fossil fuels, which are now essential to global energy production. Climate change causes humanitarian disasters by intensifying hurricanes, floods, tropical storms, heatwaves, and wildfires. Currently, 3.6 billion people live in high-risk zones, and it is projected that the climate crisis will cause an additional 250,000 deaths annually between 2030 and 2050 [1]. Since the adoption of the Kyoto Protocol in 1997, subsequent conferences like the "Paris Agreement" and the "Doha Amendment" have increasingly shaped national policies to prioritise clean energy, including nuclear and renewable sources, as responses to the climate challenge. This phenomenon is often explained by Jevons' paradox and rebound effects, whereby efficiency improvements reduce energy costs, stimulate higher energy use, and partially or fully offset expected environmental benefits. Jevons' paradox was first introduced by William Stanley Jevons in *The Coal Question* in 1865, where he observed that improvements in coal-use efficiency in England led to higher, rather than lower, overall coal consumption. Jevons argued that efficiency reduces the effective cost of energy services, which encourages greater use and expands economic activity, ultimately increasing the total energy demand. Building on this idea, the rebound effect describes the extent to which energy efficiency gains are offset by increased energy consumption, either directly through higher usage or indirectly through economy-wide growth effects. Rebound effects may be partial, complete, or even exceed initial savings, thereby limiting or reversing the anticipated environmental benefits of cleaner and more efficient technologies.

In the current "New Normal" paradigm, shaped by the COVID-19 pandemic and global sustainability challenges, this shift has become more urgent than ever. The New Normal has heightened the focus on energy security and the necessity of a robust, diversified energy mix to buffer against future global shocks. At the Climate Change Conference of the Parties (COP-26) in Glasgow, the Organization for Economic Co-operation and Development (OECD) also proposed achieving carbon neutrality by 2050. During the COP-26 summit, major commitments were made to keep the global temperature rise below 2 °C, with each country pledging to limit increases to 1.5 °C within the given timeframe. According to Jahanger et al. [2], achieving this goal depends on reducing fossil fuel use in energy production, fostering energy innovation, and increasing investments in renewable energy (RE). By 2030, Sustainable Development Goals (SDGs) 7 (Clean Energy) and 9 (Industry, Innovation, and Infrastructure) aim to significantly increase the share of RE [3]. SDG-8 aims to decouple economic growth from environmental degradation by steadily improving resource productivity, while SDG-12 strives for resource efficiency and sustainability [4]. There is a continuous tension between promoting prosperity and protecting ecological health, as greenhouse gas (GHG) emissions often rise alongside economic growth. Efforts to reconcile these objectives have led to various strategies supporting low-carbon development and the broader green energy transition. Sometimes, environmental quality (EQ) and economic progress align, while at other times they conflict. In many industrialised economies, progress in EQ has often been accompanied by economic growth due to structural changes, such as shifting from coal to gas, reducing industrial intensity, and increasing reliance on cleaner energy sources [5]. Since the 1950s, energy has been a key driver of economic growth [6]. Relying on fossil fuels significantly contributes to GHG emissions, air pollution, and ecological damage, making the transition to cleaner energy sources essential. Energy diversification involves integrating greener alternatives into the energy mix to reduce dependence on high-carbon sources, especially coal and oil, and to promote options with lower or zero emissions, such as renewable energy, nuclear power, and natural gas [7]. Diversification also reduces output volatility and decreases vulnerability to global energy shocks, supporting sustainable economic growth [6]. In 2014, approximately 59%

of electricity in OECD countries was generated from fossil fuels; this figure decreased to 48% in 2024 [8]. Since then, the environmental impacts associated with combustion have lessened as their share has declined by more than one percentage point annually.

As shown in Figure 1, overall electricity generation has somewhat increased, remaining within the range of 9000 to 11,000 TWh. Consistent with the global shift towards cleaner energy, the mix is shifting away from coal and oil towards gas and renewables. These differences highlight the importance of energy diversification when assessing how well OECD countries are performing environmentally. Since OECD nations consume a significant share of the world's energy, their transition strategies influence both the local environment and the global progress towards sustainability.

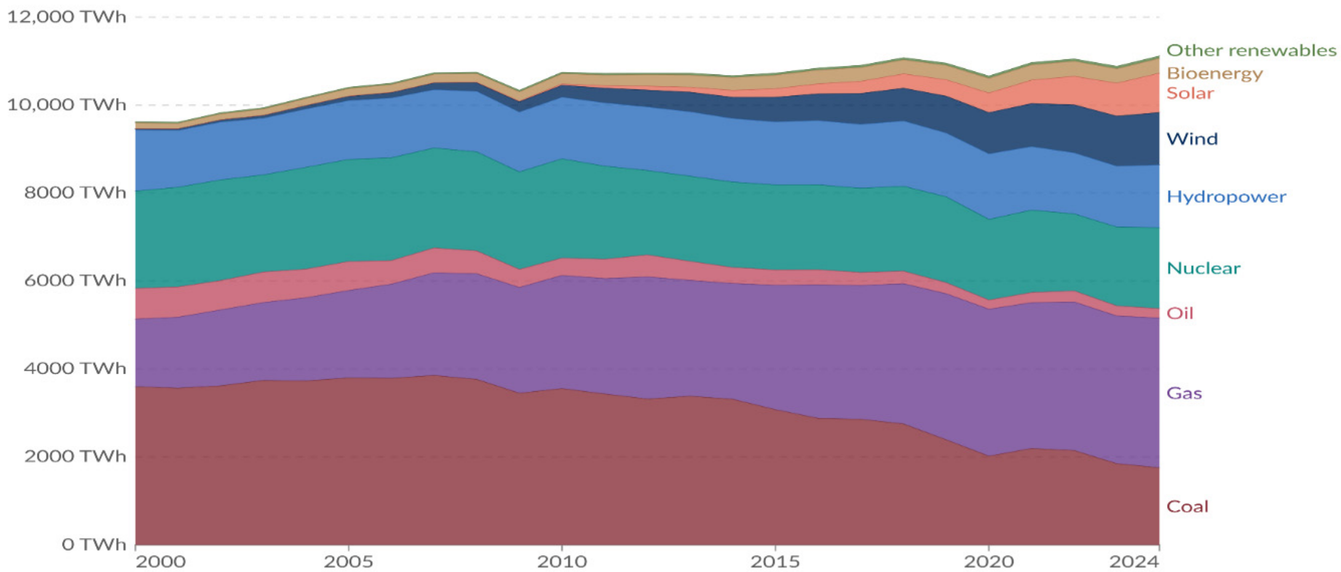

Figure 1. Electricity generation by source in OECD countries in 2025. Data source: [8] Energy Institute—Statistical Review of World Energy (2025). Note: "Other renewables" include geothermal, wave, and tidal.

Furthermore, it is crucial to understand how the economic structure impacts environmental quality across different economies. To better evaluate economic structure, Hausmann and Hidalgo [9] developed the concept of economic complexity (EC). This approach surpasses traditional aggregation methods by analysing detailed economic data through dimensionality reduction. Recent developments include relatedness metrics that predict changes in specialisation, as well as metrics that assess economic sophistication based on geographic data. Due to substantial structural changes, OECD countries often rank among the most developed worldwide in terms of EC. In 2021, seven OECD countries ranked in the top 10 of the indices (ECI): Japan held the top position, with Switzerland second, South Korea fourth, Germany sixth, and the United Kingdom tenth [10]. However, relying solely on ECI trade could give a skewed picture of complexity. For example, Mexico is placed 23rd, surpassing Australia (82nd), Canada (32nd), and Norway (38th). In addition to indicators from the Observatory of Economic Complexity, Hamrouni et al. [10] used ECI technology and ECI research to address these issues. Based on their analysis, Canada moves up to 11th and 3rd positions, respectively, while Mexico drops to 58th in technology and 32nd in research. These adjustments reveal that trade-based rankings may overlook important aspects of research and innovation capacity. Unlike countries such as Mexico, Lithuania, Hungary, and Slovakia, which display high export complexity but lack in knowledge generation, New Zealand, Chile, Australia, Norway, and Canada show a stronger connection with technology and research. Therefore, Hamrouni et al. [10] concluded that integrating ECI trade, ECI technology, and ECI research provides a more comprehensive assessment of economic complexity in OECD nations.

Within the OECD nations, environmental quality is relatively superior in Colombia, Norway, Sweden, and Canada. Nonetheless, numerous members continue to struggle with enhancing ecological performance. Figure 2 depicts the performance of the LCFs in 2022 among OECD nations. OECD member countries exhibit an ecological deficit, as their economies consume resources at a rate surpassing the replenishment capacity of their ecosystems. Concerning long-term environmental sustainability, many member nations are in a vulnerable position, as depicted in Figure 2. In 2022, their ecological footprints exceeded their biocapacity. This discrepancy highlights the necessity of recognising the factors that influence the LCFs. Debates over the legitimacy of the LCC continue, with academics analysing the impact of many elements on the LCC, such as GDP, energy consumption, geopolitical risk, tourism, renewable energy, nuclear energy, and foreign trade [11,12].

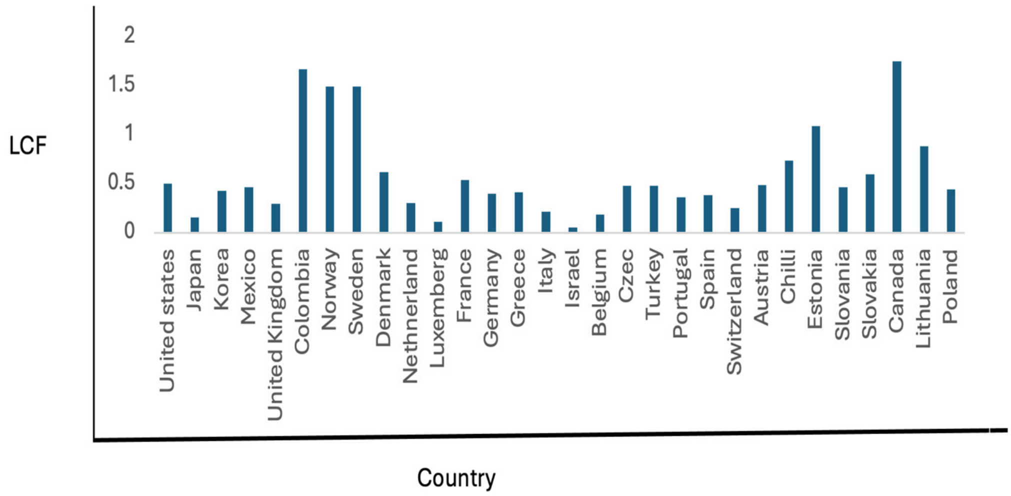

Figure 2. Load capacity factor (LCF) in 2022 across OECD nations.

