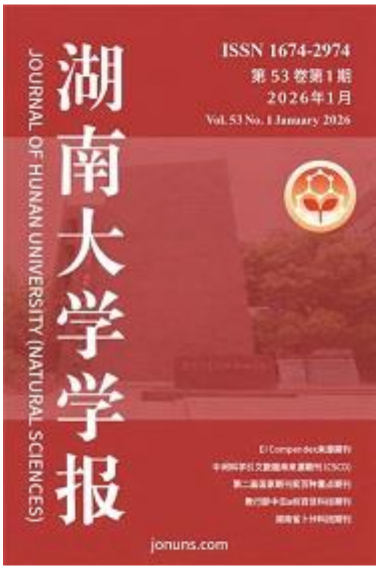

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Navigating the Energy Transition: Unravelling the Relationships between Renewable Energy Consumption, Economic Policy Uncertainty, and Environmental Quality in G7 Economies

Awais Dastgeer[1], Ali Hassan[1], Muhammad Kamran Bhatti[1]*, Fazale Naeem [1], Muhammad Naveed[1], Usman Ali[1]

[1]School of Economics and Trade, Hunan University, Changsha, 410082, China,

*Corresponding author: **kamran.bhatti977@gmail.com**

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Abstract: This study examines the interrelationships between renewable energy consumption, economic policy uncertainty (EPU), and environmental quality in G7 economies over the period 1991–2020. Specifically, it explores whether economic policy uncertainty moderates the environmental benefits of renewable energy consumption, thereby addressing an important gap in the energy–environment nexus literature. Using second-generation panel econometric methods, including fully modified ordinary least squares (FMOLS) and dynamic ordinary least squares (DOLS), the analysis confirms the existence of a long-run cointegration relationship among renewable energy consumption, EPU, carbon dioxide (CO_2) emissions, and the ecological footprint (EF).

The novelty of this study lies in explicitly modeling the interaction between renewable energy consumption and economic policy uncertainty while simultaneously employing CO_2 emissions and the ecological footprint as complementary indicators of environmental quality. The results indicate that renewable energy consumption significantly reduces both CO_2 emissions and EF, whereas economic policy uncertainty independently exacerbates environmental degradation. Notably, the interaction term reveals that, when combined with renewable energy consumption, economic policy uncertainty amplifies its mitigating effect on environmental pressure.

Among the control variables, human capital is found to alleviate environmental degradation, while GDP per capita intensifies it. In contrast, foreign direct investment contributes to reductions in both CO_2 emissions and the ecological footprint. These findings highlight the dual role of economic policy uncertainty and provide robust empirical evidence to support the formulation of stable yet flexible energy and environmental policies. The results further underscore the importance of policy coherence, renewable energy expansion, and human capital development in achieving long-term environmental sustainability in advanced economies.

Keywords: G7 economies; renewable energy consumption; economic policy uncertainty; environmental quality; CO_2 emissions; ecological footprint; energy–environment nexus.

能源转型的路径探索：G7 国家可再生能源消费、经济政策不确定性与环境质量之间关系的实证分析

摘要：本研究考察了 1991—2020 年期间 G7 国家可再生能源消费、经济政策不确定性（EPU）与环境质量之间的相互关系。研究重点在于分析经济政策不确定性是否在可再生能源消费改善环境质量的过程中发挥调节作用，从而弥补能源—环境关系研究领域中的重要研究空缺。研究采用第二代面板计量经济学方法，包括完全修正最小二乘法（FMOLS）和动态最小二乘法（DOLS），实证结果表明，可再生能源消费、经济政策不确定性、二氧化碳（CO_2）排放以及生态足迹（EF）之间存在显著的长期协整关系。

本研究的创新之处在于明确刻画了可再生能源消费与经济政策不确定性之间的交互效应，并同时采用 CO_2排放和生态足迹作为互补性的环境质量衡量指标。研究结果显示，可再生能源消费显著降低了 CO_2排放和生态足迹，而经济政策不确定性则单独加剧了环境退化。然而，交互项结果表明，当经济政策不确定性与可再生能源消费相结合时，其反而增强了可再生能源对环境压力的缓解作用。

在控制变量方面，人力资本有助于减轻环境退化，而人均 GDP 则加剧环境压力；相比之下，外国直接投资与 CO_2排放和生态足迹的降低显著相关。上述研究结果揭示了经济政策不确定性的双重作用，并为制定既稳定又具有灵活性的能源与环境政策提供了稳健的实证依据。研究进一步强调了政策协调性、可再生能源推广以及人力资本投资在发达经济体实现长期环境可持续发展目标中的关键作用。

关键词：G7 国家；可再生能源消费；经济政策不确定性；环境质量；二氧化碳排放；生态足迹；能源—环境关系

1. Introduction

Climate change and global warming remain some of the most urgent global challenges of the 21st century, with carbon emissions and fossil fuel dependence at the center of academic and policy debates for over two decades. According to NASA (2020), the Earth's average temperature has already risen by approximately 1.4 °F (0.8 °C), creating profound risks for biodiversity, ecosystems, and human societies. Greenhouse gases (GHGs) mainly carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), and fluorinated gases trap incoming solar radiation in the atmosphere, disrupting natural climate systems and increasing extreme weather events such as droughts, floods, and heatwaves (Atasoy, 2017; Tollefson, 2018). Human activities like deforestation, industrial production, agriculture, and fossil fuel combustion are identified as the main sources of these emissions (Saqib et al., 2023). Meanwhile, global economic growth has been remarkable. The world economy, measured by Gross Domestic Product (GDP), grew from $29.13 trillion in 1991 to $118 trillion in 2021 (World Bank, 2021). Industrialization, urbanization, and rapid population growth are driving exponential energy demand, which is still largely met by fossil fuels, further worsening the climate crisis. Although significant progress has been made in energy efficiency and technological development, fossil fuels continue to dominate the global energy mix, presenting a major barrier to sustainability (Mesagan & Olunkwa, 2022; Kumar et al., 2021).

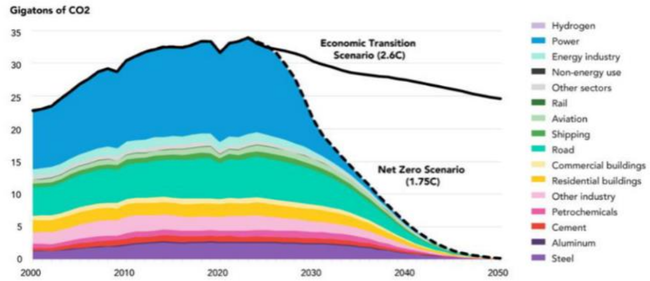

Figure 1: Current Scenario of Gigatons Carbon Dioxide Emissions (CO2)

This figure 1 illustrates global CO_2 emissions from 2000 to 2050 across multiple sectors and two future pathways: Economic Transition Scenario (2.6°C) and Net Zero Scenario (1.75°C). Emissions peaked around 2020 at over 33 gigatons of CO_2, driven primarily by energy production, steel, cement, and road transport. In the Economic Transition Scenario, emissions decline moderately, reaching just above 20 gigatons by 2050, consistent with limiting warming to about 2.6°C. By contrast, the Net Zero Scenario shows a steep reduction, approaching near-zero emissions by 2050, aligning with the 1.75°C climate target. The stacked areas highlight sectoral contributions: heavy industries (steel, aluminum, cement, petrochemicals) and energy dominate, while transport (road, shipping, aviation, rail) and buildings also contribute. Achieving net zero requires sharp cuts across all sectors, alongside scaling up hydrogen, efficiency, and clean power.

