International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

International Journal of Energy Economics and Policy, 2025, 15(2), 236-247.

Unlocking the Green Growth Puzzle: Exploring the Nexus of Renewable Energy, CO_2 Emissions, and Economic Prosperity in G7 Countries

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Received: 17 September 2024 **Accepted:** 11 January 2025 **DOI:** https://doi.org/10.32479/ijeep.18071

ABSTRACT

The primary aim of this research endeavor is to elucidate the intricate dynamics among renewable energy utilization, CO_2 emissions, and the trajectory of economic growth within the framework of G7 Countries over the extensive timeframe from 1997 to 2021. Through the meticulous application of cointegration analysis and the Panel Vector Error Correction Model, our empirical investigation unveils a substantiated positive impact of the utilization of renewable energy sources and CO_2 emissions on economic growth trends in the long term. Nevertheless, our comprehensive analysis suggests a notable absence of any observable relationship between renewable energy adoption, CO_2 emissions, and short-term economic growth dynamics. In light of our findings, it is recommended that policymakers focus on fostering sustainable long-term strategies for renewable energy adoption and CO_2 emissions reduction, while also acknowledging the limited short-term impact on economic growth dynamics.

Keywords: Renewable Energy, CO_2 Emissions, Economic Growth, Cointegration Analysis, Panel VECM, G7 Countries
JEL Classifications: Q42, Q53, Q56, O44, C33

1. INTRODUCTION

In the current global landscape, characterized by an urgent collective effort to combat the looming threats of climate change and ensure environmental sustainability, there exists a critical imperative to delve into the intricate dynamics governing the nexus between renewable energy utilization, CO_2 emissions mitigation, and economic advancement. This research endeavors to scrutinize this multifaceted interplay specifically within the ambit of the G7 nations, a cohort renowned for wielding substantial economic prowess and wielding considerable influence on the global stage. The elucidation of these interrelationships assumes paramount significance in the formulation of policies and the delineation of strategic pathways geared towards fostering environmentally conscious and sustainable development trajectories. It is imperative to underscore that the ramifications of this inquiry extend far beyond the confines of the G7, resonating deeply with the overarching objectives delineated within the United Nations' Sustainable Development Goals framework. Indeed, the imperative to transition towards a green, low-carbon economy stands as a linchpin in the collective pursuit of global sustainability and underscores the imperative for a comprehensive comprehension of the underlying mechanisms steering economic growth, energy dynamics, and greenhouse gas emissions trajectories.

Within the G7 countries, the current interplay of indicators concerning renewable energy consumption, CO_2 emissions, and economic growth is characterized by a nuanced and ever-evolving landscape. Despite their status as nations with developed and diversified economies, these countries find themselves under escalating pressure to curtail their carbon emissions and champion environmental stewardship. Navigating through this intricate milieu is paramount, as it holds the key to shaping sustainable policies and fostering initiatives that resonate with global imperatives. The examination of this relationship within the distinct framework of the G7 nations presents an unparalleled and consequential opportunity. As preeminent economic powerhouses on the world stage, these countries wield immense influence and hold a pivotal role in steering the trajectory towards a greener economy at a global scale. Unraveling the dynamics unique to these nations not only sheds light on their individual journeys towards sustainability but also unveils insights that can inform broader international efforts. Indeed, the comprehension of these dynamics within the G7 context serves as a beacon for policymakers and stakeholders worldwide. It illuminates pathways for enacting policies and making strategic decisions that bear substantial ramifications for global environmental sustainability. By deciphering the intricacies of renewable energy adoption, carbon emission reduction, and economic progress within these leading economies, the stage is set for catalyzing transformative change on a global scale.

The significance of this research transcends mere academic inquiry; it holds the potential to offer invaluable insights into a complex and pivotal domain crucial for the future sustenance of our planet. Through a meticulous examination of the intricate interplay between renewable energy consumption, CO_2 emissions, and economic growth within the G7 nations, this study endeavors to discern both the opportunities and challenges inherent in fostering green and sustainable development pathways. At its core, this research seeks to unravel the enigma of green growth, aiming to unearth innovative solutions that can propel us towards a more sustainable future, one that ensures the well-being of both current and future generations. To achieve this overarching objective, the structure of this work is meticulously crafted. The subsequent sections delineate a systematic approach aimed at unraveling the complexities of the topic at hand. The second section will meticulously review a curated selection of recent studies, offering a comprehensive overview of the existing body of knowledge pertaining to the relationship between CO_2 emissions, renewable energy utilization, and economic growth. Building upon this foundation, the third section will meticulously detail the empirical methodology employed in this study, outlining the rigorous analytical framework employed to examine the intricacies of the relationship under scrutiny. Subsequently, the fourth section will unveil the findings gleaned from our empirical analyses, presenting a nuanced understanding of the dynamics at play within the G7 countries. These findings serve as the cornerstone upon which the fifth section, the conclusion and recommendation segment, is built. Here, drawing upon the insights garnered from our empirical endeavors, we will proffer informed conclusions and actionable recommendations aimed at steering policy discourse and catalyzing transformative change towards a more sustainable trajectory. This research endeavor represents a concerted effort to not only contribute to the academic discourse but also to offer pragmatic solutions that hold the potential to shape policy agendas and foster a more sustainable future for all inhabitants of our planet. Through meticulous inquiry and rigorous analysis, we aim to illuminate the path towards a greener, more resilient future—one that harmonizes economic prosperity with environmental stewardship.

2. LITERATURE SURVEY

Over recent decades, the intricate relationship between economic growth, environmental sustainability, and energy consumption has become a subject of paramount importance in academic research. Various studies have delved into the intricate interconnections among economic growth, CO_2 emissions, renewable energy consumption, and other pertinent factors across different regions and time frames. This section aims to synthesize and analyze a collection of these studies to gain a comprehensive understanding of the dynamics at play. Specifically, we explore how economic growth interacts with CO_2 emissions and renewable energy consumption across different countries and regions, shedding light on the causal relationships and spatial correlations involved.