Nevertheless, the impact of energy diversification (ED), ECI trade, ECI technology, and ECI research on LCFs has not been considered in any of the LCF and LCC assessments conducted so far in OECD countries. This gap is significant, as recognising these interfaces is essential for designing effective recovery policies focused on a just green transition. Ecological quality is heavily influenced by the combination of EC and ED. A more complex economy accelerates the shift to sustainable industries, whereas a more diverse economy reduces emissions and enhances resilience. Conversely, economies lacking diversity and complexity are prone to perpetuating carbon-intensive growth paths, worsening environmental impacts. Environmental effects are also notably affected by EC, which refers to the variety and sophistication of a country's manufacturing structure. More complex economies are usually better at adopting new technologies, fostering eco-innovation, and integrating sustainable practices into industrial processes. Our research enriches the body of literature in several ways: First, unlike earlier studies that focused on trade-based measures of complexity, we adopt a multifaceted approach that combines research and technology. This is the first assessment of the impacts of ECI trade, ECI technology, and ECI research on LCFs, aimed at improving understanding of the environmental consequences of EC. Hamrouni et al. [10], for example, examined the effects of ECI commerce, ECI technology, and ECI research on CO_2 in OECD nations over the same period but did not consider EF and LCFs, which can serve as indicators of environmental degradation. Second, despite the substantial literature on the environmental impacts of renewable and non-renewable energy production and consumption [13–19], the topic of ED has not been thoroughly explored in academic research, and there is a lack of empirical studies investigating the influence of ED on the ecological footprint, especially concerning LCFs in OECD countries. This work is vital for supporting energy production and diversification-driven climate policies. This paper proposes examining these effects within the OECD framework using a panel quantile regression model. Additionally, this research develops an energy diversification metric for OECD nations. This study aims to unify the diverse literature by employing a method that combines both renewable and non-renewable energy sources into a single ED metric, providing actionable insights for policymakers managing the green transition.

The rest of this paper is structured as follows: Section 2 presents the literature review, Section 3 describes the methodology, Section 4 reports and discusses the results, Section 5 outlines the policy implications and conclusions, and Section 6 highlights the limitations of the study.

2. Literature Review

2.1. Energy Diversification

The purpose of this study is to ascertain how EC, ED, and per capita income affected LCFs in OECD nations between 1999 and 2021. To reduce dependency on a single fuel and increase resilience, ED involves increasing the range of energy sources within a national energy framework [20]. Advances in digital technology, especially artificial intelligence, have accelerated the search for and deployment of new energy sources, facilitating the shift to more diverse and flexible energy systems [21,22]. National energy compositions often comprise fossil fuels, coal, oil, and natural gas, alongside renewable sources such as hydro, wind, solar, geothermal, and nuclear energy. The composition of this mixture varies between countries, reflecting differences in resource endowments, developmental paths, and governmental objectives. ED is often seen to reduce environmental impact, increase energy security, and eventually foster sustainable growth [6]. In the post-pandemic age, diversification has become essential as governments aim to bolster system resilience in the "New Normal".

However, variation may not always translate into better environmental outcomes. Two notable mechanisms, the rebound effect and Jevons' paradox, illustrate this complexity. The rebound effect highlights the possibility that green technology may unintentionally raise total energy consumption due to heightened usage of or reliance on environmentally detrimental resources [23–25]. Jevons' paradox states that increased productivity and consumption can arise from increased energy source availability or efficiency, which will eventually raise emissions [26]. The magnitude of these unforeseen repercussions depends on factors such as technological readiness, family environmental awareness, and the strictness of national regulations. Furthermore, the environmental consequences of diversity vary according to income level and institutional capability. Economies characterised by advanced technologies, robust laws, and heightened environmental awareness are more adept at mitigating rebound effects and managing diversification sustainably. In contrast, nations with inadequate regulatory frameworks or significant dependence on carbon-intensive fuels may face intensified environmental degradation while diversifying their energy systems.

Environmental degradation is impacted differently by different energy uses [27]. ED was identified by De Freitas and Kaneko [28] as a strategy for developing a low-carbon society and encouraging sustainable economic growth. Bandyopadhyay et al. [29] for India, Jahanger et al. [30] for Malaysia, and Tiwari et al. [31] for Brazil and China demonstrate a deficiency of research on this subject, particularly on the use of hydroelectricity. The literature indicates that only three studies have examined the direct effects of ED on ecological conditions: [32–34]. Kouton et al. [34] focused on Côte d'Ivoire, providing country-specific evidence from a developing economy. Their findings show that ED can reduce environmental pressure by lowering dependence on carbon-intensive energy sources. However, the environmental benefits are strongly shaped by the country's energy structure and institutional capacity, implying that diversification alone is insufficient without supportive policies and governance. Sugiharti et al. [33] concentrated primarily on renewable energy diversification, although their analytical framework included both renewable and non-renewable sources. Their results suggest that diversifying renewable energy portfolios strengthens environmental sustainability by reducing emissions' intensity and improving energy resilience. Their study highlights that shifting not just toward renewables, but toward a varied mix of renewable sources, enhances environmental outcomes more effectively than reliance on a single clean technology. Hoang et al. [32] provided the most comprehensive and globally comparative evidence, analysing 66 economies from 1995 to 2018 using panel quantile regression. This approach allowed them to examine how the environmental effects of ED differ across countries with varying emission levels, income groups, and stages of economic development. However, their empirical results suggest that ED could alleviate the ecological footprint in most high-income countries and all middle-income countries.

The literature highlights significant variability in the impact of various energy sources within the mix on ecological effects. Continuous reliance on fossil fuels erodes the ecological benefits of diversification, whereas strategies with a high proportion of renewables can reduce emissions and facilitate low-carbon transitions [27,28]. Recent studies corroborate this assertion by demonstrating that the ecological impact of diversity is dependent upon context and varies among income groups and carbon-emission profiles [32–34]. High- and upper-middle-income countries frequently experience advantages from diversity when bolstered by strong governance and appropriate green policies; conversely, adverse environmental impacts may occur when diversification increases access to fossil-based energy. These findings highlight the necessity of differentiating between ED that enhances clean-energy capacity and ED that perpetuates fossil fuel reliance, especially when evaluating sustainability outcomes.

2.2. Economic Complexity

An economy's capacity for innovation, structural diversity, and green transformation is shaped by its productive knowledge and technological skills, which are reflected in EC. Due to the propensity of complex economies to generate more advanced products and exhibit superior technological skills, EC is becoming increasingly vital in national sustainability policies. However, the form of technical specialisation, institutional quality, and developmental stage all influence its diverse environmental effects. Can and Gozgor [35] first outlined the connection between environmental degradation and EC in France between 1964 and 2011, highlighting the part that EC plays in this relationship. However, their research asserts that the expected environmental impacts of EC vary based on the social strata of the country.

From a developmental standpoint, as industrial upgrading frequently depends on resource- or energy-intensive manufacturing, increases in EC may initially exacerbate environmental deterioration in lower- and middle-income nations [35]. However, as nations gain knowledge, develop their technological capabilities, and fortify their regulatory frameworks, EC can eventually enable cleaner production systems, allowing economies to shift to low-carbon industries. This dynamic is like the EKC route, which shows that environmental pressure may get worse during the early phases of growth but get better as technology advances. Therefore, the alignment of technology advancement and regulatory control shapes the link between EC and environmental quality. By encouraging businesses to pursue green innovation, resource efficiency, and pollution management, strong institutions, strict environmental legislation, and a high level of ecological consciousness can enhance the benefits of EC. In contrast, inadequate governance or policy misalignment may allow technologically advanced yet environmentally detrimental industries, such as petrochemicals, heavy manufacturing, or fossil fuel extraction, to proliferate, hence exacerbating ecological strain.

Current research expands the evaluation by including metrics such as EF and LCFs, which more thoroughly incorporate supply-side ecological restrictions than CO_2 emissions alone. Evidence from these broader indicators indicates that energy transition, renewable energy adoption, and political stability enhance environmental quality in conjunction with EC. However, it may decline under conditions of high fossil energy dependence, political risks, or increasing energy consumption. These results demonstrate that EC is not intrinsically green; rather, its environmental impact is contingent upon institutional frameworks, complementary policies, and the cleanliness of the underlying energy system. The literature highlights that EC and ED both function through complex pathways influenced by institutional quality, structural conditions, and technological capabilities. Their conditional, context-specific, and non-linear environmental effects emphasise the significance of integrated policy frameworks that balance ecological sustainability, technological advancement, and diversification.

Accordingly, it is assumed that EC increases CO_2 emissions in lower- and middle-income countries while decreasing them in high-income countries. Using fully modified ordinary least squares (FMOLS) and dynamic ordinary least squares (DOLS) approaches, Neagu and Teodoru [36] investigated the environmental impact of economic complexity in the context of European Union (EU) countries. Their research revealed that, as economic complexity increases, so do CO_2 emissions in EU nations. Feng et al. [37] discovered that EC initially has a beneficial effect on pollution in BRICS-T economies but later has a negative effect. This implies that, in these economies, the EKC theory is validated. Daghbagi et al. [38] also confirmed that the ECI of technology and increasing CO_2 emissions in G20 countries are correlated over the long run. Prior empirical research has generally utilised CO_2 emissions and EF as indicators of environmental quality; however, these metrics overlook supply-side environmental issues. Recent research utilised LCFs as a proxy for environmental deterioration to investigate the influence of economic complexity on other variables. The existing literature generally falls into three main positions: one group reports a positive relationship, indicating that higher economic complexity worsens environmental quality; another group finds a negative relationship, suggesting that economic complexity improves environmental outcomes; and a third group identifies an inverted U-shaped relationship, showing that the impact of economic complexity on the environment changes at different stages of development.

As the first to examine this relationship, Can and Gozgor [35] found that more complex economic structures contribute to the mitigation of carbon dioxide emissions in the long run in France. This suggests that, at advanced stages of economic development, greater economic complexity supports environmental sustainability by reducing carbon emissions. Using the DOLS methodology for the period 1964–2014, the study also found evidence for the existence of the EKC in France. Moreover, Bucak, Ç. & Çatık, A. N [39] also found EC to be beneficial for environmental health, as indicated by the LCF, in 25 EU countries. Using spatial econometric methods over the period 1995–2021, their study not only confirms the EC–LCF nexus but also suggests the presence of spillover effects in LCFs among EU nations, while finding no concrete evidence for the existence of the LCC hypothesis. In addition, Ullah et al. [40] provide further evidence on the determinants of environmental capacity in BRICS-T economies in a different study. Utilising the non-linear ARDL approach for the period 1990–2018, the results indicate that upward changes in EC enhance the LCF in the long run, although short-term effects are statistically insignificant. Conversely, economic growth and fossil fuel consumption were found to be harmful for environmental quality, as they decrease the LCF in both the short and long term. Extending this line of inquiry, another study conducted for the top ten emitters around the globe found that a more complex economic structure is in favour of the LCF, as the obtained results from the employed CS-ARDL estimates confirm its positive contribution to environmental quality alongside renewable energy and energy security [41]. In contrast, some studies also suggest that EC can act as a harmful driver of the LCF. For instance, Awosusi et al. [42] concluded that, in the case of Japan, EC negatively affects the LCF. The results obtained from the dynamic ARDL method over the period 1980–2017 further indicate that, in addition to EC, economic growth and financial development also exert adverse environmental effects. Likewise, recent evidence from G7 economies highlights that economic complexity alone can worsen the environment. Using the MMQR and FMOLS over the period 1995–2020, the results indicate that EC can have a positive impact on the LCF when interacting with green technological innovations, suggesting that the harmful effects of economic complexity can be mitigated only when combined with clean technologies [43]. A study by Sarabdeen et al. [44] examined the impacts of digital adaptation, energy transition, export diversification, and income inequality on the LCF using panel data from 112 countries over the period 2010–2021. In the OECD context, although no study has specifically quantified the EC–LCF relationship, the research by Lee and Olasehinde [45] used Driscoll and Kraay (DK-FE) and Generalised Method of Moments (GMM) estimation techniques to examine the link between EC, which is trade-based, and environmental performance in OECD nations for the period 2007 to 2016. The findings of the study revealed that EC positively impacted environmental performance in the OECD countries. Similarly, Hassan et al. [46] stated that high scores on the ECI increase the pressure on the ecological footprints of OECD countries, but they also used the ECI index, which was trade-based. Hamrouni et al. [10] analysed the relationship between EC and CO_2 emissions using annual data from OECD countries from 1999 to 2021. They first included measures of EC associated with non-trading activities, such as patents and research publications, to complement traditional trade-based EC. The PMG-ARDL approach shows that the different dimensions of EC have a positive and significant impact on long-term CO_2 emissions. Like that of Hamrouni et al. [10], this study adopts a multidimensional framework of EC, distinguishing between trade-based (ECI-Trade), technology-based (ECI-Technology), and research-based (ECI-Research) complexity. However, unlike their focus on CO_2 emissions, the present study employs the LCF as a comprehensive indicator of environmental sustainability, thereby capturing both ecological supply constraints and human demand pressures.