Renewable energy sources (RES) are widely recognized as a central pillar in mitigating climate change. Clean and sustainable energy alternatives, such as solar, wind, hydro, and biomass, not only reduce CO_2 emissions but also enhance energy security, ecological balance, and economic resilience (Demirbas, 2000; Hagspiel et al., 2021; Su et al., 2021). Recent technological advancements and government incentives have lowered costs and expanded renewable energy adoption worldwide (Rechsteiner, 2021). For instance, the International Energy Agency (IEA, 2022) forecasts that renewable energy sources (RES) will contribute to 70% of the global increase in electricity generation by 2030. However, adoption rates differ significantly between developed and developing nations, often due to financial, institutional, and policy-related barriers (Shrimali et al., 2016; Paramati et al., 2017). Economic Policy Uncertainty (EPU) introduces additional challenges to the global energy shift. EPU, arising from unclear fiscal, monetary, and trade policies, impacts investment decisions, technological innovation, and environmental sustainability. High levels of EPU can reduce investment in renewable energy, destabilize energy markets, and delay climate actions (Barradale, 2010; Baker et al., 2018; Hagspiel et al., 2021). On the other hand, some studies suggest that uncertainty in traditional energy markets can stimulate a shift toward renewable energy adoption (Liu et al., 2020). The connection between EPU, renewable energy consumption, and carbon emissions remains debated, with conflicting findings across different countries and research methodologies (Danish et al., 2020; Syed et al., 2022).

Beyond emissions, the ecological footprint (EF) concept offers crucial insights into the sustainability of human activities. EF evaluates the pressure placed on ecosystems and natural resources, highlighting inequalities in global resource consumption and the trade-offs between economic development and environmental degradation (Bekun et al., 2021; Zeraibi et al., 2021). Achieving a balance between economic growth and ecological sustainability requires targeted policies, stable investment frameworks, and an integrated focus on the Sustainable Development Goals (SDGs), particularly SDG 7 (affordable and clean energy) and SDG 13 (climate action). The transition to a low-carbon economy is also supported by the rise of green finance and sustainable economic practices that align ecological protection with long-term economic growth (Zahid et al., 2020; Alshater et al., 2023). Financial mechanisms for renewable energy projects can accelerate the energy transition, reduce reliance on fossil fuels, and mitigate climate risks. However, inconsistent policy frameworks and high EPU levels could hinder these efforts, especially in the most energy-intensive economies (Al-Mulali et al., 2016; Wang et al., 2019).

This study explores the interconnected roles of fossil fuel dependence, renewable energy adoption, economic growth, and Economic Policy Uncertainty (EPU) in influencing carbon emissions and environmental sustainability within G7 economies, which are selected due to their dominant share in global economic output, energy consumption, and greenhouse gas emissions, as well as their leadership in climate policy formulation and renewable energy deployment. By using advanced econometric techniques such as FMOLS, DOLS, and dynamic panel GMM, the study provides more reliable and robust results compared to previous research, which often relied on short-term or inconsistent methods. **A** unique and novel contribution of this research lies in explicitly examining the moderating role of EPU in the relationship between renewable energy consumption and environmental quality, an area that has been largely overlooked in the existing literature. From a theoretical perspective, the findings extend the energy–environment and policy uncertainty literature by demonstrating how macroeconomic uncertainty conditions the effectiveness of renewable energy in reducing environmental degradation. From a practical standpoint, the results offer actionable insights for policymakers, businesses, and investors by emphasizing the need for stable yet adaptive policy frameworks to strengthen renewable energy systems under uncertainty. Ultimately, the study supports global climate change mitigation efforts and aligns with the United Nations'

Sustainable Development Goals, particularly SDG 7 (affordable and clean energy) and SDG 13 (climate action).

2. Literature Review

Dealing with global warming is a substantial challenge for the world. Industrialization boosts a country's economic growth through increased energy consumption, leading to ecological issues. Several studies have indicated that excessive use of fossil fuels contributes to climate change and environmental damage (Mesagan & Olunkwa, 2022; Rehman et al., 2019). Energy is essential for long-term development, economic growth, and well-being (Kumar et al., 2021). The combustion of fossil fuels emits massive amounts of CO2 and other GHG into the environment. Carbon emissions contribute to global warming by retaining heat in the atmosphere. Consequences include water scarcity, food insecurity, increased tornadoes and hurricanes, severe weather, and rising sea levels in tropical regions. In the economic, social, political, and environmental spheres, labor, capital, and renewable energy are seen as essential components of production (Irena, 2022). The combustion of fossil fuels emits massive amounts of CO2 and other GHG into the environment. These gases are produced mainly by the energy sector, which is primarily dependent on fossil fuels. For many years, there have been notable advancements in energy integration and efficiency (Alharthi et al., 2021; Dai et al., 2016; Shahbaz et al., 2018; Solarin et al., 2017; Spiegel-Feld, 2022).

2.1. Relationship between Renewable Energy and Environmental Quality

Energy resources fall into three categories: fossil fuels, renewables, and nuclear power (Demirbas, 2000). Historical reliance on fossil fuels and deforestation has significantly raised CO_2 and methane concentrations, driving global warming, sea-level rise, and Arctic ice loss (Sims, 2004). Renewable energy sources (RES), also known as alternative energy, emit near-zero greenhouse gases and are vital for mitigating climate change and associated health risks (Rathore & Panwar, 2007; Tingem & Rivington, 2009). Empirical studies largely confirm renewable energy consumption’s (REC) positive environmental effects. For example, Hassine and Harrathi (2017) found REC, exports, and financial development to support growth in G7 economies, while Sinha et al. (2017) noted high implementation costs slowing adoption in developing nations.Moreover, Apergis et al. (2010), Dogan and Turkekul (2016), and Moutinho et al. (2018) confirmed causality relations of REC with reduction of CO_2, and results from China confirmed the mitigation capacity (Qi et al., 2014).

Despite differing methods, the bulk of research emphasizes the capacity of REC to curb emissions, with differing results of causality. Fossil fuel dependence remains a major driver of climate change and requires policies, R&D, and investment support towards transition (Shahbaz et al., 2015; Acheampong et al., 2019; Adedoyin & Zakari, 2020; Qamruzzaman & Jianguo, 2020). Some of the studies posit one-way causation from emissions to REC (Ben Jebli & Ben Youssef, 2015; Paramati et al., 2017), while others reflect bidimensional feedback of REC and emissions (Dogan & Seker, 2016; Dong et al., 2017; Waheed et al., 2018). Results of neutrality also occur as we witnessed in Italy where no causation of the long-run type held (Bento & Moutinho, 2016). Recent evidence consolidates this literature further in advanced nations. Among the G7 nations, panel studies indicate that REC and eco-innovation reduce emissions of CO_2 considerably and sizably while economic growth continues to hike emissions (Chen et al., 2023; Borgi et al., 2024; Altın et al., 2024). Quantile-based evidence also captures abatement impact at elevated emissions as being much greater (Chen et al., 2023).