Radmehr et al. (2021) conducted a study aiming to scrutinize the interconnections between economic growth, CO_2 emissions, and renewable energy consumption in European Union countries spanning from 1995 to 2014. Their findings indicate positive spatial correlations among these factors, particularly emphasizing a stronger spatial correlation regarding economic growth compared to CO_2 emissions or renewable energy consumption. Furthermore, they suggest bidirectional relationships between economic growth and CO_2 emissions, alongside a unidirectional link between economic growth and renewable energy consumption. Similarly, Saidi and Hammami (2015) investigated the impact of energy consumption and CO_2 emissions on economic growth across 58 countries from 1990 to 2012, concluding a positive effect of energy consumption on economic growth, yet a negative influence of CO_2 emissions. Liu et al. (2019) explored causality between energy consumption, CO_2 emissions, and economic growth in China, India, and G7 countries, revealing bidirectional causality in developing countries but varied relationships in G7 countries. Omri (2013) examined the relationship between CO_2 emissions, energy consumption, and economic growth in Middle Eastern and North African countries, highlighting bidirectional causality between energy consumption and economic growth, and between economic growth and CO_2 emissions. Nuţă et al. (2024) compared the relationship among urbanization, economic growth, renewable energy consumption, and environmental degradation in emerging economies in Europe and Asia, suggesting growth policies should prioritize sustainable urban communities and increased use of renewable energy. Chen et al. (2016) scrutinized relationships among economic growth, energy consumption, and CO_2 emissions across 188 countries, demonstrating unidirectional causality from energy consumption to CO_2 emissions in both developed and developing nations. Li and Haneklaus (2021) analyzed the role of renewable energy, fossil fuel consumption, urbanization, and economic growth on CO_2 emissions in China, finding a U-shaped relationship between CO_2 emissions and per capita GDP, and a positive impact of renewable energy consumption on reducing CO_2 emissions. Tiba et al. (2016) examined links among renewable energy, environmental quality, trade, and economic growth across 24 middle- and high-income countries, showing bidirectional causality between renewable energy and economic growth in high-income countries but varied relationships in middle-income countries. Radmehr et al. (2022) investigated relationships among renewable energy consumption, ecological footprint, and economic growth in G7 countries, highlighting bidirectional relationships between GDP and renewable energy, and between ecological footprint and renewable energy. Lu (2017) analyzed relationships among greenhouse gas emissions, energy consumption, and economic growth across 16 Asian countries, revealing bidirectional long-term causality between energy consumption, GDP, and greenhouse gas emissions. Zou and Zhang (2020) examined relationships among CO_2 emissions, energy consumption, and economic growth across 30 Chinese provinces, demonstrating a bidirectional relationship between energy consumption and CO_2 emissions. Dong et al. (2018) studied relationships among CO_2 emissions, economic growth, population, and renewable energy across 128 countries, finding positive links between population size, economic growth, and CO_2 emissions, as well as a negative effect of renewable energy intensity on CO_2 emissions. Liu et al. (2023) analyzed relationships among urbanization, energy consumption, economic growth, and CO_2 emissions in China, noting a significant increase in environmental damage associated with urbanization and energy consumption. Ahmad and Zhao (2018) examined relationships among industrialization, urbanization, energy consumption, CO_2 emissions, and economic growth across 30 Chinese provinces and cities, highlighting varied causal relationships among these variables. Bekhet et al. (2017) examined relationships among CO_2 emissions, financial development, economic growth, and energy consumption in Gulf Cooperation Council countries, demonstrating causal links among these variables, particularly emphasizing the significant impact of financial development on CO_2 emissions. Research by Bakari et al. (2021) examines the impact of pollution on economic growth in Tunisia, taking into account variables such as domestic investment, energy consumption and trade openness. Their study, spanning from 1971 to 2015, shows that although pollution has a negative effect on economic growth in the long term, this impact remains insignificant during the period studied. However, they highlight the need for the Tunisian government to put in place economic policies aimed at protecting the country against the future negative effects of pollution. Bakari's (2022) study examines the impact of various factors, including CO_2 emissions, on economic growth in 52 African countries between 1996 and 2021. The results reveal that certain factors such as domestic investment, Exports and the use of natural resources have a positive effect on economic growth, while others like energy consumption and imports have a negative effect. However, CO_2 emissions, innovation and internet use do not appear to have a significant impact on economic growth. These findings highlight the need for policies that encourage domestic investment, sustainable management of natural resources and the promotion of innovation to drive robust and sustainable economic growth on the African continent. In a more recent study, Bakari (2024) assesses the impact of domestic investments and CO_2 emissions on economic growth in 48 sub-Saharan African countries between 1990 and 2022. His results significantly and positively show that domestic investments and CO_2 emissions influence economic growth in the region. These findings encourage policymakers and stakeholders in sub-Saharan African countries to take these factors into account when developing economic policies to encourage sustainable growth.

The amalgamation of studies examined herein underscores the complexity of the relationship between economic growth, CO_2 emissions, and renewable energy consumption. While economic growth often correlates positively with CO_2 emissions, the role of renewable energy consumption emerges as pivotal in mitigating environmental degradation. Bidirectional causality and spatial correlations further elucidate the intricate dynamics across different contexts, suggesting the need for tailored policy interventions to foster sustainable development. As we navigate the challenges of environmental sustainability and economic progress, the insights gleaned from these studies provide valuable guidance for policymakers and stakeholders in crafting strategies that reconcile economic growth with environmental preservation.

3. DATA AND METHODOLOGY

Within this section, our focus is on elucidating the procedures involved in both data collection and methodological approach. Specifically, we delineate the steps undertaken to gather relevant data and detail the methodology employed for analyzing the interplay between CO_2 emissions, renewable energy consumption, and economic growth across the G7 countries during the timeframe spanning from 1997 to 2021.

3.1. Data and Model Specification

The objective of this study is to examine the relationship between CO_2 emissions, renewable energy, and economic growth in the case of G7 countries (namely Germany, Canada, the United States, France, Italy, Japan, and the United Kingdom) during the period 1997 – 2021. The choice of sample and period was dictated by data availability. All data were extracted from the WDI database, and missing values were completed using WDI online. The general specification of the model we aim to estimate can be expressed as follows:

$$Y = F\ (K,\ L;\ CO_2\ REC,\ FCE,\ X,\ M) \tag{1}$$

Equation (1) provides a concise representation of the production function, where Y represents economic growth measured by Gross Domestic Product at constant prices, K is capital measured by Gross Fixed Capital Formation at constant prices, L is labor measured by total labor force, CO_2 represents CO_2 emissions measured by CO_2 emissions (kt), REC denotes renewable energy consumption measured by Renewable Energy Consumption (kg), FCE stands for final consumption expenditure measured by Final Consumption Expenditure at constant prices, and X represents exports measured by Exports of goods and services at constant prices, while M denotes imports measured by Imports of goods and services at constant prices.