2.3. Theoretical Literature

Within the framework of the energy ladder hypothesis and fuel stacking model, Van der Kroon et al. [47] emphasised the importance of contemporary fuels in promoting social and economic development and stressed the need to switch to cleaner and more efficient energy sources to reduce environmental impact. Consequently, the framework of this research aligns significant theories identified in the literature on the energy–environment nexus. The treadmill of production theory is the first idea. The treadmill of production hypothesis, developed by Schnaiberg [48] in 1980, cites patterns of energy production as the main factor explaining the growing environmental problems in the context of modern globalisation. It asserts that the exploitation of natural resources is a catalyst for these problems [49]. Since the demand for natural resources in affluent countries appears to be directly responsible for environmental degradation, the focus here is on underdeveloped countries. In reaction to increased competition due to globalisation, we witness the intensification of manufacturing processes, motivated by companies' quest for profit maximisation. Ultimately, this production rate results in significant resource consumption and the release of harmful elements into the environment [48]. Owing to limited resources and rising energy demand, energy sources are becoming more diverse. The energy mix of a nation consists of diverse energy production resources, encompassing both renewable and non-renewable sources, which are affected by several factors, including the nation's level of development.

The second theory is the EKC theory, which asserts an inverted U-shaped relationship between environmental pollutants and income levels. Environmental pollutants, including greenhouse gas emissions [50–52], water contamination [53,54], and deteriorating air quality, have been the primary focus of the EKC theory. To circumvent this limitation, broader environmental sustainability metrics have been employed. The load capacity factor (LCF) is particularly relevant, since it may demonstrate how the production and consumption of natural resources are balanced in a sustainable way [18]. Pata [18] described ecosystems' yearly capacity to generate renewable biological resources and absorb waste, in addition to their ecological footprint, which measures the total biologically productive space needed for a population's consumption and waste absorption.

Dogan and Pata [55] were the pioneers in identifying a U-shaped correlation between LCFs and per capita income, which they referred to as the load capacity curve (LCC) theory. Figure 3 shows how the LCC theory works. According to the hypothesis, human activities that disregard environmental concerns and the usage of fossil fuels seriously degrade environmental quality in the early phases of economic development. Reduced ecological footprints and increased biocapacity can improve environmental quality as income rises because, after a certain point, wealthier people are more likely to use renewable energy sources and buy ecologically friendly items.

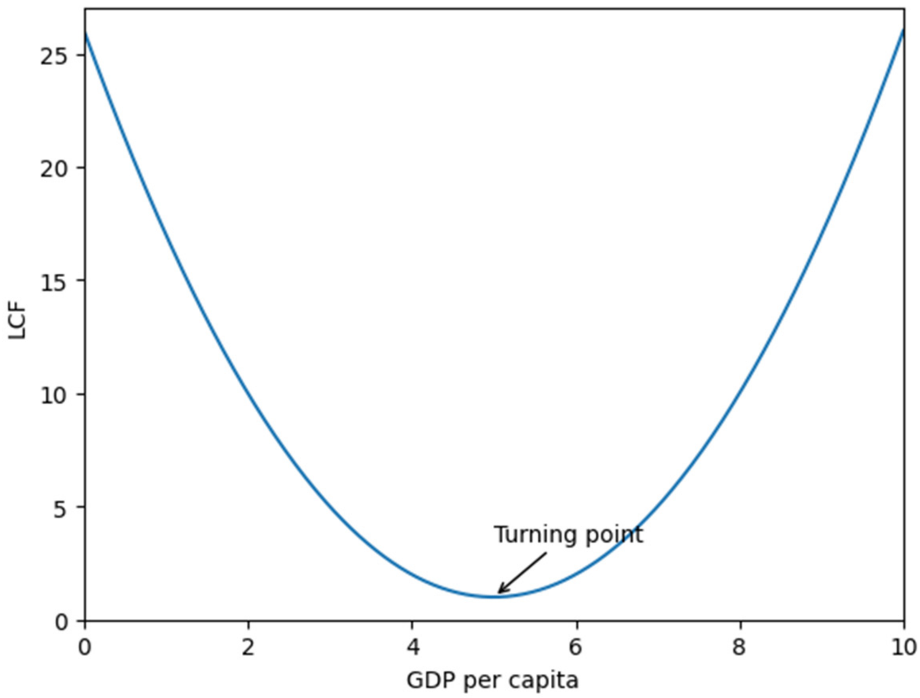

Figure 3. Load capacity curve (LCC).

The third strategy, called ecological modernisation, was created in the 1980s and posits that economic expansion and environmental protection may coexist [56]. This can be accomplished through creative production and management techniques, as well as increased energy and resource efficiency. Therefore, the implementation of clean technologies and renewable energy is strongly encouraged. Pollutant emissions and resource exploitation are reduced when these suggestions are put into practice. New energy sources that are more environmentally friendly and efficient are now being considered. As a result, the energy composition is improved and purified. It is believed that energy production techniques that focus on a single energy source and rely primarily on production capacities may accelerate environmental degradation. This appears to pertain to energy variety, characterised by a blend of energy sources that is optimally rich in renewable energy.

2.4. Research Hypotheses

This study, which is based on Dogan and Pata's [55] LCC theory, looks at the non-linear link between environmental capacity and economic growth. The LCC hypothesis posits that environmental quality, as assessed by the LCF, initially declines with increasing income due to reliance on fossil fuels and production growth, but then subsequently improves beyond a specific income threshold as economies transition to cleaner energy sources, sustainable technologies, and eco-friendly consumption practices.

H1: *The LCF and per capita income have a U-shaped relationship (while economic growth initially decreases environmental capacity, it eventually increases it above a certain income threshold).*

Building on this relationship between growth and the environment, this study examines how various aspects of EC impact environmental capacity. It acknowledges that EC is multifaceted and that its effects on the environment vary depending on the type of productive specialisation. Trade-based EC signifies the sophistication of exports and their integration into global value chains. Although heightened export complexity may indicate economic progress, the current evidence implies that when export structures are energy- and carbon-intensive, trade-induced complexity can escalate production scale, energy consumption, and environmental strain, especially in the lack of stringent environmental regulations and clean energy incorporation.

H2: *The environmental LCF is negatively impacted by trade-based economic complexity (ECI-Trade).*

The accumulation of non-trading knowledge such as patents and scientific research, which supports innovation, green technologies, and resource efficiency gains, is captured by research-based EC. Previous research suggests that knowledge-based complexity improves long-term environmental sustainability by promoting cleaner industrial methods and aiding low-carbon structural transformation, especially in developed economies.

H3: *The LCF is positively impacted by research-based economic complexity (ECI-Research).*

EC based on technology reflects the spread and use of modern production technologies. While technical enhancement enhances efficiency, empirical data reveals rebound effects and scale growth that could elevate energy consumption and environmental strain unless paired with green technological innovation and a shift to clean energy. Figure 4 shows the study's theoretical framework.

H4: *The LCF is negatively impacted by technology-based economic complexity (ECI-Technology).*

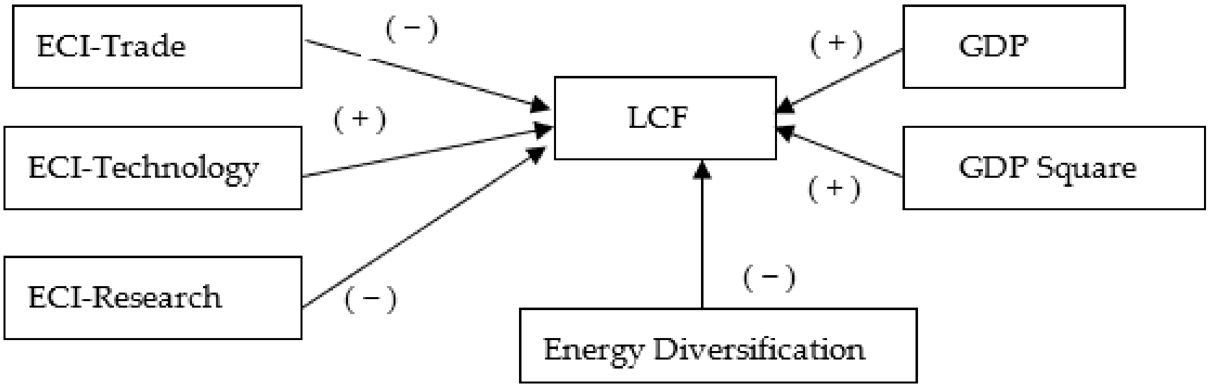

Figure 4. Theoretical framework of the study.

3. Methodology

3.1. Econometric Model

An essential tool in ecological education, the LCC offers important insights into the intricate relationships among environmental sustainability, economic stability, and human growth [57]. Because it shows whether the ability to recover its resources (biocapacity) and the ways in which it uses human resources are balanced, this curve is significant. It is believed that GDP and GDP squared act as the main factors in the U-shaped relationship of the LCC hypothesis [58–60], suggesting that the effects of GDP and GDP squared on environmental quality follow distinct patterns. Wu et al. [61] claimed that resource exploitation and energy consumption are initially inversely correlated with GDP growth. The LCC theory has been studied in the literature by several researchers [62–65]. The following equation can be taken into consideration for LCC theory:

$$LCF_{it} = \beta_0 + \beta_1 GDP_{it} + \beta_2 GDPsq_{it} + \beta_3 EMCI_{it} + \beta_4 ECIR_{it} + \beta_5 ECITR_{it} + \beta_6 ECIT_{it} + \varepsilon_{it} \quad (1)$$

where LCF is considered as a proxy of environmental degradation, which is the dependent variable, while the independent variables are GDP, GDPsq, EMCI, ECIR, ECITR, ECIT, which represent economic growth, economic growth squared, energy diversification index, and ECI in research, trade, and technology, respectively, while ε_{it} indicates the stochastic error term. To prevent heteroscedasticity and variation, all of the variables are transformed into the natural logarithm, except for ECI.