Aggregated research also sheds light on the economic policy uncertainty (EPU) contribution toward determining REC–environment relations. Some assert that uncertainty represents an innovation push as firms insuring against risks of fossil fuels (Ivanovski et al., 2021), while others note that it discourages renewable investment and dilutes the environmental payoff (Iorember et al., 2025). For the world's leading economies (G7), climate policy uncertainty (CPU) has also itself been implicated as a catalyst of higher emissions (Hashmi, 2025). Supporting evidence indicates that publicly funded research and innovation and green innovation both intensify the mitigation effect of REC and buffer the uncertainty–REC–environment channel (Ahmed et al., 2022; Borgi et al., 2024). System-level data reinforces such findings as well: renewables reached 30% of world-generation in 2023 with wind and photovoltaic/solar driving the growth (Ember, 2024), and the IEA (2024) predicts continued increases through 2030. Considered as a group, this evidence puts a spotlight on the insight that REC can substantially improve environmental outcomes in the world's leading economies (G7), yet success hinges upon the stability of policies and innovation from technology and system integration (Chen et al., 2023; Hashmi, 2025; IEA, 2024).

2.2. Nexus between Economic Policy Uncertainty and the Environment

Economic policy uncertainty (EPU) has emerged as a major investment, energy demand, and environmental performance driver. Monetary, fiscal, and trade shocks are channeled into business decisions and production and emissions of CO_2 (Tiwari et al., 2019; Al-Thaqeb & Algharabali, 2019). Empirical research finds elevated EPU often discourages investment in clean energy, slows innovations toward the green path, and hastens environmental deterioration while sometimes reducing emissions through moderating economic growth (Baker et al., 2018; Danish et al., 2020; Syed & Bouri, 2021). These contrasting effects mirror the subtlety of EPU's impact on the energy–environment nexus.

Studies examining ecological footprints and emissions emphasize that industrial production and use of energy remain key drivers of environmental degradation (Aşıcı & Acar, 2016; Ozturk et al., 2016). Causality tests of renewable energy use (REC) and emissions yield inconclusive results: while one-way or reciprocity causality outcomes are documented from a series of works, others yield neutrality as a function of research approach and national context (Ben Jebli & Ben Youssef, 2015; Dogan & Seker, 2016; Sinha & Shahbaz, 2018). Evidence also shows opposite implications of EPU regarding energy choices—whereas a series of results suggests that policymaking uncertainty negatively influences investment in renewables (Burns, 2019; Hagspiel et al., 2021), others suggest that it may indirectly promote renewables while discouraging investment in oil and other fuels (Liu et al., 2020).

New evidence further vindicates the context-dependent nature of EPU. In advanced economies, uncertainty has a penchant to disrupt energy diversification and climate governance while in emerging markets it might promote renewable adoption as insurance against volatility of fossil fuels (Abbasi & Adedoyin, 2021; Zhang et al., 2019). Fresh work also vindicates that high EPU greatly inhibits renewable shifts while raising emissions significantly, particularly in the G7 countries where regime stability counts (Li, 2025; Albassam et al., 2025). However, renewable energy most particularly hydropower still performs effectively at reducing emissions if accompanied with stable regulation and innovation support (Altın et al., 2024). Across the board, the research shows that although REC has a prominent role to play at promoting sustainability, efficacy remains low at high EPU and emphasizes the imperatives of credible prospective policy architecture.

2.3. The Moderating Effect of Economic Policy Uncertainty on the Relationship between Environmental Deterioration and the Use of Renewable Energy

Energy consumption contributes considerably to economic growth, yet fuel dependency on fossil fuels escalates CO_2 emissions, evoking climate change and degradation of the environment. In contrast, renewable energy utilization (REC) offers a clean alternative with sources of clean energy (CE) emitting little or no CO_2. Recent work highlights the moderating role of economic policy uncertainty (EPU) in this regard. Greater EPU often deters renewable investment and innovation and therefore dilutes emission mitigation through REC.

For example, Albassam et al. (2025) illustrate that an increase of 1% of policy uncertainty inflates the level of emissions of CO_2 through a reduction of investment in renewable energies and a reallocation of economic activities toward polluting activities. Also, P. Zhang et al. (2024) provide US-industry level evidence that indicates that policy uncertainty cancels out the green voice of REC. However, with stable settings of policy, under which REC more efficiently mitigates emissions: Hashmi et al. (2025) report that stability of climate policy increases renewable adoption through the G7 economies, and other contributions emphasize the reinforcing nature of green innovation and energy efficiency in increasing the environmental effectiveness of REC (Borgi et al., 2024; Altın et al., 2024).

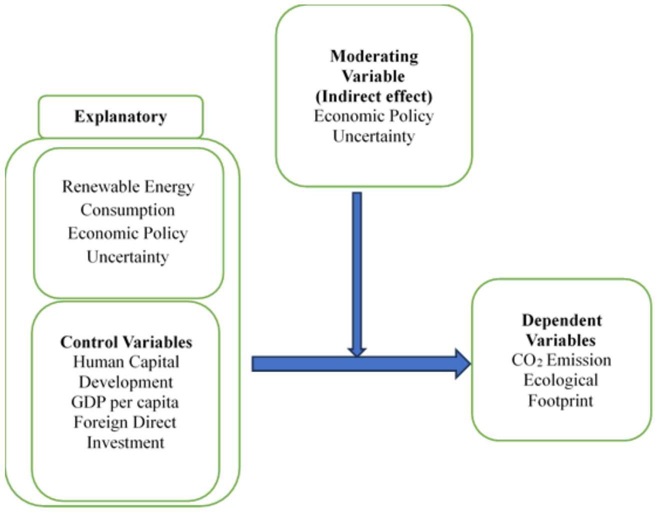

Figure 2: Conceptual and Theoretical Framework

This figure 2 presents the conceptual framework of the study. The explanatory variables include renewable energy consumption and economic policy uncertainty (EPU), which are hypothesized to influence environmental outcomes. Control variables such as human capital development, GDP per capita, and foreign direct investment account for additional economic and social effects. The dependent variables are CO_2 emissions and ecological footprint, representing environmental degradation. Importantly, EPU is also considered a moderating variable, showing its indirect effect by altering the relationship between renewable energy consumption and environmental outcomes. This framework highlights how economic conditions shape the environmental impact of renewable energy policies. Recent empirical evidence supports this framework. Li (2025) shows that a 1% increase in EPU reduces renewable energy transition by 0.28–0.56%, while Albassam et al. (2025) find that EPU significantly raises CO_2 emissions in high-income countries by discouraging green investments. In the G7 context, renewable energy and hydropower reduce emissions, but their effectiveness is contingent on stable policy environments (Altın et al., 2024). Similarly, Vitenu-Sackey et al. (2022) demonstrate that ecological innovation and REC mitigate emissions only under low policy uncertainty.