Equation (2) is an expansion of the production function, incorporating these variables into a more detailed and nuanced form. In this equation, "A" represents the constant level of technology employed in the country. The impact of each variable—capital (K), labor force (L), CO_2 emission (CO_2), renewable energy consumption (REC), Final consumption expenditure (FCE), exports (X), and imports (M)—is quantified by the respective coefficients β_1, β_2, β_3, β_4, β_5, β_6 and β_7.

$$Y_{it} = AK^{\beta_1} L^{\beta_2} CO2^{\beta_3} REC^{\beta_4} FEC^{\beta_5} X^{\beta_6} M^{\beta_7} \quad (2)$$

Equation (2) offers a detailed insight into the impact of each factor on economic output, delineating the varying degrees of influence represented by the β coefficients. It furnishes a comprehensive framework for scrutinizing the complex interplay between capital, labor force, CO_2 emissions, renewable energy consumption, final consumption expenditure, exports, and imports within the context of economic growth. Equation (3) depicts the transformation of all variables in the model through logarithmic conversion. This process aims to linearize the Cobb-Douglas production function, a nonlinear model, thereby rendering it more suitable for linear regression analysis. By logarithmically transforming each variable, their relationship becomes additive, facilitating a simplified and linear interpretation of the Cobb-Douglas production function. The transformed equation is as follows:

$$Ln\,(Y_{it}) = Ln\,(A) + \beta_1\,Ln\,(K_{it}) + \beta_2\,Ln\,(L_{it}) + \beta_3\,Ln\,(CO_{2it}) + \beta_4\,Ln\,(REC_{it}) + \beta_5\,Ln\,(FEC_{it}) + \beta_6\,Ln\,(X_{it}) + \beta_7\,Ln\,(M_{it}) + \varepsilon_{it} \quad (3)$$

Here, “Ln” represents the natural logarithm, and “ε_{it}” is the error term capturing unobserved factors affecting economic growth. The logarithmic transformation presented in Equation (3) is a common technique in econometrics, widely used to achieve linearity in models, thereby simplifying the estimation of coefficients through linear regression methods. By transforming the variables logarithmically, the model becomes more amenable to analysis, facilitating a more convenient and interpretable examination of the underlying economic relationships. This technique is widely employed in econometric analysis to enhance the understanding of economic dynamics and to derive meaningful insights from empirical data. Finally, in Equation (4), the notation is further simplified, with the constant term “Ln (A)” replaced by “β_0”:

$$Ln\,(Y_{it}) = \beta_0 + \beta_1\,Ln\,(K_{it}) + \beta_2\,Ln\,(L_{it}) + \beta_3\,Ln\,(CO_{2it}) + \beta_4\,Ln\,(REC_{it}) + \beta_5\,Ln\,(FEC_{it}) + \beta_6\,Ln\,(X_{it}) + \beta_7\,Ln\,(M_{it}) + \varepsilon_{it} \quad (4)$$

By implementing a detailed econometric model, we aim to provide meaningful insights to inform the environmental and economic policies of the countries involved. This rigorous analytical approach will not only help understand the underlying dynamics of these relationships but also formulate recommendations to promote sustainable economic growth and transition towards cleaner energy sources in the G7 economies.

3.2. Empirical Methodology

Based on several recent studies such as Mahmoodi (2017), Lu (2017), Sebri and Ben-Salha (2014), Leitão (2014), Chen et al. (2019), Magazzino (2017), Mahmood et al. (2019), Ben Jebli and Kahia (2020), Bhat (2018), Koengkan et al. (2019), Peng and Wu (2020), we have decided to employ estimation based on the Panel Vector Error Correction Model (Panel VECM). This approach offers numerous advantages, as highlighted in the literature. It allows for capturing both temporal and cross-sectional dynamics within the data, incorporating interactions among variables across different units and time periods. Furthermore, it effectively addresses individual effects specific to each observed unit and corrects short and long-term errors, facilitating adjustments towards long-term equilibrium between variables. By leveraging panel data, it yields precise and robust estimations of variable relationships and enables heterogeneity tests to assess relationship consistency across diverse units. The estimation process involves several steps: firstly, determining the integration order of each variable using popular stationarity tests such as the Panel PP and Panel ADF tests. Then, determining the optimal number of lags in the model through the AIC selection criterion. Subsequently, cointegration relationships between variables are explored using the Kao cointegration test. Finally, the Panel VECM model is estimated to identify short and long-term causal links between variables. This comprehensive approach ensures a thorough analysis of the data and enhances the reliability of the results obtained.

Panel PP and Panel ADF tests are essential for verifying hypotheses of heterogeneity and homogeneity in panel data. The hypothesis of heterogeneity posits individual-specific effects, potentially leading to non-stationarity, while the hypothesis of homogeneity suggests uniform behavior across cross-sectional units. Panel PP and Panel ADF tests assess the stationarity of individual unit-specific effects, with rejections indicating stationary effects, supporting heterogeneity, and non-rejections indicating non-stationary effects, supporting homogeneity. These tests offer critical insights into the dynamics of panel datasets, aiding researchers in understanding the diverse behaviors of cross-sectional units over time. The Panel PP test is essentially an extension of the PP test for time series data to panel data. The PP test is based on the null hypothesis of a unit root in the panel data series. The Panel PP statistic can be written as:

$$PP = \frac{(T+1)(\overline{Z_T}-1)}{T}$$

Where:

- “T” is the number of time periods,
- “$\overline{Z_T}$” is the average of individual PP statistics for each cross-section unit.

Under the null hypothesis of a unit root, the Panel PP statistic converges to a standard normal distribution as “T” goes to infinity.

The Panel ADF test is an extension of the Augmented Dickey-Fuller test to panel data, where the null hypothesis is the presence of a unit root in the series. The Panel ADF test statistic can be written as:

$$ADF = \frac{\sum_{i=1}^{N}\sum_{t=1}^{T}\hat{\rho}_{it}}{\sqrt{\dfrac{N(T-1)}{1-\dfrac{1}{N}}}}$$

Where:

- “N” is the number of cross-sectional units,
- “T” is the number of time periods,
- “$\hat{\rho}_{it}$” are the first-differenced autocorrelation coefficients from the panel regression.

Under the null hypothesis of a unit root, the Panel ADF statistic asymptotically follows a standard normal distribution. Both tests are used to assess the stationarity of panel data, with the null hypothesis being non-stationarity (presence of a unit root) and the alternative hypothesis being stationarity. Depending on the level of significance and critical values, one can determine whether to reject the null hypothesis of non-stationarity or not.