3.2. Data

The objective of this study is to analyse the impact of economic growth, ED, and EC on LCFs in OECD countries for the years 1999 to 2021. Table 1 presents the variables' acronyms, along with descriptions and sources of the dependent and independent variables. In Table 1, the dependent variable is the LCF. As previously discussed, only two studies using spatial econometric methodologies have analysed the relationship between environmental degradation and complexity [66,67], but neither used the LCF as an environmental indicator. We calculate the LCF by dividing the biocapacity by the ecological footprint. The LCF captures the supply side of environmental sustainability, i.e., ecological assets (biocapacity), and the demand side of environmental sustainability, i.e., ecological footprint. It can be argued that this is more comprehensive, as it does not present a single-sided indicator, such as CO_2 emissions per capita or EF alone, and presents a clear picture of environmental sustainability. If a country's LCF is greater than 1, it indicates that the country is extracting fewer resources than its biocapacity can sustain. Conversely, if the LCF is less than 1, it indicates that the country is extracting more resources than its available biocapacity.

Table 1. Descriptions of dependent and independent variables.

Variables	Acronym	Description	Source
Load Capacity Factor	LCF	Biocapacity/ecological footprint (per capita, global hectares)	Global Footprint Network. (2023). National Footprint and Biocapacity Accounts. https://data.footprintnetwork.org [68],
Economic Growth	GDP	GDP per capita (constant 2015 US$)	World Bank Development Indicator. https://databank.worldbank.org/source/world-development-indicators [69],
Energy Mix Concentration Index	EMCI	Herfindahl–Hirschman Index	World Bank Development Indicator https://databank.worldbank.org/source/world-development-indicators [69],
Economic Complexity-Trade	ECITR	Trade complexity	Observatory of Economic Complexity. (2023). *The Atlas of Economic Complexity*. Massachusetts Institute of Technology. https://oec.world [70],
Economic Complexity-Technology	ECIT	Technology complexity	Observatory of Economic Complexity. (2023). *The Atlas of Economic Complexity*. Massachusetts Institute of Technology. https://oec.world [70],
Economic Complexity-Research	ECIR	Research complexity	Observatory of Economic Complexity. (2023). *The Atlas of Economic Complexity*. Massachusetts Institute of Technology. https://oec.world [70],

Economic growth and the square of economic growth are considered as the independent variables, as presented in Table 1. Economic growth is measured by GDP per capita in constant 2015 US dollars. Another independent variable is ED. We measured this through an Energy Mix Concentration Index (EMCI), which was calculated using the Herfindahl–Hirschman Index (HHI) [71,72]. The market concentration of an industry in a geographic area can be measured by the HHI, which is based on a firm's size compared to that of the industry among the firms [70]. The HHI is expressed as follows:

$$EMCI_t = \sum_i^t S_i^2 \quad (2)$$

where S_i represents the firm's i market share.

The EMCI measures energy diversity, which denotes the mix of generation sources, renewable (hydro, nuclear, solar, and thermal) and non-renewable (coal, oil, gas), used to produce electricity. Economies with higher dependence on non-renewable sources typically exhibit greater environmental pollution over the long term.

$$EMCI = \sum_i^t P_i^2 \quad (3)$$

where P_i represents the share of the energy source i in the energy mix. As part of the index calculation for the current study, where i (coal, oil, gas, hydro, nuclear, solar, thermal, biofuels, waste), lower EMCI values signify more energy diversity, with 0 being the lowest concentration and 1 denoting the highest concentration.

Since the EMCI is a concentration index, lower EMCI values indicate greater energy diversification, while higher values reflect greater concentration in a small number of energy sources. Accordingly, a negative coefficient on EMCI implies that higher concentration is associated with a deterioration in environmental capacity (lower LCF), whereas greater diversification improves the LCF, but only conditionally. Specifically, diversification contributes positively to environmental capacity when it is driven by low-carbon and renewable energy sources. In contrast, diversification that incorporates or expands fossil fuel use may fail to improve, or may even worsen, environmental outcomes. Therefore, the estimated negative relationship between the EMCI and LCF should be interpreted as evidence that energy concentration, particularly when carbon-intensive, undermines environmental sustainability, while diversification enhances the LCF only when aligned with decarbonisation objectives.

Figure 5 shows how the average EMCI values (2016–2021) varied among OECD nations, emphasising variations in the degree of diversity in each country's energy mix. The highest EMCI values were found in nations like Norway, Belgium, and Lithuania, suggesting a more concentrated reliance on a small number of energy sources, frequently because of a heavy reliance on nuclear or hydropower. The EMCI scores of Germany, Austria, and Turkey, on the other hand, are lower, indicating more balanced and diverse energy structures. Most OECD nations exhibit a moderate range (0.30–0.36), indicating a combination of fossil fuels, renewable energy, and nuclear power in their energy supply. Overall, the figure shows a great deal of variation in the concentration of the energy market throughout the OECD: lower EMCI values often indicate greater energy security and resilience, whereas higher values indicate susceptibility to price volatility or supply shocks.

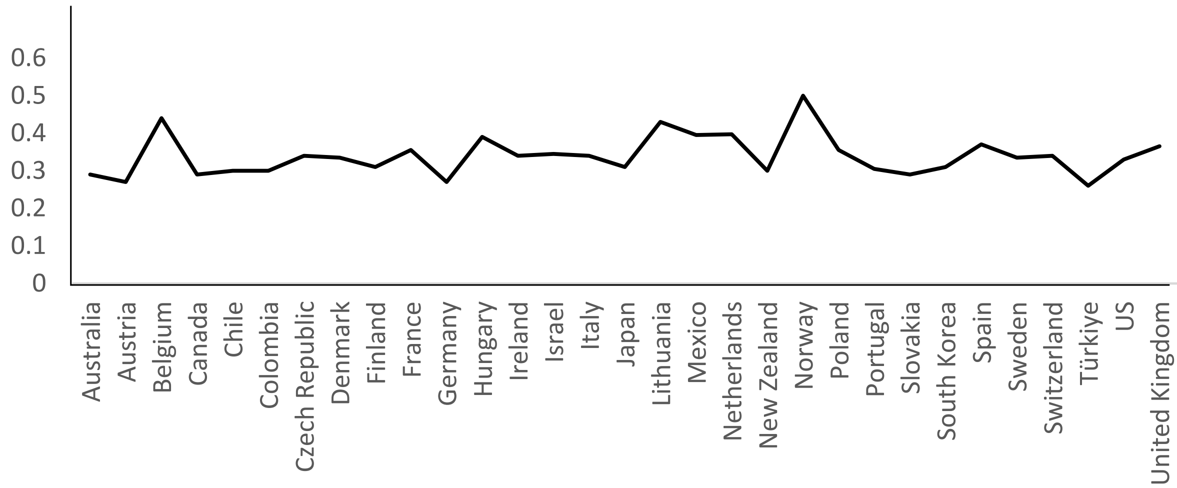

Figure 5. Average EMCI values (2016 to 2021) for OECD countries.

Lastly, ECI is also an independent variable in Table 1. ECI measures the sophistication of a society's network of interactions to represent the extent of productive knowledge sharing. A higher ECI indicates that the society or country produces goods that cannot be easily replicated by others, thereby increasing its exports and income [73]. Previous studies mostly used the ECI-Trade, but the problem with ECI-Trade is that it cannot present the significant side of the research and innovation of a country. By incorporating ECI-Research and -Technology, it is expected that this study can overcome this problem.

Figure 6 shows the average ECI-Research values for OECD countries from 2016 to 2021. According to Figure 6, the countries with the highest ECIR values (2.0–2.5) are the United States, Canada, Germany, and the United Kingdom. These economies possess advanced research infrastructure, substantial R&D expenditure, and robust connections between universities and the high-tech industry. Additionally, the figure demonstrates that the ECIR (<0.5–1.0) is lower in Turkey, Mexico, Poland, Slovenia, the Czech Republic, Lithuania, South Korea, and Slovakia. Less knowledge is required for their exports and R&D, or they are still moving towards higher-tech industries.

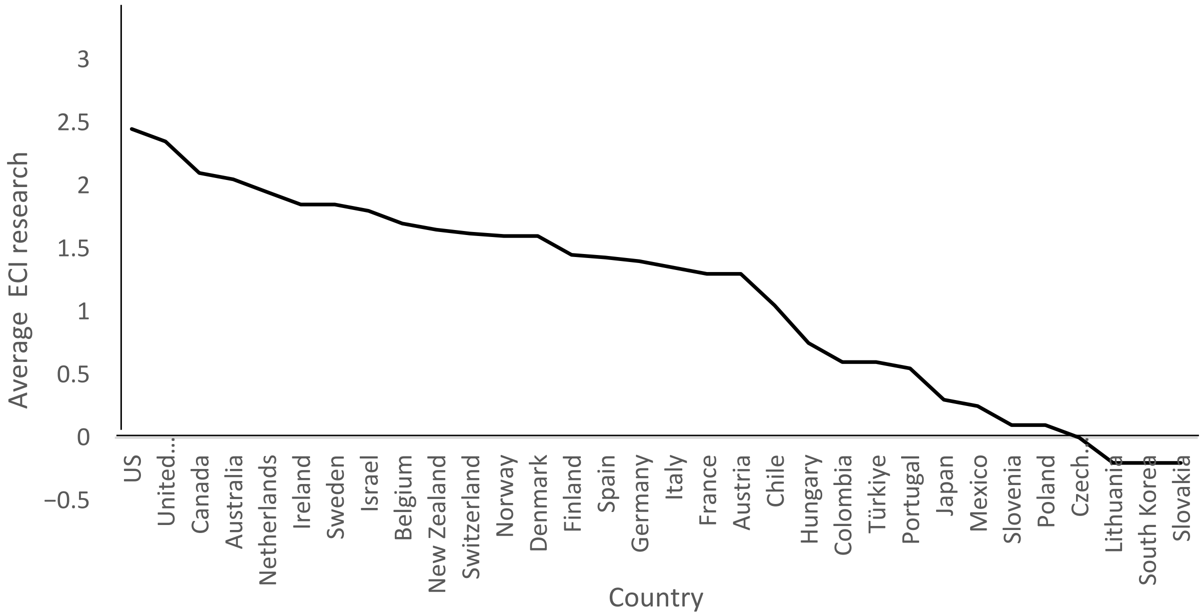

Figure 6. Average ECI-Research values (2016 to 2021) for OECD countries.

Figure 7 shows the average ECI-Technology values for OECD countries from 2016 to 2021. Figure 6 shows that Sweden, Austria, Germany, Italy, and France lead with ECIT values near 1.4–1.5, indicating high technological innovation and sophisticated industrial structures. The figure also shows that Mexico, South Korea, Colombia, and Lithuania show ECIT below 0.5, signalling less advanced technological diversification or dependence on mid-tech sectors.