3. Methodology and Data

3.1. Data and Variables

Table 1: Variable Description, Measurement, their Role, and Sources

Symbol	Variable	Unit of measurement	Main/Control	Source
CO_2	Carbon emissions	Kiloton(kt)	Main	WDI
EF	Ecological footprint	Global hectares(gha)	Main	Global Footprint Network (GFN)
EPU	Economic policy uncertainty	Index built on three sources of uncertainty: news, tax code, forecasters	Main	(Baker et al.,2016)
REC	Renewable energy consumptio n	% of total energy consumption	Main	WDI
HCI	Human Capital Index	indicators of health and education	Control	Penn World Table
GDP	GDP	Constant 2015 US$	Control	WDI
FDI	Foreign direct Investment	Net inflow % of GDP	Control	WDI

This table 1 summarizes the study's key variables, their measurements, classifications, and data sources. Main variables include CO_2 emissions (kilotons, from WDI), ecological footprint (global hectares, from GFN), economic policy uncertainty (index by Baker et al., 2016), and renewable energy consumption (% of total energy use, from WDI). These represent the core focus of the analysis on environmental and policy dynamics. Control variables ensure robustness: the Human Capital Index (health and education indicators, from Penn World Table), GDP (constant 2015 US$, from WDI), and FDI inflows (% of GDP, from WDI). Together, these variables provide a comprehensive dataset for examining environmental impacts.

3.2. Empirical Model

The key objective of the current study is to empirically look at the causal connection of CO2, EF with REC, EPU, GDP per capita, human capital index, and FDI. The functional form that expresses the link among these chosen variables is as follows;

$$CO2_{it} = f(REC_{it}, EPU_{it}, HCI_{it}, GDP_{it}, FDI_{it}, REC_{it} * EPU_{it}) \quad (1)$$
$$EF_{it} = f(REC_{it}, EPU_{it}, HCI_{it}, GDP_{it}, FDI_{it}, REC_{it} * EPU_{it}) \quad (2)$$

$$EQ_{it} = \beta_0 + \beta_1[REC]_{it} + \beta_2[EPU]_{it} + \beta_3[HCI]_{it} + \beta_4[GDP]_{it} + \beta_5[FDI]_{it} + \beta_1([RE]_{it} * [EPU]_{it}) + \varepsilon_{it} \quad (3)$$

In this case: β0 indicates the intercepts, giving the projected result of EQ (environmental quality) if all independent variables stay 0.

More specifically, equation (3) can be written in the following form:

$$EPI_{it} = a_0 + a_1[REC]_{it} + a_2[EPU]_{it} + a_3[HCI]_{it} + a_4[GDP]_{it} + a_5[FDI]_{it} + a_6([REC]_{it} * [EPU]_{it} + \varepsilon_{it}) \quad (4)$$

$$EF_{it} = f(\, b_{0i} + b_{1i}[REC_{it}] + b_{2i}[EPU_{it}] + b_{3i}[HCI_{it}] + b_{4i}[GDP_{it}] + b_{5i}[FDI_{it}] + b_{6i}[REC_{it} * EPU_{it}] + \varepsilon_{it}) \quad (5)$$

In equations (1) to (5), i=1, 2, 3 …. N refers to each country in the panel (N=7 in this study), t refers to the time period (T=18 in this study) α_i and β_i are regression coefficients in the equations (4) and (5).

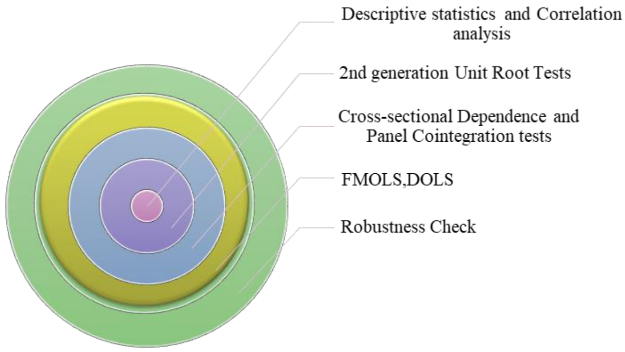

Figure 3: Estimation Strategy

Figure 4 Estimation Strategy. The strategy adopted above enhance the accuracy of our estimates because most of econometric issues like cross section dependence, serial correlation, heterogeneity of unknown nature, Endogeneity etc. are comprehensively addressed. So, we will get reliable parameter estimates.

4. Results and Discussions

4.1. Descriptive and Correlation Statistics

Table 2 Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
lnCO2	210	13.559	0.880	12.496	15.569
lnEF	210	19.996	0.759	19.237	21.826
lnREC	210	24.339	0.886	23.228	25.892
lnEPU	210	7.129	0.217	6.733	7.935
lnHC	210	1.213	0.098	0.947	1.328
lnGDP	210	10.522	0.183	10.235	11.014

lnFDI	210	1.093	0.523	-1.091	2.656

The descriptive statistics for every variable under investigation are shown in Table 2. With a mean value of 24.33988, InREC has the greatest mean value, while InFDI has the lowest mean value, at 1.09306. Furthermore, the standard deviation analysis indicates that InREC is more volatile than changes in InCO2 and InEF.

Table 3 Correlation Matrix

	lnCO2	**lnEF**	**lnREC**	**lnEPU**	**lnHC**	**lnGDP**	**lnFDI**
lnCO2	1.000						
lnEF	0.478*	1.000					
lnREC	-0.064*	-0.041**	1.000				
lnEPU	0.069*	0.049*	0.436*	1.000			
lnHC	-0.477*	0.374*	0.376*	0.147*	1.000		
lnGDP	0.377*	0.477*	0.455**	0.171*	0.399*	1.000	
lnFDI	-0.102*	-0.121**	0.029**	0.131**	0.242*	0.371*	1.000

Note: *** p<0.01, ** p<0.05, * p<0.1

Table 3 presents a more complex view of the rapport between CO2 emissions and the different regressors. Positive correlations have been identified between InEF, InHC, and InGDP and CO_2 emissions, suggesting that rises in these variables are generally associated with higher emissions levels. Conversely, variables such as InREC, InEPU, and InFDI exhibit negative correlations with CO_2 emissions, indicating that their increases are linked to reductions in emissions. These findings highlight the intricate relationships among various determinants of CO_2 emissions and underscore the need for comprehensive analysis in shaping effective environmental policies and making informed decisions.

4.2. Analysis of Cross-Sectional Dependence

With increasing global interconnectedness and the ongoing reduction of trade barriers, panel data analysis is becoming more susceptible to cross-sectional dependence. Adebayo et al. (2020) argue that ignoring cross-sectional dependence while assuming independence can result in biased and unreliable outcomes. In this study, the presence of cross-sectional dependence is tested using the Pesaran (2007) method, which is calculated as follows:

$$\mathrm{CSD}_{TM} = \left[\frac{TN(N-1)}{2}\right]^{1/2} \bar{\rho}_N$$

where: ρ ̄_N The pair-wise correlation parameters are represented by N for cross-sectional units and T for the time period. It's important to note that assuming a common slope coefficient across units without testing for heterogeneity can lead to misleading estimates (Conyon & He, 2017; He et al., 2022). To address this, Hashem Pesaran and Yamagata (2008) proposed evaluating the variation in slope coefficients across cross-sectional units.