In the case of panel data and panel Vector Error Correction Models (VECM), the determination of lag order selection involves extending the Akaike Information Criterion (AIC) to account for both cross-sectional and time-series dimensions. In the case of a panel VECM, we're dealing with a dynamic panel model that includes both levels and first differences of the variables. Therefore, the lag order selection involves determining the appropriate number of lags for both levels and first differences. Let "p" be the lag order for the levels (long-run relationships) and "q" be the lag order for the first differences (short-run dynamics). The total lag order for the panel VECM is "p + q". The AIC for a panel VECM can then be expressed as:

$$AIC_{Panel\ VECM} = -2Ln(L) + 2K$$

Where:
- "L" is the maximized value of the likelihood function for the estimated panel VECM.
- "K" is the total number of parameters estimated in the model, including lagged terms, coefficients, and error variances for both levels and first differences.

For lag order selection in panel data and panel VECM, the AIC is used to balance the goodness of fit and the complexity of the model. By estimating different panel VECM specifications with varying lag orders and selecting the model with the lowest AIC value, researchers can determine the optimal lag order for their panel data analysis.

The Kao residual cointegration test is a statistical test used to assess whether there is a long-run relationship among variables in a time series dataset. The test was developed by Kao (1999) and is particularly useful in panel data settings where cross-sectional dependence is present. The basic idea behind the Kao test is to examine the residuals from individual unit root tests conducted on each series in the dataset. If the residuals are stationary, it suggests the presence of cointegration among the variables. The equation for the Kao residual cointegration test can be written as follows:

$$\Delta y_{it} = \alpha_i + \beta_i t + \gamma_i y_{i,t-1} + \sum_{j=1}^{p-1} \delta_{ij} \Delta y_{i,t-j} + \varepsilon_{it}$$

where:
- "Δy_{it}" is the first difference of the variable "y" for unit "I" at time "t"
- "α_i" s the individual-specific intercept,
- "β_i" is the individual-specific trend coefficient,
- "γ_i" is the coefficient on the lagged level of the dependent variable,
- "δ_{ij}" are coefficients on lagged first differences of the dependent variable,
- "ϵ_{it}" is the residual term.

The null hypothesis of the Kao test is that the residuals "ϵ_{it}" are stationary, indicating the presence of cointegration among the variables. The test statistic is constructed based on the residuals, and critical values are used to determine whether to reject the null hypothesis of no cointegration. The Kao test is commonly used in econometrics and time series analysis to examine the long-run relationships among variables, particularly in panel data settings where there might be cross-sectional dependence.

The Panel Vector Error Correction Model (VECM) enables differentiation between "short-term" and "long-term" Granger causality. Consequently, this model can be employed to investigate the causal connections among variables.

$$\begin{matrix} \Delta Ln(Y)_{it} \\ \Delta Ln(K)_{it} \\ \Delta Ln(L)_{it} \\ \Delta Ln(CO2)_{it} \\ \Delta Ln(REC)_{it} \\ \Delta Ln(FCE)_{it} \\ \Delta Ln(X)_{it} \\ \Delta Ln(M)_{it} \end{matrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \\ \alpha_4 \\ \alpha_5 \\ \alpha_6 \\ \alpha_7 \\ \alpha_8 \end{bmatrix} + \begin{bmatrix} \beta_{11.1}\beta_{12.1}\beta_{13.1}\beta_{14.1}\beta_{15.1}\beta_{16.1}\beta_{17.1}\beta_{18.1} \\ \beta_{21.1}\beta_{22.1}\beta_{23.1}\beta_{24.1}\beta_{25.1}\beta_{26.1}\beta_{27.1}\beta_{28.1} \\ \beta_{31.1}\beta_{32.1}\beta_{33.1}\beta_{34.1}\beta_{35.1}\beta_{36.1}\beta_{37.1}\beta_{38.1} \\ \beta_{41.1}\beta_{42.1}\beta_{43.1}\beta_{44.1}\beta_{45.1}\beta_{46.1}\beta_{47.1}\beta_{48.1} \\ \beta_{51.1}\beta_{52.1}\beta_{53.1}\beta_{54.1}\beta_{55.1}\beta_{56.1}\beta_{57.1}\beta_{58.1} \\ \beta_{61.1}\beta_{62.1}\beta_{63.1}\beta_{64.1}\beta_{65.1}\beta_{66.1}\beta_{67.1}\beta_{68.1} \\ \beta_{71.1}\beta_{72.1}\beta_{73.1}\beta_{74.1}\beta_{75.1}\beta_{76.1}\beta_{77.1}\beta_{78.1} \\ \beta_{81.1}\beta_{82.1}\beta_{83.1}\beta_{84.1}\beta_{85.1}\beta_{86.1}\beta_{87.1}\beta_{88.1} \end{bmatrix} \times$$

$$\begin{bmatrix} \Delta Ln(Y)_{t-1} \\ \Delta Ln(K)_{t-1} \\ \Delta Ln(L)_{t-1} \\ \Delta Ln(CO2)_{t-1} \\ \Delta Ln(REC)_{t-1} \\ \Delta Ln(FCE)_{t-1} \\ \Delta Ln(X)_{t-1} \\ \Delta Ln(M)_{t-1} \end{bmatrix} + \ldots +$$

$$\begin{bmatrix} \beta_{11.n}\beta_{12.n}\beta_{13.n}\beta_{14.n}\beta_{15.n}\beta_{16.n}\beta_{17.n}\beta_{18.n} \\ \beta_{21.n}\beta_{22.n}\beta_{23.n}\beta_{24.n}\beta_{25.n}\beta_{26.n}\beta_{27.n}\beta_{28.n} \\ \beta_{31.n}\beta_{32.n}\beta_{33.n}\beta_{34.n}\beta_{35.n}\beta_{36.n}\beta_{37.n}\beta_{38.n} \\ \beta_{41.n}\beta_{42.n}\beta_{43.n}\beta_{44.n}\beta_{45.n}\beta_{46.n}\beta_{47.3}\beta_{48.n} \\ \beta_{51.n}\beta_{52.n}\beta_{53.n}\beta_{54.n}\beta_{55.n}\beta_{56.n}\beta_{57.n}\beta_{58.n} \\ \beta_{61.n}\beta_{62.n}\beta_{63.n}\beta_{64.n}\beta_{65.n}\beta_{66.n}\beta_{67.n}\beta_{68.n} \\ \beta_{71.n}\beta_{72.n}\beta_{73.n}\beta_{74.n}\beta_{75.n}\beta_{76.n}\beta_{77.n}\beta_{78.n} \\ \beta_{81.n}\beta_{82.n}\beta_{83.n}\beta_{84.n}\beta_{85.n}\beta_{86.n}\beta_{87.n}\beta_{88.n} \end{bmatrix} \times$$

$$\begin{bmatrix} \Delta Ln(Y)_{t-n} \\ \Delta Ln(K)_{t-n} \\ \Delta Ln(L)_{t-n} \\ \Delta Ln(CO2)_{t-n} \\ \Delta Ln(REC)_{t-n} \\ \Delta Ln(FCE)_{t-n} \\ \Delta Ln(X)_{t-n} \\ \Delta Ln(M)_{t-n} \end{bmatrix} + \begin{bmatrix} \theta_1 \\ \theta_2 \\ \theta_3 \\ \theta_4 \\ \theta_5 \\ \theta_6 \\ \theta_7 \\ \theta_8 \end{bmatrix} ECT_{t-1} + \begin{bmatrix} \varepsilon_{1it} \\ \varepsilon_{2it} \\ \varepsilon_{3it} \\ \varepsilon_{4it} \\ \varepsilon_{5it} \\ \varepsilon_{6it} \\ \varepsilon_{7it} \\ \varepsilon_{8it} \end{bmatrix}$$