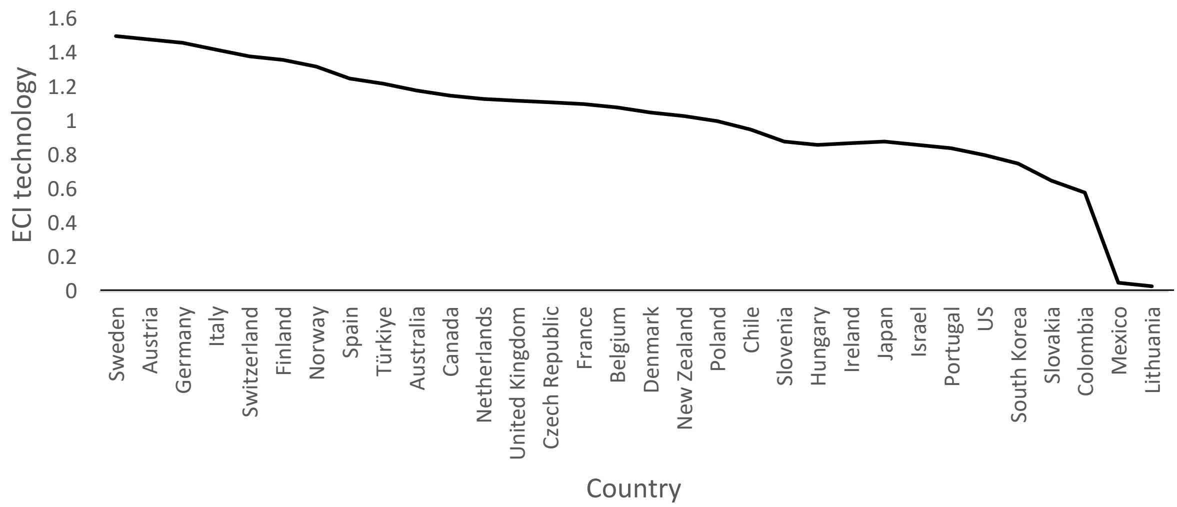

Figure 7. Average ECI-Technology values (2016 to 2021) for OECD countries.

Figure 8 shows the average ECI-Trade values for OECD countries from 2016 to 2021. The figure reveals that Japan, Switzerland, Germany, South Korea, and the Czech Republic exhibit the strongest trade complexity, averaging between 1.8 and 2.2. These economies export high-tech goods such as electronics, automobiles, and precision instruments, supported by advanced R&D and innovative ecosystems. Figure 7 also shows that Portugal, Spain, Norway, Mexico, New Zealand, Chile, and Australia display scores below 1.0, reflecting lower technological content and heavier reliance on primary or medium-tech exports.

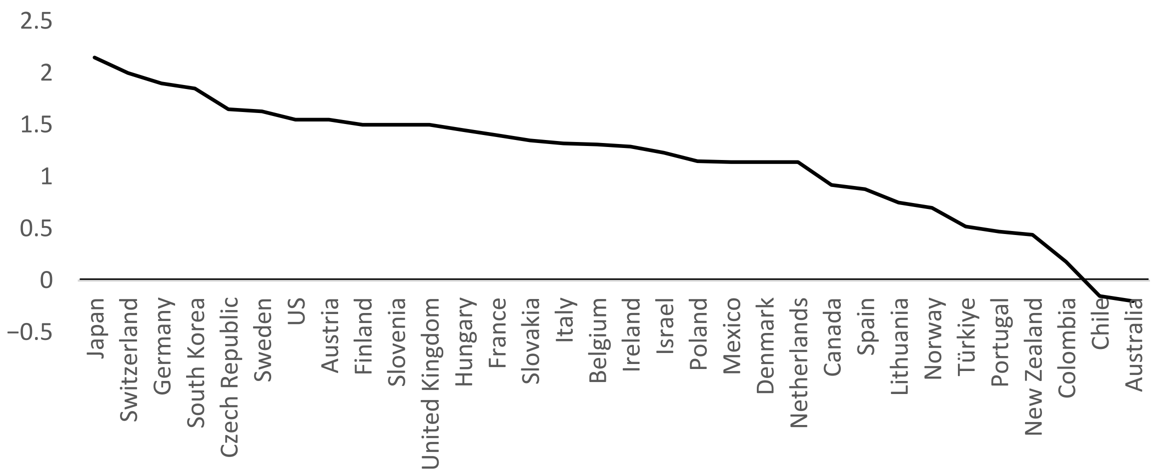

Figure 8. Average ECI-Trade values (2016–2021) for OECD countries.

3.3. Summary Statistics and Correlation Analysis

Table 2 provides the summary statistics of time-series data. If we convert the lnLCF value of −0.704 to the actual LCF value, it becomes 0.497. Hence, the mean LCF value of 0.497 indicates an ecological deficit. This illustrates that the OECD countries are extracting natural resources more than their biocapacity.

Table 2. Summary of descriptive statistics.

	lnLCF	lnGDP	lnGDPSQ	lnEMCI	ECIR	ECIT	ECITR
Mean	−0.704	10.167	103.951	−1.029	1.029	1.125	0.875
Median	−0.695	10.347	107.071	−1.049	1.167	1.244	1.005
Maximum	0.900	11.567	133.796	−0.513	2.858	2.228	1.594
Minimum	−6.832	7.715	59.534	−1.398	−1.335	−0.360	−2.076
Std. Dev.	1.103	0.763	15.074	0.174	0.924	0.580	0.490
Skewness	−1.293	−0.798	−0.627	0.326	−0.223	−0.615	−1.680
Kurtosis	5.824	3.136	2.807	2.274	2.095	2.608	6.977
Jarque–Bera	449.721	78.709	49.380	29.248	31.243	51.102	831.801
Probability	0	0	0	0	0	0	0

All other variables were also transformed from their natural logarithms to their original values. The findings demonstrate that the average GDP per capita is significantly elevated, indicating the overall economic robustness of OECD nations. Nonetheless, there is a notable discrepancy between the minimum GDP per capita (2243.642) and the greatest GDP per capita (105,561.1), indicating notable economic inequality across OECD nations. Table 2 indicates that the average EMCI value is 0.36, suggesting that OECD countries predominantly depend on a narrow spectrum of energy sources. To improve sustainability, these nations are progressively adding renewable energy sources like hydropower, wind, solar, and biomass to their energy mix, even while fossil fuels like coal, oil, and natural gas still account for most of their energy. Moreover, Table 2 underscores discrepancies in the interaction factors of EC, encompassing ECI-Trade, ECI-Technology, and ECI-Research. The relative levels of these measures allow OECD nations to be divided into three groups [38]: The initial category includes nations characterised by elevated levels of ECI-Research, ECI-Trade, and ECI-Technology, namely, the United States, Germany, Switzerland, Sweden, the United Kingdom, and Finland. The second category includes nations like Lithuania, Slovakia, and Mexico that have substantial ECI-Trade but comparatively low levels of ECI-Technology and -Research. The nations in the third group, New Zealand, Chile, Australia, Norway, and Canada, have lower levels of ECI-Trade but are still leaders in ECI-Research and -Technology. The Jarque–Bera (JB) test was performed to evaluate the normality of the variables. The JB test findings (refer to Table 2) refute the null hypothesis of normality, signifying that the variables are not normally distributed.

Table 3 presents the correlation among datasets. GDP is moderately and negatively related to the LCF. This indicates that if the GDP of any country among the OECD nations increases, it lowers the environmental quality of that country. It can also be seen that the square value of GDP is negatively related to the LCF. That means that if the country undergoes more economic development, it reduces the environmental quality of the country. The correlation between the EMCI and LCF is negative and low, at about −0.24. This indicates that more concentration in the energy mix is associated with a lower level of LCF, revealing that if any OECD country does not diversify its energy mix, its EMCI value tends to have a low value. Concentrating on certain energy sources, specifically on fossil fuels, would deteriorate the environment and lower the LCF value. On the other hand, ECI-Research is positively related to the LCF, whereas ECI-Trade and -Technology are negatively related to the LCF.

Table 3. Correlation among the variables.

	lnLCF	lnGDP	lnGDPsq	lnEMCI	ECIR	ECITR	ECIT
LnLCF	1						
lnGDP	−0.0841	1					
lnGDPsq	−0.0727	0.9989	1				
lnEMCI	−0.2385	0.009	0.011	1			
ECIR	0.1535	0.6927	0.6967	−0.1304	1		
ECITR	−0.0531	0.677	0.6679	−0.1927	0.5598	1	
ECIT	−0.3416	0.549	0.5394	0.0756	0.1953	0.4302	1

3.4. Empirical Approach

The cross-sectional dependence (CSD) test was used to decide which approach was best for this study. Because the units are adjacent to one another and may share the same characteristics, it is extremely dangerous to use panel data that exhibits CSD. As a result, there is a chance that the regression will produce biased estimates and inferences [74]. The CSD test was used in this study. The null hypothesis of the test is as follows, and it may be rejected at the 1%, 5%, or 10% significance levels:

$$CSD = \sqrt{2T/N(N-N)}\left(\int_{i=1}^{N-1}\int_{k=i+1}^{N}\hat{\rho_{i,k}}\right) \tag{4}$$

To prevent erroneous results, the first-generation unit root test by Maddala and Wu [75] and the second-generation CIPS test by Im et al. [76] and Pesaran [77] were both used as preliminary checks to determine whether the null hypothesis could be rejected. The CIPS test, which is an enhanced variant of the Im et al. [76] unit root test, is written as follows:

$$CIPS(N,T) = \overline{T} = N^{-1}\int_{i=1}^{N} t_i(N,T) \tag{5}$$

where N and T stand for the number of years and cross-sections, respectively. The unit root test for heterogeneous panels is on the left side of Equation (5), and the ordinary least squares (OLS) t_i statistics used in the cross-sectional averaged augmented Dickey–Fuller (ADF) regression are on the right.

In case of macroeconomic or cross-country contexts where countries are different in terms of institutional policy structure or technological conditions, the assumption of slope homogeneity may not be true [76,77]. If we ignore the slope heterogeneity, it can lead to biased and inconsistent parameter estimates. We used the Pesaran and Yamagata slope heterogeneity test [78] to test whether the slopes across the countries were homogeneous or heterogeneous. To determine whether there was a long-term link between the variables, we then used the second-generation panel cointegration tests that Westerlund [79] suggested. This approach enables the rejection of the null hypothesis that there is no cointegration at the 1%, 5%, or 10% significance levels, and it is appropriate when CSD is present.