Table 4 Pesaran (2004) CDS Test

Variables	CD-test	p value	corr	abs(corr)
lnCO2	10.55***	0.000	0.42	0.597
lnEF	7.22***	0.000	0.288	0.485
lnREC	25.1***	0.000	1	1
lnEPU	18.20***	0.000	0.725	0.725
lnHC	24.68***	0.000	0.983	0.983
lnGDP	21.33***	0.000	0.85	0.85
lnFDI	6.73***	0.000	0.268	0.312

Note: *** p<0.01, ** p<0.05, * p<0.1

Table 4 presents the correlation matrix of key variables along with the results of the cross-sectional dependence (CSD) test. The findings clearly indicate the presence of significant cross-sectional dependence within the panel data. The corr column displays the correlation coefficients between variables, which range from 0.268 to 1, reflecting varying degrees of association. The abs (corr) column gives the correlation coefficients' absolute values, which show how strongly the variables are related in either direction. The findings indicate a significant level of dependency across cross-sections in the dataset. Furthermore, each variable in the panel series is strongly linked; InREC, InEPU, InHC, and InGDP all have significant correlations. These findings show how interconnected the components under examination are, and how critical it is to factor their combined effects into any future modeling or analysis efforts.

4.3. Panel Unit Root Tests

Pesaran introduced tests such as CADF and CIPS in 2007 to assist in explaining the stationary properties of the variable under consideration. The CADF is computed utilizing Equation, as illustrated below:

$$\Delta Y_{i,t} = \gamma_i + \gamma_i Y_{i,t-1} + \gamma_i \bar{X}_{t-1} + \sum_{l=0}^{p} \gamma_{il} \Delta \overline{Y_{t-l}} + \sum_{l=1}^{p} \gamma_{il} \Delta Y_{i,t-l} + \varepsilon_{it}$$

where: Y ̄_(t-1) explains the average lagged; Δ(Y_(t-l)) ̄depicts the first difference of the averages.

For CIPS, the Equation below details its computation as follows:

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

The formula illustrates the correlation among multiple variables within the model, incorporating lagging values and average differences.

The equation above specifies the computation to be performed for CIPS as follows:

The average is computed utilizing the provided formula. CADFi denotes cross-sectional augmented IPS and cross-sectional ADF, respectively. Second-generation unit root testing is the term used to describe these unit root methodologies. In contrast to the original approaches to unit root testing, these methods yield accurate approximations when tackling CSD.

Table 5 Unit Root Results

	CADF				CIPS	
	Level		First Difference		Level	First Difference
Variables	t-Stat	P-value	t-Stat	P-value	t-Stat	t-Stat
lnCO2	0.796	0.516	3.035***	0.000	-1.848	-5.471***
lnEF	1.443	0.807	2.667***	0.007	-1.160	-5.623***
lnREC	0.661	0.782	2.923***	0.004	1.765	2.432**
lnEPU	1.776	0.832	3.623***	0.003	1.776	2.610***
lnHC	1.684	0.582	2.584***	0.005	-0.023	-4.459***
lnGDP	0.949	0.986	2.950***	0.001	-1.266	-4.85***
lnFDI	1.914	0.337	3.599***	0.000	-1.235	-5.901***

Note: *** p<0.01, ** p<0.05, * p<0.1

Table 5 shows the unit root test findings for many selected series, including InCO2, InEF, InREC, InEPU, InHC, InGDP, and InFDI. The findings added to our understanding of these series' stationarity. With the exception of the InEF and InHC series, Pesaran's 2007 test data, which includes substantial P-values for the CADF and CIPS tests, suggests that the initial difference series is stationary. This implies that these series do not exhibit any recurrent patterns, making them acceptable for a wide range of statistical tests because their initial differences do not contain unit roots. In contrast, non-significant P-values indicate that none of the series are stationary at their respective levels, and all test statistics surpass critical values at all levels. This shows that the series exhibits long-term trends and has unit roots. As a result, these series may cause problems for some statistical processes that need steady data. Overall, the findings highlight the need of addressing the stationarity elements of time series data, particularly when doing statistical analysis or modeling, as well as the suitability of first difference transformations for achieving stationarity in the chosen series.

4.4. Second-Generation Cointegration Test (Westerlund 2007)

The Westerlund (2007) test is used to assess cointegration among the variables under study.

Table 6 Westerlund Cointegration Test

Statistics	Values	Z-values	P-values	Robust P-values
Constant				
Gt	-3.42	2.148	0.016	0.00
Ga	-8.243	2.161	0.985	0.30
Pt	-6.819	0.5	0.309	0.04
Pa	-5.741	1.77	0.962	0.46
Constant and trend				
Gt	-3.416	1.154	0.124	0.03
Ga	-5.534	3.942	1	0.89
Pt	-5.539	1.839	0.967	0.02
Pa	-4.487	3.283	1	0.01

Note: *** p<0.01, ** p<0.05, * p<0.1

Table 6 presents the results, showing that in the constant-only model, the high and statistically significant p-values indicate cointegration between the variables Gt and Pt. Furthermore, when both a constant and a trend are included, the results demonstrate strong cointegration among Gt, Pt, and Pa at the 5% significance level. This confirms a long-run relationship among the variables InEF, InREC, InEPU, and InHC. These findings underscore the importance of analyzing long-term effects within the model. Cointegration analysis proves valuable for informing policy design and decision-making processes. Overall, the results highlight the need to consider variable dynamics when evaluating their interactions and long-term implications.

4.5. Methodology for Panel Estimators FMOLS and DOLS

This research employs panel estimation methods FMOLS (Fully Modified Ordinary Least Squares) and DOLS (Dynamic Ordinary Least Squares) to assess long-run relationships, following the confirmation of variable cointegration through the Westerlund (2007) test. Traditional Ordinary Least Squares (OLS) is unsuitable in such contexts, as it fails to generate consistent long-run estimates when variables have different orders of integration. FMOLS, introduced by Phillips and Hansen (1990) and extended to panel data by Pedroni (2001), corrects for issues of heterogeneity, endogeneity, and serial correlation using a nonparametric approach. It incorporates individual intercepts and accounts for cross-sectional dynamics in the error structure. In contrast, DOLS, developed by Stock and Watson (1993) and extended by Kao and Chiang (2001), employs a parametric approach, adding leads and lags of explanatory variables to reduce endogeneity and feedback effects. Monte Carlo simulations by Kao and Chiang (2001) showed DOLS outperforms FMOLS and OLS in small samples, producing less biased and more reliable estimates. Furthermore, Fei et al. (2011) highlight that both FMOLS and DOLS effectively mitigate serial correlation and endogeneity, but DOLS is particularly robust for cross-sectional dependence. Kula (2014) also supports DOLS as a suitable method for analyzing the link between energy, environment, and economic growth. Given these strengths, the study employs weighted DOLS, which incorporates heterogeneity in long-run variances. Together with FMOLS, these estimators validate the ARDL long-run estimates and ensure robust elasticity computation in the presence of cointegration. By addressing both serial correlation and endogeneity, FMOLS and DOLS provide asymptotically consistent and unbiased estimates, making them the most appropriate long-run estimators for this research context. Hamit-Haggar (2012) asserts that FMOLS is the approach most suited for the panel's heterogeneous cointegration. Taking into account that a panel FMOLS estimation of model 1's coefficient β was:

$$\beta_{NT}^{*} - \beta = \left(\sum_{i=1}^{N} L_{22i}^{-2} \sum_{i=1}^{T} (\chi_{it} - \bar{\chi}_{it})^2\right) \sum_{i=1}^{N} L_{11i}^{-1} L_{22i}^{-1} \left(\sum_{i=1}^{T} (\chi_{it} - \bar{\chi}_i)\mu_{it}^{*} - T\hat{\gamma}_i\right)$$

where,

$$\mu_{it}^{*} = \mu_{it} - \frac{\hat{L}_{21i}}{\hat{L}_{22i}} \Delta\chi_{it}, \hat{\gamma}_i = \hat{\Gamma}_{21i}\hat{\Omega}_{21i}^{0} - \frac{\hat{L}_{21i}}{\hat{L}_{22i}}\left(\Gamma_{22i} + \hat{\Omega}_{22i}^{0}\right)$$

and L ˆ_i was the lower triangulation of Ω ˆ_i.

This is how the DOLS is calculated:

$$y_{it} = \alpha_i + \beta_i X_{it} + \sum_{k=-Ki}^{Ki} \gamma_{ik} \Delta X_{it-k} + \epsilon_{it}$$

where K_i and -K_i, respectively, represent the leads and lags.

Equation specifies the functional form of FMOLS estimations as follows:

$$\hat{\beta}_{\text{EFFMOLS}}^{*} = \mathrm{N}^{-1} \sum_{n=1}^{N} \hat{\beta}_{FMOLS,n}^{*}$$

where the FMOLS regression parameter used on cross-sections n is expressed by βˆ_GFM^*, and the corresponding t-statistic coefficient is shown in Eq. 11 as follows:

1

$$\mathrm{t}_{\hat{\beta}_{\text{EFMOLS}}} = \mathrm{N}^{-1/2} \sum_{n=1}^{N} \mathrm{t}_{\beta_{\text{FMOLS},\,n}}$$

$$\hat{\beta}_{\text{EFDOLS}}^{*} = \mathrm{N}^{-1} \sum_{n=1}^{N} \hat{\beta}_{\text{DOLS}\,,n}^{*}$$

In Equation, the dynamic ordinary least square estimator applied to the n nations is denoted by βˆ_(DOLS,n)^*. Equation 14 expresses the tstatistics of the DOLS technique as follows:

$$\mathrm{t}_{\hat{\beta}_{\text{DOLS}\,,n}} = \mathrm{N}^{-1/2} \sum_{n=1}^{N} \mathrm{t}_{\hat{\beta}_{\text{DOLS}\,,}}$$

The Dynamic OLS estimator's asymptotic distribution and the panel FMOLS estimation obtained by Pedroni (1996) were identical. To verify the consistency of the result, the estimations for both DOLS and FMOLS were carried out as demonstrated.

FMOLS and DOLS are effective techniques for mitigating serial correlations among error terms and endogeneity issues among regressors. One significant differentiation between FMOLS and DOLS is their methodologies for mitigating endogeneity and autocorrelation. While FMOLS is nonparametric, Lead and delay values are used by DOLS, a parametric technique, as explanatory factors (Sun et al., 2018). Although the sample size is relatively small, the DOLS method has shown considerable efficiency and robustness in results (Danish et al., 2020; Neagu & Teodoru, 2019). By producing country-specific coefficients, DOLS helps ensure reliable, efficient, and balanced outcomes, and can mitigate issues related to cross-sectional dependence. According to Dogan and Seker (2016), integrating weighted criteria into both DOLS and FMOLS algorithms is an effective way to manage heterogeneity in long-run cointegrated panel datasets. Additionally, these techniques have been widely used in previous research to capture long-term dynamics (Dogan & Aslan, 2017; Sadorsky, 2009).

4.6. Long Run Regression Estimates

The panel FMOLS and DOLS techniques are employed because all variables are integrated of order I(1) and exhibit long-run cointegration behavior. Ordinary least squares (OLS) is unsuitable for estimating variables with differing integration orders. FMOLS is particularly valuable because it provides reliable estimates that are robust to heterogeneity and endogeneity. This method effectively addresses issues of endogeneity and serial correlation due to its inherent features. Similarly, DOLS incorporates lagged dependent variables to correct for endogeneity and is well-suited for analyzing dynamic relationships in panel data. Even in the presence of endogeneity and serial correlation, DOLS delivers consistent and accurate results, making it a powerful tool for modeling panel data of this nature.

Table 7 Panel FMOLS and DOLS Regression Results for CO2 Emissions

Dependent Variable: CO2						
Methods	FMOLS			DOLS		
Variables	Coefficients	Std. Err	t-stat	Coefficients	Std. Err	t-stat
lnREC	-0.132***	0.021	-6.21	-0.253***	0.060	-4.21
lnEPU	0.025**	0.012	2.16	0.126***	0.036	3.52
lnHC	-1.017**	0.454	-2.24	-0.731**	0.338	-2.16
lnGDP	0.310***	0.080	3.89	0.029***	0.011	2.68
lnFDI	-0.114***	0.028	-4.071	-0.202***	0.062	-3.258

Note: ***, ** and * denote the significance level at 1%, 5% and 10%, respectively.

Table 7 presents the panel FMOLS and DOLS findings. REC has a significant negative effect on long-run CO_2 emissions (coefficient = -0.132). On the other hand, a 1% increase of the REC corresponds with a 0.132% decrease of CO_2 emissions per panellist. These findings are supported by Dogan et al. (2020), Huang et al. (2023), and Shahbaz et al. (2017). On the contrary, EPU and CO_2 emissions share a significant and positive correlation (0.025). Uncertainty regarding government and policymaking action is referred to as EPU. EPU can stem from a chain of events like shifts of public opinion, political unpredictability, and landed events like economic crises.The statistics reveal that for every 1% upsurge in EPU, CO2 emissions increase by 0.025% and 0.126% for the FMOLS and DOLS estimators, respectively. Adams et al. (2020) and Anser et al. (2021) support these findings. These data demonstrate that REC can assist G7 countries cut carbon emissions and enhance environmental quality. However, in G7 countries, EPU leads to increasing CO2 emissions. Regulatory institutions may lose control over industrial sectors during high EPU times, and businesses may engage in environmentally unfavorable production techniques, increasing CO2 emissions.