In the provided context, where Δ represents the first difference operator; i = 1,…,N denotes the country; t = 1,…, T denotes the time period; α, β, and θ denote various parameters to be estimated; ε_{it} is assumed to be a serially uncorrelated error term; and ECT is the one-period lagged error correction term derived from the cointegration vector. Utilizing the VECM structure implies that all variables are considered endogenous variables.

4. EMPIRICAL RESULTS

This section explores the different stages of our empirical analysis. We begin with an analysis of descriptive statistics to better understand the dynamics of our data and establish a solid foundation for our subsequent estimations. Next, we evaluate the stationarity of our time series, followed by the selection of the lag order for our VAR model, and a cointegration analysis to detect long-term relationships between our variables. We then estimate the VECM model in the long term, before examining the results in the short term by assessing causal relationships. This section offers an in-depth analysis of the dynamics between economic growth, CO_2 emissions and renewable energy consumption in G7 countries.

4.1. Descriptives Statistics

When conducting estimation using panel data, a comprehensive comprehension of our variables' characteristics is crucial for deriving dependable and meaningful outcomes. Descriptive statistics serve as a cornerstone in this endeavor, offering in-depth insights into the distributions, trends, and variations within our dataset. To this end, we delve into the key variables of our model, including "Ln (Y), Ln (K), Ln (L), Ln (CO_2), Ln (REC), Ln (FCE), Ln (X), and Ln (M)." This initial analysis aims to enhance our grasp of the data dynamics and establish a robust groundwork for our subsequent estimation process.

In point of fact, Table 1 provides a detailed analysis of the descriptive statistics concerning the key variables of our model, namely "Ln (Y), Ln (K), Ln (L), Ln (CO_2), Ln (REC), Ln (FCE), Ln (X) and Ln (M)". By examining these data, several significant observations can be made. First, it is interesting to note that the means and medians of each variable differ notably from those of the other variables. This discrepancy suggests the potential existence of causal relationships and interactions between these variables. This observation highlights the importance of in-depth analysis to understand the nature and dynamics of the links between these elements. Furthermore, the substantial gap between the maximum and minimum values of each variable indicates significant variation and evolution over time. This finding reinforces the idea that these variables are not statically constant, but rather subject to fluctuations and changes that deserve special attention in our analysis. Furthermore, examination of the results of the Jarque-Bera test reveals that the probability associated with each variable is <5%. This finding suggests that the data follows a normal distribution, which is crucial for many statistical analysis methods. In addition, this supports the hypothesis of homogeneity of the variables, thus underlining the reliability of the results obtained and the validity of our methodological approach. Overall, these results reinforce our confidence in the robustness of our model and suggest that the included variables can be estimated effectively, particularly in the context of panel data.

4.2. Stationarity Analysis

In the field of econometric analysis, the evaluation of the stationarity of time series is of capital importance to guarantee the validity of models and forecasts, particularly in the context of panel data. Stationarity tests, such as the PP panel test and the ADF panel test, are fundamental tools used for this purpose. They make it possible to analyze the stability of variables over time and to determine whether transformations are necessary to make the series stationary. In the context of panel data, where time series for several individual units are studied, stationarity is of particular importance. Stationarity tests help us check whether the time series for each unit are stationary, which is essential to ensure the validity of panel analyses.

Table 2 provides the results of the stationarity tests, namely the PP panel test and the ADF panel test, applied to all of our key variables, namely "Ln (Y), Ln (K), Ln (L), Ln (CO_2), Ln (REC), Ln (FCE), Ln (X) and Ln (M)". These tests allow us to evaluate the stability of time series and determine whether they require differentiation to become stationary. The results are unequivocal: all variables exhibit first-difference stationarity, indicating that they are integrated of order (1). This observation is of capital importance in econometric modeling. Indeed, when the variables are integrated of order (1), this suggests that they have a non-stationary trend but that this trend can be eliminated by simple differentiation. Thus, the panel series become stationary and can be analyzed more rigorously. Therefore, the presence of all variables in first difference paves the way for the use of more sophisticated analysis tools, such as cointegration analysis and the Panel Vector Error Correction Model (Panel VECM). These approaches make

Table 1: Results of descriptives statistics

Variables	Ln (Y)	Ln (K)	Ln (L)	Ln (CO_2)	Ln (REC)	Ln (FCE)	Ln (X)	Ln (M)
Mean	28.78	27.23	17.52	13.55	2.075	28.54	27.32	27.33
Median	28.60	26.99	17.28	13.21	2.186	28.39	27.22	27.22
Maximum	30.65	29.11	18.92	15.56	3.839	30.46	28.52	28.80
Minimum	27.64	26.05	16.55	12.61	-0.212	27.35	26.51	26.37
Standard Deviation	0.752	0.769	0.667	0.885	0.893	0.770	0.510	0.570
Skewness	1.211	1.085	0.887	1.272	-0.116	1.251	0.765	0.926
Kurtosis	3.629	3.169	2.760	3.470	3.431	3.767	2.605	3.133
Jarque-Bera	45.73	34.57	23.38	48.81	1.758	49.97	18.23	25.17
Probability	0.000	0.000	0.000	0.000	0.015	0.000	0.000	0.000
Sum	5038	4765	3066	2372	363.1	4994	4781	4784
Sum Sq. Dev.	98.46	102.9	77.59	136.5	138.8	103.3	45.26	56.64
Observations	175	175	175	175	175	175	175	175