Hence, in the fourth stage, the present study employed the novel Method of Moments Quantile Regression (MMQR) approach introduced by Machado and Silva [80]. The MMQR approach was preferred for the following reasons: First, this approach is suitable for determining the covariance effects under conditional heterogeneity. Second, it provides the sensible presence of endogenous properties in the independent variables. Third, the MMQR approach is reliably employed even where individual effects distort the panel data model. Fourth, this approach provides robust estimations even in the case of a non-linear model. Fifth, it provides reliable results for non-normally distributed data and is designed to produce different estimation results for each quantile rather than estimations based on the average. Finally, the MMQR method has location and scale functions. All these qualities enhance the functionality of the MMQR approach. The contingent quantiles $QY(\frac{\tau}{X})$ for the locational-scale variant are described in Equation (6):

$$Y_{it} = \alpha_i + X_{it}'\beta + \left(\delta_i + Z_{it}'\vartheta\right)U_{it} \tag{6}$$

where the probability $P\{\delta_i + Z_{it}'\vartheta > 0\} = 1$. $(\alpha, \beta', \delta, \vartheta')$ is to be estimated: $(\alpha_i, \delta_i), i = 1, \ldots, n$ describes the individual i fixed effects, whereas Z shows the k-vector of recognised components of x, which are distinguishable transformations with element I in Equation (7):

$$Z_I = Z_I(X),\ I = 1, \ldots.., k \tag{7}$$

U_{it} is independent and identically distributed across units and time. It is also statistically independent of X_{it} and normalised to satisfy the moment condition in the method. U_{it} and X_{it} are similarly distributed beyond time-period (t) and individual (i) effects. For any fixed U_{it} and X_{it}, it is normally distributed and time-independent (t). As stated by Machado and Silva [80], U_{it} represents standardised momentum conditions orthogonal to X_{it}. This can be illustrated as follows:

$$Q(\tau|X) = (\alpha_i + \delta_i q(\tau)) + X_{it}'\beta + Z_{it}'\gamma(\tau) \tag{8}$$

In Equation (8), the scalar coefficient $(\alpha_i + \delta_i q(\tau))$ represents the quantile-τ constant effect for the individual i or the distributional effect in τ. The distributional effect differs from the fixed effect, as there is generally no position shift; it shows the effects of individual characteristics that do not change over time. $\sum_0^1 q(\tau)d\tau$ reveals that α_i can be expressed as the average effect for the individual (i). Accordingly, τ, the sample quantile, is calculated by solving the optimisation problem in Equation (6) [80].

$$\min_q \sum_i \sum_i \rho_\tau\left(\hat{R}_{it} - \left(\hat{\delta}_i + Z_{it}'\gamma\right)q\right) \tag{9}$$

In Equation (9), $\rho_\tau(A) = (\tau - 1)AI\{A \leq 0) + TAI\{A > 0]$ denotes a control function. To check the robustness of the findings from MMQR, this study also used feasible generalised least squares (FGLS) and fully modified ordinary least squares (FMOLS). Figure 9 shows the methodology of this study, including the approaches or techniques used. All empirical analyses were performed using Stata 17, which was used for data cleaning, construction of the EMCI, and estimation of the panel regression models, including diagnostic tests and robustness checks.

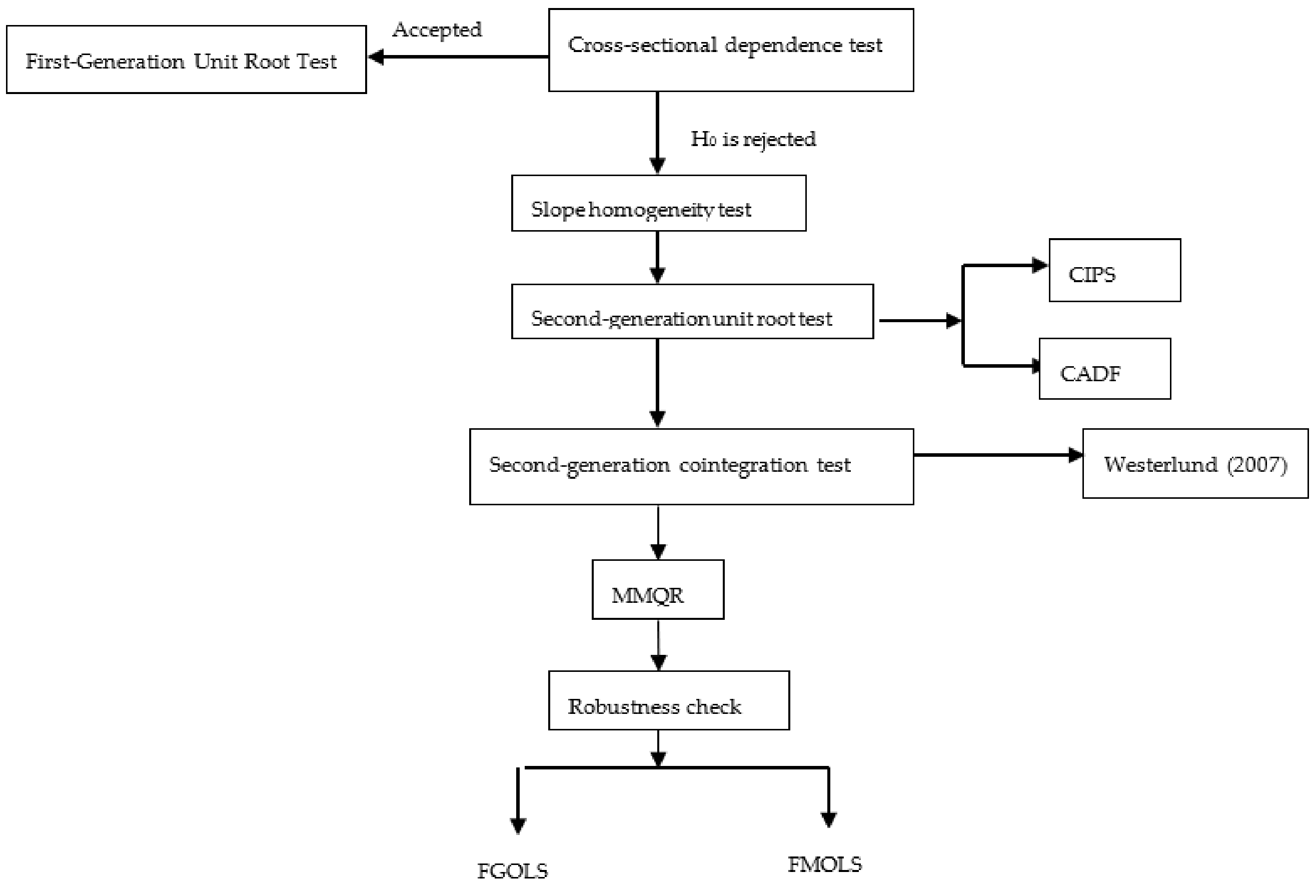

Figure 9. A framework of the methods [79].

4. Results and Discussions

4.1. CSD, Unit Root, and Cointegration

The findings of the unit root and Pesaran CSD tests are shown in Table 4. According to the CSD test, the presence of cross-sectional dependence among the variables is confirmed, as all test statistics are statistically significant at the 1% and 5% levels. This implies that economic and environmental indicators across OECD countries are interrelated and influenced by common shocks or spillover effects, meaning that shocks in one have an impact on the others. We used both the second-generation unit root test by Pesaran [77], which takes cross-sectional dependence into account, and the first-generation unit root test by Maddala and Wu [75], which assumes cross-sectional independence, to evaluate the stationarity of the variables. According to the results of both unit root tests, most variables are non-stationary at their level but become stationary after first differencing, confirming that they are integrated of order one, I (1). Specifically, variables such as lnLCF and ECIR exhibit stationarity at their level, while others, such as lnGDP, lnGDPsq, EMCI, ECITR, and ECIT, become stationary after differencing. These findings suggest the suitability of panel cointegration analysis to explore long-term relationships among the variables. A long-term link between the variables was confirmed by cointegration analysis as described by Westerlund [79].

Table 4. CSD and Pesaran (2007) [77] CIPS, CADF.

	Pesaran (2004) [81] CSD	Pesaran (2007) [77] CIPS		CADF Unit Root Test	
		Level	1st Difference	Level	1st Difference
lnLCF	14.287 ***	−2.227 **	−4.187 ***	−3.168 **	−2.730 **
lnGDP	95.11 ***	−2.022	−3.976 ***	−2.286	−2.534 *
lnGDPsq	94.83 ***	−2.301	−3.942 ***	−2.240	−2.140 **
lnEMCI	44.61 ***	−2.332	−5.012 ***	−1.861	−2.007 **
ECIR	45.51 ***	−2.867 *	−4.701 ***	−2.842 ***	−3.390 ***
ECITR	43.17 ***	−2.487	−4.205 ***	−2.412	2.606 **
ECIT	4.437 **	−2.149	−4.067 ***	−1.761	−2.124 **

Westerlund (2007) [79] cointegration test. Variance ratio = −1.461 **; Significant *, **, *** at 10%, 5% and 1% respectively.

4.2. Slope Heterogeneity Test

To assess heterogeneity, Pesaran et al. [77] presented the slope heterogeneity test, which is shown in Table 5. The findings of this study show how important variability is among OECD countries.

Table 5. Slope Heterogeneity Test.

H_0: Slope Coefficients Are Homogeneous			
$\hat{\Delta}$	p-value	Adjusted $\hat{\Delta}$	p-value
9.962	0	12.336	0

4.3. Estimated Results of the Regressions (MMQR)

Table 6 presents the results of the panel MMQR analysis, revealing that the coefficient of GDP is negative and statistically significant across all quantiles at the 1% level of significance, except for the 0.5 quantile. The coefficient of GDP is not significant at the 50th quantile. This result indicates that a 1% increase in GDP leads to a reduction in LCF ranging from 1.67% to 5.18% across all quantiles. These results are consistent with the findings of previous studies, including those of Pata and Samour [65], Aybudak et al. [82], Awosusi et al. [42], and Wu et al. [61]. On the other hand, the coefficient of GDP squared is positive and statistically significant at the 1% level of significance across all quantiles (0.08–0.27). This depicts that economic growth increases the LCF after a threshold level of economic growth. This result validates the U-shaped LCC hypothesis in OECD countries. This result is consistent with the findings of Wu et al. [61], Pata et al. [11], Dogan & Pata [55].

The estimation results indicate that the EMCI has a significant negative impact on the LCF across all quantiles at the 1% significance level. A 1% increase in EMCI leads to a reduction in LCF by approximately 3.53% to 2.14% at the 10th and 25th quantiles, respectively. In 2021, this quantile range includes countries such as Germany (0.3583), Switzerland (0.2372), Italy (0.2188), and the United Kingdom (0.2785). The magnitude of elasticity gradually decreases from the 25th to the 90th quantiles. At the 90th quantile, a 1% rise in EMCI is associated with only a 0.563% decline in LCF, indicating that the negative impact of ED weakens among higher-LCF countries.

ECI-Research, which is based on scientific publications, is a key component of economic complexity related to innovation in knowledge-intensive sectors. The estimation results show that the coefficient of ECI-Research is positive and significant at the 10th, 75th, and 90th quantiles at the 1% level of significance. This contrasts with the findings of Hamrouni et al. [10], who reached different conclusions regarding the role of research publications in emissions. Due to the uneven effect, it appears at both the top and the bottom. In low-LCF OECD countries (10th quantile), a 1% increase in ECI-Research increases the LCF by 0.35%.

Table 6. Results of panel MMQR.