Control variables employed in this investigation included the human capital index, GDP growth, and FDI. The control variable results demonstrate a negative relationship between CO2 emissions and the human capital index (-1.017). This advocates that a 1% upsurge in the human capital index results in a 1.017% fall in CO2 emissions. The development of human and social capital addresses the need for a high-quality, clean environment while also reducing CO2 emissions. Previous studies, such as those conducted by Huang et al. (2023) and Jahanger et al (2022) produced comparable findings. CO2 emissions and GDP per capita have a long-term, positive, and statistically significant relationship in terms of economic growth (0.31). To put it another way, GDP has a long-term, positive, and elastic impact on the environment, implying that increased wealth will gradually erode ecosystem conditions. With a GDP per capita coefficient of 0.31, the G-7 might experience a 0.31% increase in CO2 emissions per person for every 1% increase in GDP per capita. Shah et al. (2022) and Rafat & Salama. (2017) both find a favorable association between the two parameters. These numbers demonstrate that the G7 countries' quick advancement typically results in the utilization of fossil fuels, which increases CO2 emissions. CO2 emissions fall by -0.14% with every 1% increase in FDI. This demonstrates the importance of FDI in transferring knowledge and green technology to improve environmental quality. Huang et al. (2023) and Dastgeer et al. (2023) found empirical evidence to corroborate their findings. In addition, Table 7 shows the panel DOLS estimation results. DOLS findings support the postulated linkages, which are congruent with the DOLS findings.

Table 8 Panel FMOLS and DOLS Regression Results Ecological Footprint

Dependent Variable: EF						
Methods	FMOLS			DOLS		
Variables	Coefficients	Std. Err	t-stat	Coefficients	Std. Err	t-stat
lnREC	-0.421**	0.199	-2.119	-0.271***	0.100	-2.719
lnEPU	0.015***	0.005	3.304	0.017***	0.007	2.594
lnHCI	-1.234**	0.564	-2.189	-0.722**	0.355	-2.033
lnGDP	0.392***	0.151	2.603	0.123***	0.037	3.292
lnFDI	-0.058**	0.026	-2.231	-0.194***	0.070	-2.752

Note: ***, ** and * denote the significance level at 1%, 5% and 10%, respectively.

Table 8 shows the findings of the FMOLS and DOLS investigations, which were carried out to determine the long-term correlations between the EF and independent variables. The approaches employed in panel data analysis are trustworthy in delivering results that are resistant to problems like heterogeneity and CSD. According to Table 8, a one-percent rise in the REC can cause the EP level for FMOLS and DOLS to decrease by 0.421% and 0.271 percent, respectively. There is a strong correlation between EF printing and EPU. The data revealed that for both FMOLS and DOLS estimators, a 1% rise in EPU raises the EF by 0.015% and 0.017%, respectively. Acheampong et al. (2019), (Dastgeer et al., 2023), and Sun et al. (2023) are only a few of the research that show how adopting renewable energy minimizes environmental effect. However, Anser et al. (2021) as well as Liu and Zhang (2022) revealed that EPU had a significant negative influence on the G-7 economies' EF. EPU may cause environmental initiatives to be postponed, resulting in higher EF.

Moreover, human capital also has negative coefficient suggesting that a 1 % increase in human capital declines the ecological foot print level by 1.234% as per FMOLS estimator and 0.722% for DOLS estimator. In terms of economic growth measured by GDP per capita, a one percent augmentation in GDP will boost ecological footprint level by 0.392% in FMOLS and a significant positive coefficient (0.123) in DOLS also confirms the results. FDI is important injectors for both industrialized and underdeveloped nations. Table 8 revealed a negative connection between FDI and EF indicating that a 1 % upsurge in FDI will cause to diminish the EF lever by 0.058% and 0.194% for both estimators.

The empirical literature suggests that HCI has the potential to increase the EF of the G-7 countries. Ahmad et al. (2022), Iorember et al. (2021), and Jahanger et al. (2022) established that HCI greatly increases environmental pollution. This indicates that greater human capital can help to develop new, environmentally friendly and energy-efficient practices and technologies, hence reducing the ecological footprint. Furthermore, improving human resources in areas such as environmental science, engineering, and policy can result in making the more proficient and skilled workforce capable of addressing environmental concerns. Accordingly, policies as well as technologies that could otherwise mitigate the EF may be created and established (Nathaniel et al., 2021). Moreover, a growth of GDP may trigger a greater use of resources and energy with unsuitable environmental effects. Accordingly, Baloch et al. (2021), Khan et al. (2019), Makhdum et al. (2019), and Usman et al. (2022) reaffirmed a negative relationship of FDI and EF. It suggests that higher cross-border financial flows allow corporations to invest in clean technologies and therefore diminish countries such as the G-7's ecological footprint.

Table 9 Moderation of EPU on CO2

Dependent Variable: CO2

Methods	FMOLS			DOLS		
Variables	Coefficients	Std. Err	t-stat	Coefficients	Std. Err	t-stat
lnREC	-0.132 ***	0.036	-3.651	-0.312**	0.134	-2.321
lnEPU	-0.112 ***	0.026	-4.325	-0.252**	0.112	-2.251
lnHC	-1.116***	0.325	-3.436	-0.923***	0.262	-3.521
lnGDP	0.321***	0.112	2.875	0.427***	0.082	5.224
lnFDI	-0.223***	0.061	-3.655	-0.026**	0.011	-2.363
lnREC*EPU	-0.156***	0.054	-2.864	-0.719***	0.222	-3.235

Note: ***, ** and * denote the significance level at 1%, 5% and 10%, respectively.

Moreover, this study investigates the moderating impact of EPU across the mitigation effect of REC on emissions of CO_2. For this purpose, the regression uses the EPU-REC interaction term (LnREC*LnEPU). Table 9 shows that LnREC*LnEPU has a significant negative coefficient. For the FMOLS regression, a 1% rise of LnREC*LnEPU decreases emissions of CO_2 by 0. 156.. The DOLS regression supports these findings. This shows that the REC will help to reduce CO2 emissions as the EPU grows in G7 countries. Given that efforts to achieve environmental sustainability are hindered by high levels of uncertainty, this conclusion appears reasonable. This is due to the fact that during financial crises and recessions, economic interests are frequently given priority (Ahmad et al., 2022).

Table 10 Moderation of EPU on EFP

Dependent Variable: EFP

Methods	FMOLS			DOLS		
Variables	Coefficient	Std. Err	t-stat	Coefficient	Std. Err	t-stat
lnREC	-0.212**	0.095	-2.238	-0.321**	0.142	-2.253
lnEPU	0.031***	0.012	2.608	0.034**	0.016	2.137
lnHCI	-1.668***	0.441	-3.786	-0.355***	0.114	-3.125
lnGDP	0.789***	0.291	2.716	0.246***	0.058	4.273
lnFDI	-0.116**	0.048	-2.427	-0.378***	0.109	-3.467
LnREC*EPU	-0.601***	0.113	-5.313	-0.316***	0.059	-5.351

Note: ***, ** and * denote the significance level at 1%, 5% and 10%, respectively.