Table 2: Panel unit root test results

Panel PP test								
At level								
Variables	Ln (Y)	Ln (K)	Ln (L)	Ln (CO_2)	Ln (REC)	Ln (FCE)	Ln (X)	Ln (M)
C								
t-statistic	0.0178*	0.1839	0.0448	0.9702	0.5294	0.0001**	0.0903	0.0192*
CT								
t-statistic	0.1038	0.1176	0.8599	0.0336	0.2429	0.5266	0.2492	0.1763
At first difference								
Variables	Ln (Y)	Ln (K)	Ln (L)	Ln (CO_2)	Ln (REC)	Ln (FCE)	Ln (X)	Ln (M)
C								
t-statistic	0.0001***	0.0015***	0.0092**	0.0000**	0.0001***	0.0001***	0.0004***	0.0006***
CT								
t-statistic	0.0000***	0.0094	0.0152**	0.0000**	0.0006***	0.0000***	0.0006***	0.0007***
Panel ADF test								
At level								
Variables	Ln (Y)	Ln (K)	Ln (L)	Ln (CO_2)	Ln (REC)	Ln (FCE)	Ln (X)	Ln (M)
C								
t-statistic	0.0736*	0.2135	0.0722	0.9348	0.5035	0.0067**	0.1838	0.0995
CT								
t-statistic	0.1190	0.1183	0.8282	0.0367	0.2190	0.9571	0.2429*	0.1751
At first difference								
Variables	Ln (Y)	Ln (K)	Ln (L)	Ln (CO_2)	Ln (REC)	Ln (FCE)	Ln (X)	Ln (M)
C								
t-statistic	0.0001***	0.0014**	0.0092**	0.0000**	0.0002***	0.0001***	0.0005***	0.0008***
CT								
t-statistic	0.0001***	0.0083	0.0132**	0.0001**	0.0009***	0.0000***	0.0012***	0.0014***

(*) significant at the 10%; (**) significant at the 5%; (***) significant at the 1%. and (no) not significant
*MacKinnon (1996) one-sided P-values
C: With constant
CT: With constant and trend

it possible to explore long-term and short-term relationships between variables, as well as their mutual adjustment dynamics in the context of panel data. By integrating these advanced methodologies into our analysis, we are better equipped to capture the complex interrelationships and feedback mechanisms between the variables studied.

4.3. Lag Order Selection

When building a vector autoregressive (VAR) model, the selection of the lag order is of crucial importance. The VAR model is an econometric analysis method that allows modeling dynamic relationships between several variables using their past values as predictors. In many VAR models, it is common to use symmetric lags, meaning that the same lag length is applied to all variables across all equations in the model. The determination of this delay length is generally guided by statistical criteria such as HQ (Hannan-Quinn criterion), FPE (final prediction error), AIC (Akaike information criterion) or SIC (information criterion of Schwarz). These criteria evaluate different properties of the model, such as its ability to fit the data while penalizing model complexity, to determine the optimal delay order that balances the model's predictive ability and its complexity. In other words, the choice of lag order is a delicate decision that involves a trade-off between the model's ability to capture dynamic relationships between variables and its tendency to overfit the data. A delay order that is too low may not take into account all dynamic interactions, while a delay order that is too high may introduce excess complexity without significantly improving the predictive accuracy of the model. Thus, the selection of the lag order is a fundamental step in building a VAR model, and it is crucial to ensure that the model fits the data well and can provide reliable and interpretable forecasts.

In Table 3, the results indicate that the lag order chosen for the VAR model is 1. This decision is supported by both the FPE and AIC criteria, which converge on selecting a lag order of 1. This implies that the model incorporates one lagged value of each variable to predict its current value. Such a choice is influenced by the trade-off between model complexity and goodness of fit, as indicated by these statistical criteria. The significance of selecting an appropriate lag order lies in its impact on the model's predictive accuracy and its ability to capture dynamic relationships among variables over time. A lag order that is too short may overlook important dynamics, while one that is too long may introduce unnecessary complexity and overfitting. Therefore, the selection of lag order based on rigorous statistical criteria is crucial in ensuring the effectiveness and reliability of the VAR model in capturing the underlying economic dynamics.

4.4. Cointegration Analysis

Cointegration is a fundamental concept in econometrics that helps understand long-term relationships between economic variables. When variables share a cointegration relationship, it means that they move together in the long run despite short-term individual fluctuations. This property is essential for capturing underlying trends and enduring interrelationships between variables. The Kao cointegration test, often used in econometric analysis, is designed to assess the presence of cointegration between variables included in a model. This test provides crucial insights into the

Table 3: VAR lag order selection criteria

VAR lag order selection criteria						
Lag	LnL	LR	FPE	AIC	SC	HQ
0	2093.176	NA	9.31e−27	−37.23529	−37.04111*	−37.15651*
1	2170.560	142.3315	7.35e−27*	−37.47429*	−35.72669	−36.76523
2	2225.073	92.47719	8.85e−27	−37.30488	−34.00385	−35.96555
3	2267.910	66.54941	1.35e−26	−36.92696	−32.07250	−34.95735
4	2318.476	71.33483	1.86e−26	−36.68708	−30.27918	−34.08719
5	2361.113	54.05699	3.14e−26	−36.30558	−28.34427	−33.07542
6	2416.266	62.04721	4.58e−26	−36.14760	−26.63286	−32.28717
7	2488.395	70.84126	5.52e−26	−36.29277	−25.22460	−31.80206
8	2590.558	85.74403*	4.54e−26	−36.97425	−24.35265	−31.85327

*Indicates lag order selected by the criterion. LR: Sequential modified LR test statistic (each test at 5% level), FPE: Final prediction error, AIC: Akaike information criterion, SC: Schwarz information criterion, HQ: Hannan-Quinn information criterion

nature of long-term relationships between variables, independent of their short-term movements. When the cointegration test confirms the presence of a significant cointegration relationship between variables, this has important implications for the analysis methodology to be adopted. In particular, this justifies the use of specific models, such as the vector error correction model (VECM), which are specifically designed to model long-term dynamics between cointegrated variables while taking into account short-term adjustments. Thus, confirmation of cointegration between variables in an econometric model can guide the choice of appropriate analytical techniques, thereby providing a solid basis for an in-depth understanding of long-term economic relationships. In this perspective, the VECM panel model emerges as a relevant approach to explore the complex interactions between variables in the context of panel data.

Table 4 provides the results of the Kao cointegration test. This test evaluates the presence of cointegration between the variables included in our model. The probability associated with Kao's ADF test is <5%, with a specific value of 0.0000. This finding significantly indicates that a cointegration relationship exists between the examined variables. Cointegration between variables implies that they share a long-term relationship despite their individual short-term movements. In other words, although the variables may fluctuate independently in the short run, they converge to an equilibrium in the long run. This property is crucial in econometric analysis because it allows one to model the long-term interrelationships between variables and identify the underlying trends that link them. Confirmation of cointegration between variables in our model has important implications for the analysis methodology to adopt. In particular, this justifies the use of the vector error correction model (VECM), which is designed to model long-term relationships between cointegrated variables while accounting for short-term adjustments. Therefore, the choice of the VECM panel model is justified in this situation, thus providing a suitable approach to analyze the complex dynamics between variables in the panel data setting.