Variables	Values	0.1	0.25	0.5	0.75	0.9
lnGDP	Coefficient	−5.176	−4.69972	−1.66003	−2.42478	−2.58622
	Std. err.	1.641	0.997899	1.052574	0.964511	0.429151
	$p > t$	0.002	0	0.115	0.012	0
lnGDPsq						
	Coefficient	0.274	0.24812	0.086834	0.117709	0.121171
	Std. err.	0.082	0.047808	0.054548	0.047188	0.021722
	$p > t$	0.001	0	0.112	0.013	0
lnEMCI						
	Coefficient	−3.52802	−2.14457	−0.8486	−0.38868	−0.56355
	Std. err.	0.504563	0.41728	−0.8486	0.185933	0.148101
	$p > t$	0	0	0.004	0.037	0
ECIR						
	Coefficient	0.353818	0.114205	0.107626	0.457368	0.219908
	Std. err.	0.162413	0.064416	0.092027	0.050066	0.052306
	$p > t$	0.03	0.077	0.092027	0	0
ECITR						
	Coefficient	−0.47101	−0.3514	−0.14217	−0.12171	0.118329
	Std. err.	0.172592	0.128355	0.180337	0.122201	0.170714
	$p > t$	0.007	0.006	0.077	0.002	0.004
ECIT						
	Coefficient	−0.629	−0.66669	−0.7001	−0.42216	−0.03816
	Std. err.	0.105766	0.093111	0.060376	0.106949	0.063608
	$p > t$	0	0	0	0	0.549

Trade-related ECI is the second variable associated with EC. Between the 10th and 50th quantiles, the coefficient of ECI-Trade is negative and statistically significant at the 1% level of significance, but at the 50th quantile it stays negative but is statistically insignificant. Notably, the coefficient becomes positive and statistically significant at the 90th quantile. The 10th to 25th quantiles of LCF encompass nations including Italy (0.2188), Switzerland (0.2372), the United Kingdom (0.2785), Germany (0.3583), Portugal (0.3838), Spain (0.4293), Poland (0.4117), France (0.5195), Austria (0.4605), Slovenia (0.4959), Turkey (0.4421), and the United States (0.4843). Numerous countries occupy prominent global standings in ECI-Trade, ECI-Research, and ECI-Technology.

The last variable, ECI-Technology, is derived from patent data and indicates the complexity of technical innovation, potentially associated with energy-intensive industrial methods. The coefficient is negative and statistically significant at the 1% level from the 10th to the 75th quantiles, but it becomes negligible at the 90th quantile. The 10th to 75th quantiles of LCF encompass countries including Italy (0.2188), Switzerland (0.2372), the United Kingdom (0.2785), Germany (0.3583), Portugal (0.3838), Spain (0.4293), Poland (0.4117), France (0.5195), Austria (0.4605), Slovenia (0.4959), Turkey (0.4421), the United States (0.4843), Denmark (0.5926), Ireland (0.9863), Lithuania (0.9033), Chile (0.9891), Belgium (0.9826), Slovakia (0.6291), Hungary (0.6448), and Sweden (1.4695). The quantile regression estimates are displayed visually in Figure 3. The GDP coefficient rises from the lower to middle quantiles (ascending slope) and subsequently stabilises. This implies that, in the medium and upper quantiles, economic growth has a more beneficial effect on the LCF. Heterogeneity is evident because the 95% CI of quantile estimates occasionally deviates from the OLS confidence band, indicating that the impact of GDP on the LCF varies across the distribution. It can be clearly seen from Figure 10 that all other variables also cross the significance level after a certain percentile, confirming the existence of a heterogeneous feature in all of the variables.

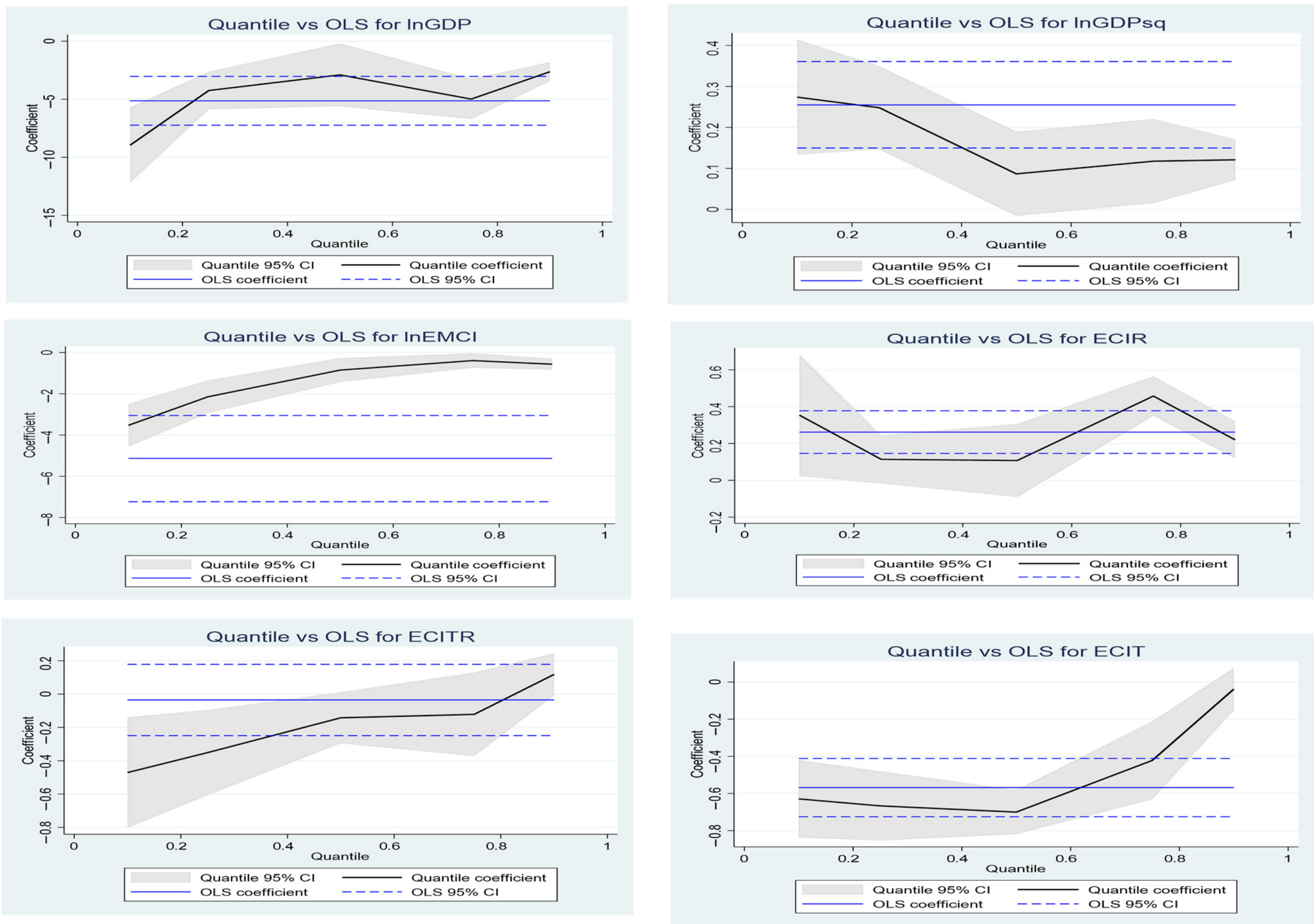

Figure 10. Panel Quantile Régression Estimâtes.

4.4. Robustness Remarks

This study also utilised FGLS and FMOLS regression to check the robustness of the MMQR results, as presented in Table 7. For the FGLS results, the lnGDP, lnGDPsq, lnEMCI, ECI-Research, and ECI-Technology variables are statistically significant for the LCF at the 1% level of significance. Given these findings, if GDP increases by 1%, the LCF will decrease by 1.58%. Moreover, if GDPsq increases by 1%, it will increase the LCF. Hence, these results follow the LCC hypothesis. Moreover, if the EMCI increases by 1%, the LCF decreases by 1.10%. In addition, a 1% increase in ECI-Research increases the LCF by 0.19%. In contrast, a 1% increase in ECI-Technology decreases the LCF by 0.61%. According to the results of FMOLS, the coefficients of all the variables have similar signs to those of FGLS. Lastly, the results and significance of all coefficients from FGLS, FMOLS, and the MMQR method's specifications are considerably similar and virtually identical. The results from these two models confirm the reliability and robustness of the estimations.

Table 7. Estimated results of FGLS and FMOLS.

	FGLS		FMOLS	
Variables	**Coefficient**	***p* > z**	**Coefficient**	***p* > z**
lnGDP	−1.58258	0.002	0.859	0.000
lnGDPsq	0.075719	0.004	0.075	0.004
lnEMCI	−1.10348	0.000	−1.103	0.000
ECIR	0.189281	0.000	0.189	0.000
ECITR	−0.08473	0.116	−0.084	0.116
ECIT	−0.61137	0.000	−0.611	0.000

4.5. Discussion

This study offers a fresh perspective on applying the MMQR approach to examine the diverse impacts of economic development, ED, and EC on the LCF across OECD nations from 1999 to 2021, a period marking the "New Normal" era. It also aims to evaluate the validity of the LCC hypothesis within the OECD context. To do so, we developed an ED metric, the Energy Mix Concentration Index (EMCI), based on the Herfindahl–Hirschman Index, using annual data on each country's energy sources. Additionally, the model includes three dimensions of economic complexity (ECI-Trade, ECI-Technology, and ECI-Research), GDP per capita, and the square of GDP per capita as key explanatory variables.

This study focuses on three main objectives: first, to assess the current state of energy diversification in OECD countries; second, to test whether the LCC hypothesis holds for these nations; and third, to analyse the impact of energy diversification on the LCF in these countries, along with examining whether ECI-Trade, ECI-Technology, and ECI-Research influence the LCF. The application of MMQR enabled us to investigate how ED and EC affect different quantiles of LCF within OECD nations.

Our findings indicate that Finland, Canada, and Norway exhibit high EMCI values due to their substantial reliance on hydroelectric energy, whereas South Korea and Israel show lower EMCI values owing to their more diversified energy portfolios. Iceland, which utilises a wholly renewable electricity mix from geothermal energy and hydropower, stands out for its minimal environmental impact. Similarly, the carbon intensity in Sweden, Finland, Norway, Switzerland, France, Canada, and Costa Rica is significantly lower, as they generate less than 10% of their electricity from fossil fuels. Their elevated EMCI values reflect a lack of energy diversity caused by dependence on one or two clean sources, rather than a mix of solar, wind, and biomass options. Conversely, Mexico (75 per cent in 2024) and Israel (87 per cent in 2023) continue to heavily depend on gas-fired electricity, yet they hold low EMCI ratings, indicating a more diversified energy mix. These countries utilise various sources, such as coal, gas, oil, and renewables, but they still predominantly rely on polluting energy sources, increasing environmental risks. In total, 8% of OECD countries (Finland, Canada, Norway) possess highly concentrated energy mixes, sustainable yet less diverse; 70% have balanced systems suitable for achieving both SDG-7 (clean energy) and SDG-8 (sustained economic growth); and 10% display high diversity, exemplifying resilience and energy innovation. This variety of energy strategies provides valuable insights into post-pandemic recovery policies aiming at a fair green transition. Most OECD nations are progressing towards SDG-7 and SDG-8; however, countries dependent on hydropower should improve diversification to ensure long-term sustainability and economic resilience.