Finally, this study introduces the interaction term between EPU and REC (LnREC*LnEPU) to evaluate the effect of REC on EF print in the presence of EPU. The results in table 10 revealed that the LnREC*LnEPU has a negative coefficient showing that this moderation will reduce the EF. Specifically, 1% upsurge in the LnREC*LnEPU results in the diminished EF by 0.601% and 0.316% in FMOLS and DOLS regressions, respectively. These findings demonstrated that the use of REC rises with EPU. EPU has a moderating influence on REC and EF in G7 countries. This hypothesis is also acceptable. EPU can help to support the development of innovative financing techniques that will aid in the advancement and implementation of renewable energy technology. Green bonds and other sustainable financial instruments can now be used to fund renewable energy projects and other environmentally friendly initiatives. These findings are similar with previous studies by Darrat et al. (2016) Ali et al. (2022), Dastgeer et al. (2023), Ahmad et al. (2022), and Iorember et al. (2021).

5. Conclusion and Implications

5.1. Conclusion

We use panel data from 1991 until 2020 to explore the interaction among renewable energy consumption (REC), economic policy uncertainty (EPU), and ecological quality in G7 nations. Utilizing high-order econometric methods involving second-generation unit root tests (CIPS, CADF), Westerlund cointegration, and estimations such as FMOLS and DOLS, the research controls for cross-sectional dependence, serial correlation, heteroscedasticity, and endogeneity, thereby ensuring robust findings. The results indicate that economic policy uncertainty and globalization intensify ecological degradation, whereas renewable energy consumption has a substantial beneficial effect on ecological quality. We contribute to the scholarship by providing empirical evidence on the moderating role of EPU in the renewable energy–environment nexus, offering important implications for policymakers, investors, and firms in structuring adaptive energy policies under uncertainty.

From an academic perspective, this study advances the existing energy–environment literature in several important ways. First, it extends conventional energy–growth–environment frameworks by explicitly incorporating economic policy uncertainty as a moderating variable, an aspect largely neglected in prior empirical research. Second, the use of second-generation panel econometric techniques and dual environmental indicators (CO_2 emissions and ecological footprint) enhances methodological rigor and provides more comprehensive insights into environmental sustainability. Finally, by focusing on G7 economies, the study offers new evidence on how policy uncertainty shapes the effectiveness of renewable energy transitions in advanced economies, contributing to broader theoretical debates on sustainability and climate policy under uncertainty.

5.2. Implications

These findings illuminate the crucial role of economic policy uncertainty (EPU) as a catalyst of the renewable energy consumption (REC)-environmental quality nexus of the G7 countries. Having established the process through which EPU amplifies environmental degradation and insulates the beneficial impact of REC, the study presents evidence-based results as a pathway towards the formulation of effective policies balancing growth and sustainability and protection of the environment. With the G7 countries exerting global economic leadership, the study has international relevance and could act as a template towards global carbon reduction, nature resource protection, and climate mitigation initiatives. Beyond the policy contributions, the study closes an important knowledge gap through the integration of social, political, and environmental perspectives with advanced econometric instruments and deepens the theoretical scholarship of sustainability and presents practical prescriptions as a template towards the promotion of resilient and environmentally friendly energy transitions.

In order to safeguard environmental quality, G7 countries should ramp up commitments of reducing GHG emissions, increasing the use of renewable energy sources, and preserving biodiversity. These include raising carbon pricing, renewable energy targets, energy efficiency standards, and conservation techniques alongside clean technologies and investment in sustainable agriculture. Reducing economic policy unpredictability through stable, clear, and sure rules contributes towards investor confidence-building regarding shifts to renewable energy. Furthermore, promoting responsible globalization, advocating green trade policies, and investment in the human capital through training and schooling will lead towards greater sustainability. Emplacing circular economy action at the center of green infrastructure and resource efficiency will quicken the transition toward low-carbon growth faster and yield a global standard of sustainability.

5.3. Policy Recommendations

To expedite the transition of growth as sustainable as possible, G7 governments should adopt integrated policies with goals of accelerating renewable energy use through subsidies, tax incentives, and R&D innovations in wind, solar power, bioenergy, geothermal power, hydropower, and marine energy. Transparent and clear long-term policy mechanisms can reduce uncertainty, build investor confidence, and promote energy efficiency from business-as-usual. Enhancing education and training of workforces will upgrade the stock of human capital and promote innovation and environmentally benign behaviors that break links of carbon emissions from economic growth. Synergistically tougher emissions standards, enhanced protection of biodiversity, and effective waste management are required to safeguard ecological systems. Promotion of clean technologies through foreign investment and enforcing of environmental norms of incoming capital can further enhance environmental quality and promote economic growth. Integrating these measures enables the centers of business and investment of the G7 to achieve a balance among prosperity and green sustainability and build a template of global leadership on climate.

5.4. Limitations

These findings are prone to limitations necessitating caution in drawing conclusions from this study, particularly with regard to causal links among ecological and economic variables of the G7. Though variables such as renewable energy sources, fuel sources, natural resources, and economic policy uncertainty (EPU) are controlled for, future research with advanced econometric methods and a more diversified panel of environmental indicators will be desirable. Generalization of the geographic coverage beyond the G7 nations and extension of the coverage to nations with different levels of development will allow comparative research elucidating how heterogeneous socioeconomic configurations mediate environment–economy interactions and mitigation policies. Moreover, further research may also improve knowledge regarding the Environmental Kuznets Curve (EKC) using methods such as the panel smooth transition regression test and adding a greater diversity of ecological indicators. These steps will enrich research on environmental economics with greater robustness, generalizability, and relevance to policymaking.

5.5. Future Research Agenda

Future research should also encourage interdisciplinary research interaction among stakeholders, economists, environmental scientists, and policymakers towards the establishment of integrated frameworks addressing the social, economic, and ecological dimensions of sustainability. Priority research areas should integrate an evaluation of the effectiveness of policy tools such as subsidies of renewable energy, eco-taxation, and carbon pricing with particular interest regarding their implications on growth, the environment and equity. Particular consideration of the distributional impact of environmental policies should become a priority with the aim of ensuring equitable distribution of costs and benefits with a particular consideration of the vulnerable. Also, technologies such as blockchain and artificial intelligence are worthwhile since they could enhance governance, monitoring and enforcement and encourage further accountability and transparency and win greater citizens' confidence in environmental decision-making. Lastly, it remains vital that future research adopt a long-term vision and consider how economic activities and environmental policymaking shape global sustainability and intergenerational fairness. By weighing the trade-offs of short-run financing benefits and long-run environmental hazards, scientists could aid the establishment of policymaking that favors the interest of the current and future generations. Generally, researchers could aid the establishment of evidence-based policymaking and methods that effectively address the environment while ensuring sustainable and equitable economic growth through the inclusion of the above recommendations as part of their future research agenda.

Declarations

Author Contributions

AD: writing-original draft, formal analysis, and methodology; AH: writing-review, and conceptualization; MKB: writing methodology; FM visualization; MN: conceptualization; UA: data collection and arranging the data.

Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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Institutional Review Board Statement

Rigorous ethical guidelines were adhered to throughout the study to ensure participant privacy and data confidentiality in compliance with institutional and national research standards.

Informed Consent Statement

Participation in the study was voluntary, and informed consent was obtained from all participants prior to their involvement.

Conflicts of Interest

The author declares that there are no conflicts of interest regarding the publication of this manuscript.

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