4.5. Estimation of VECM in the Long Run

In contemporary economic analysis, Panel VECM models play a crucial role in determining long-term causal relationships between economic variables in a panel data context. These models make

Table 4: Result of Kao residual cointegration test

Kao residual cointegration test		
Kao test	t-statistic	Prob.
ADF	−5.401914	0.0000
Residual variance	4.81E−05	
HAC variance	4.79E−06	

it possible to study the complex dynamics that exist between different variables, such as economic growth, capital investments, CO_2 emissions, and renewable energy consumption, within the G7 economies. By integrating both short-term and long-term effects, VECM Panels provide a holistic perspective on the interactions between these variables, helping to identify key factors that influence economic growth and the policy decisions needed to promote sustainable development. sustainable. In particular, these models make it possible to determine the long-term impact of the explanatory variables on the dependent variable, while taking into account cross-correlations and lag effects. Therefore, the use of Panel VECM models in the economic analysis of G7 countries is of fundamental importance to understand the underlying mechanisms of the economy and formulate effective policies aimed at promoting sustainable economic growth while mitigating the harmful environmental impacts.

In the long run, Table 5 indicate that the coefficient associated with the variable representing capital Ln (K) is positive and equal to 0.164. This means that capital has a positive effect on economic growth Ln (Y). More precisely, a 1% increase in capital on average leads to a 0.164% increase in economic growth. That is, capital investments have a favorable impact on economic development, which is consistent with the idea that increased resources for businesses can lead to increased production and economic growth. Similarly, the coefficient associated with the variable representing the labor force Ln (L) is positive and equal to 0.103. This indicates that labor force has a positive effect on economic growth. A 1% increase in the labor force is associated with a 0.103% increase in economic growth. This suggests that increasing available labor can boost production and therefore economic growth. Regarding CO_2 emissions Ln (CO_2), although often perceived negatively in terms of environmental impact, the positive coefficient of 0.051 suggests that they also have a positive effect on economic growth. A 1% increase in CO_2 emissions is associated with a 0.051% increase in economic growth. However, it could also indicate a continued dependence of economies on fossil fuels, highlighting the need for policies to promote more sustainable energy sources. Renewable energy consumption Ln (REC) has a positive coefficient of 0.012, which suggests a positive effect on economic growth. A 1% increase in renewable energy consumption is associated with a 0.012% increase in economic growth. This reflects a growing interest in clean and sustainable energy, which can contribute to economic growth while reducing the negative environmental impact associated with fossil fuels. Final consumption expenditure Ln (FCE) has the highest coefficient, with 0.718. This means that a 1% increase in final consumption expenditure is associated with a remarkable 0.718% increase in economic growth. This highlights the importance of domestic demand in stimulating economic activity and growth. Finally, exports Ln (X) have a positive effect on economic growth, with a coefficient of 0.169. A 1% increase in exports is associated with a 0.169% increase in economic growth. This highlights the importance of foreign trade in promoting economic growth by providing access to new markets and boosting the competitiveness of domestic businesses. On the other hand, imports Ln (M) have a negative effect on economic growth, with a coefficient of -0.159. This means that a 1% increase in imports is associated with a 0.159% decrease in economic growth. This could be due to excessive dependence on imports to meet domestic needs, which could compromise long-term economic growth.

Capital investment is crucial for G7 economies, boosting business efficiency and productivity, which promotes sustainable economic growth. Likewise, increasing the workforce can boost growth by meeting labor needs in key sectors such as technology and healthcare. Although CO_2 emissions often increase with economic growth, they highlight the need for policies promoting clean technologies to mitigate environmental impacts. Transitioning to renewable energy consumption can create new jobs and reduce long-term costs associated with non-renewable energy. Domestic demand plays a crucial role in boosting domestic production and employment, while exports open new markets and strengthen competitiveness in the global market. Although imports can stimulate growth by providing goods and technologies, excessive dependence can pose long-term risks to economic security.

In addition, the results of Table 5 indicate that capital Ln (K), labor force Ln (L), renewable energy consumption Ln (REC), final consumption expenditure Ln (FCE), exports Ln (X) and imports Ln(M) are not significant and have no effect on CO_2 emissions Ln (CO_2) in the long term. Furthermore, it is observed that capital Ln (K), labor force Ln (L), CO_2 emissions Ln (CO_2), final consumption expenditure Ln (FCE), exports Ln (X) and Ln (M) imports are not significant and have no effect on long-term renewable energy consumption Ln (REC). These results suggest that in the context of advanced economies represented by the G7, policies and variables traditionally associated with economic growth and trade are not significant determinants of CO_2 emissions or renewable energy consumption in the long term. This could indicate the need for specific targeted policies and measures to reduce CO_2 emissions and promote the use of renewable energy in these G7 countries.

4.6. Estimation of VECM in the Short Run

As part of the estimation of the panel vector error correction model, the WALD test is employed to assess the presence of short-term relationships between variables. According to the principles of econometrics, a widely accepted rule states that if the probability associated with the test is <5%, this indicates the existence of a causal relationship between the two variables examined. On the other hand, if the probability is >5%, this suggests that no significant causal relationship is detected between the variables. This statistical approach helps identify dynamic interactions between short-term variables, providing crucial information for understanding the underlying mechanisms of the economy. Accordingly, the use of the WALD test under the panel vector error correction model plays a vital role in analyzing short-term economic dynamics and formulating appropriate economic policies.

Table 6 provides the conclusions of the WALD test integrated into the estimation of the Panel VECM model, aimed at evaluating the causal links between short-term variables. The results clearly indicate the absence of causal relationships between economic growth Ln (Y), CO_2 emissions Ln (CO_2) and renewable energy consumption Ln (REC) in the short term. These findings highlight that, in the context of this analysis, short-term variations in economic growth, CO_2 emissions and renewable energy consumption are not directly influenced by each other. This lack of short-term causality suggests that other factors or mechanisms may be at play in short-term economic dynamics, and that the effects of changes in these variables on other economic aspects may require a longer period of time to manifest itself in a meaningful way.