The MMQR results show that the coefficient of GDP is negative, while the square of the GDP coefficient is positive, confirming that the LCC hypothesis is valid for OECD countries. This suggests that lower levels of economic growth tend to overstate natural resource extraction, especially at lower quantiles. In these segments, maintaining manufacturing output and trade competitiveness often relies on increased use of natural resources such as fossil fuels, minerals, and timber, activities closely linked to industrial expansion. Furthermore, economic growth leads to higher consumption, which results in more solid and chemical waste, reducing the LCF. Conversely, once economic growth reaches a certain threshold, countries tend to adopt environmentally friendly technologies and renewable energy sources in their production and consumption, thereby improving environmental quality and increasing the LCF value [83]. This trend highlights the critical role of policy interventions that facilitate the transition beyond this threshold.

According to the empirical results, higher EMCI is linked to lower LCF across all quantiles. However, this overall negative effect obscures an important underlying distinction in the composition of energy concentration. The environmental consequences of the EMCI depend not only on the degree of concentration but also on the types of energy sources used by countries with concentrated energy systems. Several OECD economies, such as Norway, Canada, and Iceland, exhibit high EMCI values while maintaining strong environmental performance due to their heavy reliance on low-carbon renewable energy sources, particularly hydro and geothermal power. Despite high concentration, this form of "green concentration" is generally associated with ecological sustainability. In contrast, "brown concentration", where fossil fuels dominate the energy portfolio, is more consistent with the observed negative relationship between the EMCI and LCF. This distinction highlights a key conceptual point: energy concentration and energy diversification are not inherently environmental outcomes unless their carbon composition is considered. The EMCI captures the level of concentration but does not reflect carbon intensity. Similarly, diversification per se, defined as expanding the energy mix to include multiple sources, including fossil fuels, may enhance energy security but does not necessarily improve environmental capacity. In high-energy-demand OECD economies, diversification without decarbonisation can increase overall energy availability and reduce effective energy costs, thereby encouraging higher production and consumption. This mechanism reinforces rebound effects and can place additional pressure on ecological systems, resulting in lower LCF values despite apparent structural improvements in the energy mix. Accordingly, the empirical association between higher EMCI and lower LCF largely reflects the dominance of carbon-intensive energy sources within concentrated or diversified systems, rather than concentration itself. These findings underline the importance of distinguishing between green and brown forms of energy concentration and diversification when evaluating environmental performance. To better capture how the composition of energy systems shapes LCF outcomes, future research could develop separate indices for green and brown concentration or combine the EMCI with renewable energy shares or carbon intensity measures.

This study further finds that ED is associated with lower LCF across all quantiles, with the strongest negative effects observed in countries already experiencing low environmental capacity. These findings can be explained through Jevons' paradox and rebound effects, which suggest that improvements in energy efficiency or diversification may unintentionally stimulate higher energy use. As energy becomes more accessible and cost-effective through a diversified energy mix, production and consumption can expand, offsetting anticipated environmental gains. This effect is particularly pronounced in countries with weaker environmental conditions and less stringent regulatory frameworks, where efficiency-driven cost reductions encourage higher energy demand. In high-income economies, strong purchasing power combined with insufficient demand-side regulation can further amplify rebound effects, leading to increased emissions despite improvements in energy structure and economic sophistication.

This study broadens the traditional application of trade-based economic complexity (ECI-Trade) in empirical research by adding two more dimensions that reflect technological and innovative activity: ECI-Technology, derived from patent applications, and

ECI-Research, based on scientific publications. The MMQR results show clear differences across these dimensions. Specifically, ECI-Research was found to boost the load capacity factor (LCF), while ECI-Trade and ECI-Technology are linked to declines in LCF across OECD countries. The positive impact of ECI-Research suggests that research-driven complexity fosters a structural shift away from environmentally harmful, resource-heavy sectors towards cleaner, higher-value activities, thereby improving environmental capacity. This effect is especially noticeable at lower LCF quantiles, where countries such as Italy (0.2188), Switzerland (0.2372), the United Kingdom (0.2785), and Germany (0.3583) display relatively weak environmental capacity but high research activity. In these economies, small increases in research-based complexity lead to significant environmental improvements, as innovation replaces polluting processes with more efficient, cleaner alternatives. In the middle LCF quantiles, the average effect of ECI-Research weakens and becomes less statistically stable, showing the influence of opposing forces. While greater complexity drives technological advancement, rising incomes, higher consumption, and fossil-fuel-dependent energy structures continue to sustain large ecological footprints. Consequently, the overall environmental benefits of research-driven complexity are partly offset. At higher LCF quantiles, represented by countries such as Norway (1.5004), Finland (1.9992), Australia (1.7769), New Zealand (1.7154), and Canada (2.0980), the positive effect of ECI-Research further declines or becomes insignificant. These nations are already at advanced stages of technological development and environmental regulation, meaning that many of the environmental gains from research-led complexity have already been achieved. Additionally, high levels of consumption, energy demand, and reliance on resource-intensive exports (e.g., minerals, oil, and energy commodities) diminish further benefits, leading to decreasing environmental returns from additional research-based complexity. Conversely, ECI-Trade consistently reduces the LCF across most quantiles, reflecting the scale effects associated with complex, export-focused industrial structures. Trade-driven complexity often increases production volumes and lengthens supply chains, escalating energy use and emissions faster than efficiency improvements or biocapacity gains. This aligns with the findings of Li et al. [84], Martins et al. [85], and Kosifakis et al. [86], who reported that higher economic complexity can harm environmental quality when industrial production remains fossil-fuel-dependent. However, at the highest quantile (90th percentile), ECI-Trade shows a positive link with the LCF. In these advanced economies, high trade complexity is supported by low-carbon energy systems, strict environmental regulations, sustainable value chains, and knowledge-intensive exports. In such contexts, complexity fosters eco-innovation and low-carbon trade networks, reducing ecological pressure and improving the LCF. Lastly, the findings indicate that ECI-Technology, measured by general patent activity, tends to a lower LCF, as increased demand for complex manufactured products boosts manufacturing activity, energy consumption, and CO_2 emissions. This contrast between ECI-Technology and ECI-Research highlights a key policy insight: not all types of innovation equally promote environmental sustainability. While environmental and clean-energy research can enhance ecological capacity, broad technological expansion without environmental focus might worsen environmental harm. Therefore, policymakers should prioritise mission-driven research and development, especially in clean energy, energy efficiency, and climate-resilient infrastructure. Governments should implement targeted fiscal incentives, such as tax credits and subsidies for environmental patents, and regulate innovation in energy-intensive sectors. Redirecting economic complexity towards environmentally aligned research and innovation is crucial to ensuring that post-pandemic growth in OECD countries supports a sustainable and resilient green transition.

In summary, the many complex indices examined in this paper demonstrate that several factors influence the increase in LCF. It is crucial to create monitoring instruments

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specifically made for every aspect of EC and the associated environmental effects, depending on a nation's area of expertise. Countries like Sweden, Austria, Germany, Italy, and France may have greater advancement in the technology sector compared to export complexity. On the other hand, nations like Japan, Switzerland, Germany, South Korea, and the Czech Republic, which score higher in terms of export complexity, would find it simpler to improve in their export development than in their technological advancement. As a result, OECD nations might successfully adopt a strategic approach to economic development that links emission reduction goals with tools like trade, patents, and education. Our findings offer a nuanced empirical basis for legislators, business executives, and researchers attempting to negotiate the challenges of the "New Normal" and create a fair and sustainable future via a more intelligent and focused green transition.

5. Conclusions and Policy

The findings demonstrate that one of the main causes of environmental deterioration is still economic expansion. Consequently, policymakers should prioritise sustainable growth models such as the circular economy and eco-innovation, which are central to the green energy transition. OECD nations must encourage investment in clean industries and low-carbon sectors like services to disentangle economic growth from carbon emissions. Considering how important energy use is to environmental sustainability, it is crucial to provide energy infrastructure that facilitates a quick switch to renewable energy sources and lessens reliance on fossil fuels. In 2021, the high-income countries inside the highest LCF quantile were the Czech Republic (0.8426), Norway (1.5004), Finland (1.9992), Australia (1.7769), New Zealand (1.7154), and Canada (2.0980). The energy policies of these nations are centred on decarbonising industry and transportation, pricing carbon, and leveraging their substantial non-emitting electrical base (hydro, etc.) to transition to a low-emissions economy.

It is suggested that the OECD countries implement strategic policy bundles to raise their LCF values and advance the green transition. Enhancing the degree of energy diversification in OECD nations is a key goal, but it must be pursued with a clear direction. A more diverse energy mix that encourages and raises the proportion of other available sources in the overall mix (renewable energies: biomass, solar, hydroelectricity), without concentrating on a single source, is the goal to achieve an ED scenario comparable to the one that existed before 1999. The energy mix should be reorganised to fulfil the increasing demand for energy while simultaneously easing the environmental strain on energy production sources. Additionally, boosting the proportion of renewable energy in the energy mix will reduce overall emissions linked to energy use, improving energy efficiency and having a positive impact on the environment.

Promoting the use of clean technology and renewable energies while restricting the export of carbon-intensive items is essential, considering the EC. This may involve integrating environmental standards into trade agreements, advancing the export of low-carbon products, and fostering responsible supplier chains. Our results specifically call for a strategic shift in innovation policy. The rise in carbon emissions, according to the research-based ECI, is attributable to insufficient emphasis on sustainability. To counter this, prioritisation of financing for research on green innovation and energy transition is essential, moving beyond general technological advancement to mission-oriented R&D in clean energy. This requires enhancing collaboration among researchers, industry leaders, and policymakers to transform these breakthroughs into implementable policies that build climate-resilient infrastructure and foster a just transition towards a sustainable future in the New Normal era.

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6. Limitations of the Study

As is frequently the case in empirical research, there are several limitations to our work. Although our policy suggestions for the group are based on panel data, the analysis might be strengthened by accounting for the heterogeneity of the member nations of the panel. More thorough insights and country-specific policy recommendations may be obtained using time-series data, which would be particularly valuable for understanding national pathways within the evolving "New Normal" paradigm. The sectors involved, the economic impact of scientific research areas, the kinds of patents awarded, and the sectors themselves are not the subject of our analysis. A deeper dive into these areas, especially distinguishing between green and brown technologies, would yield more precise policy levers for steering the green transition.

Furthermore, assessing ED and EC is a problem, especially in the integration of many data sources, including energy, exports, patents, and research publications. Developing more nuanced indicators that can better capture the dynamics of the post-pandemic energy landscape remains a challenge. These restrictions provide future studies with the chance to improve these metrics and delve deeper into these areas. A more comprehensive analysis that considers the specific features of EC, ED, and LCF is essential for a deeper understanding of their interrelationship. To explain the LCF in a single composite index, it would also be intriguing to investigate the combination of several economic complexity metrics. In addition to the individual effects, the search for interaction effects may uncover complementarity or substitution linkages between various indices, improving our understanding of environmental quality and allowing for more pertinent policy suggestions. Future research could employ methods like wavelet analysis or panel causality to better uncover these dynamic relationships in the context of global sustainability challenges. Lastly, considering the diversity of OECD member nations, assessments conducted at the individual or homogeneous group level may yield more focused and pertinent policy suggestions for achieving a just and sustainable future.

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