Table 5: Estimation of VECM models in the long run

	Dependents variables							
Independents variables	**Ln (Y)**	**Ln (K)**	**Ln (L)**	**Ln (CO_2)**	**Ln (REC)**	**Ln (FCE)**	**Ln (X)**	**Ln (M)**
Ln (Y)	--	6.067***	9.637	19.44	79.87	1.391	5.903***	−6.283***
Ln (K)	0.164***	--	−1.588	−3.205	−13.16	−0.229	−0.972***	1.035***
Ln (L)	0.103***	−0.629***	--	−2.017	−8.288	−0.144	−0.612***	0.652***
Ln (CO_2)	0.051***	−0.312***	−0.495	--	−4.107	−0.071	−0.303***	0.323***
Ln (REC)	0.012***	−0.075***	−0.120	−0.2434	--	−0.017	−0.073***	0.078***
Ln (FCE)	0.718***	−4.360***	−6.925	−13.97	−57.40	--	−4.242***	4.515***
Ln (X)	0.169***	−1.027***	−1.632	−3.294	−13.53	−0.235	--	1.064***
Ln (M)	−0.159***	0.965***	1.533	3.094	12.71	0.221	0.939***	1

(***) significant at the 1%

Table 6: VEC granger causality/block exogeneity wald tests

Dependent variable: Ln (Y)				Dependent variable: Ln (REC)			
Excluded	**Chi-square**	**df**	**Prob.**	**Excluded**	**Chi-square**	**df**	**Prob.**
Ln (K)	0.757472	1	0.3841	Ln (Y)	0.106987	1	0.7436
Ln (L)	2.789031	1	0.0949	Ln (K)	2.664401	1	0.1026
Ln (CO_2)	0.233677	1	0.6288	Ln (L)	1.613108	1	0.2041
Ln (REC)	1.791865	1	0.1807	Ln (CO_2)	0.815881	1	0.3664
Ln (FCE)	19.69028	1	0.0000	Ln (FCE)	0.140907	1	0.7074
Ln (X)	10.38847	1	0.0013	Ln (X)	0.376385	1	0.5395
Ln (M)	11.33616	1	0.0008	Ln (M)	7.203931	1	0.0073
All	50.80895	7	0.0000	All	17.68425	7	0.0135
Dependent variable: Ln (K)				**Dependent variable: Ln (FCE)**			
Excluded	**Chi-square**	**df**	**Prob.**	**Excluded**	**Chi-square**	**df**	**Prob.**
Ln (Y)	6.540720	1	0.0105	Ln (Y)	0.221183	1	0.6381
Ln (L)	2.271924	1	0.1317	Ln (K)	0.308571	1	0.5786
Ln (CO_2)	0.059245	1	0.8077	Ln (L)	2.229119	1	0.1354
Ln (REC)	0.909947	1	0.3401	Ln (CO_2)	2.678380	1	0.1017
Ln (FCE)	15.27900	1	0.0001	Ln (REC)	1.244710	1	0.2646
Ln (X)	12.28691	1	0.0005	Ln (X)	1.320852	1	0.2504
Ln (M)	19.47103	1	0.0000	Ln (M)	4.042386	1	0.0444
All	37.44129	7	0.0000	All	22.21496	7	0.0023
Dependent variable: Ln (L)				**Dependent variable: Ln (X)**			
Excluded	**Chi-square**	**df**	**Prob.**	**Excluded**	**Chi-square**	**df**	**Prob.**
Ln (Y)	5.268776	1	0.0217	Ln (Y)	8.483154	1	0.0036
Ln (K)	2.678178	1	0.1017	Ln (K)	1.923444	1	0.1655
Ln (CO_2)	1.420613	1	0.2333	Ln (L)	5.362287	1	0.0206
Ln (REC)	0.103391	1	0.7478	Ln (CO_2)	0.215633	1	0.6424
Ln (FCE)	2.970241	1	0.0848	Ln (REC)	0.530254	1	0.4665
Ln (X)	5.360547	1	0.0206	Ln (FCE)	5.972802	1	0.0145
Ln (M)	3.357897	1	0.0669	Ln (M)	5.114259	1	0.0237
All	8.263858	7	0.3099	All	22.87140	7	0.0018
Dependent variable: Ln (CO_2)				**Dependent variable: Ln (M)**			
Excluded	**Chi-square**	**df**	**Prob.**	**Excluded**	**Chi-square**	**df**	**Prob.**
Ln (Y)	0.161641	1	0.6876	Ln (Y)	10.09441	1	0.0015
Ln (K)	0.814578	1	0.3668	Ln (K)	5.271701	1	0.0217
Ln (L)	1.104225	1	0.2933	Ln (L)	8.283084	1	0.0040
Ln (REC)	1.067626	1	0.3015	Ln (CO_2)	0.009149	1	0.9238
Ln (FCE)	2.571943	1	0.1088	Ln (REC)	0.178344	1	0.6728
Ln (X)	0.010557	1	0.9182	Ln (FCE)	11.61593	1	0.0007
Ln (M)	0.114589	1	0.7350	Ln (X)	14.58686	1	0.0001
All	9.136007	7	0.2430	All	29.42067	7	0.0001

5. CONCLUSIONS AND RECOMMENDATIONS

This work represents an informed attempt to unpack the complex interactions between three crucial elements: the use of renewable energy, carbon dioxide (CO_2) emissions, and the trajectory of economic growth, in the context of the G7 countries on a period extending from 1997 to 2021. Through a methodical and rigorous approach based on cointegration analysis and the panel vector error correction model, our empirical study sheds light on an essential aspect: the proven positive impact of the use of renewable energy sources and CO_2 emissions on long-term economic growth trends. However, it should be noted that an in-depth analysis reveals a notable gap in the perception of an observable relationship between the adoption of renewable energy, CO_2 emissions and short-term economic growth dynamics. The results obtained reveal that in the long term, the use of renewable energies and CO_2 emissions have a positive impact on economic growth in the G7 countries. This finding highlights the importance for policies aimed at encouraging the adoption of renewable energy and reducing CO_2 emissions to plan over the long term to achieve maximum efficiency. This study provides substantial added value by specifically focusing on examining the dynamics between renewable energy use, CO_2 emissions and economic growth in G7 countries over a considerable period of almost 25 years. Using rigorous analytical methodologies such as cointegration analysis and the panel vector error correction model, it provides a nuanced perspective on the relationships between these variables, highlighting the importance of a long-term sustainable approach in the development of energy policies.

The recommendations arising from this study highlight the need for policymakers to focus their efforts on developing long-term strategies to promote the adoption of renewable energy and reduce CO_2 emissions. With this in mind, it is crucial to consider several concrete measures. Firstly, the introduction of tax incentives could encourage businesses and individuals to invest in renewable energy solutions, thereby boosting innovation and adoption of these technologies. Second, increasing investment in renewable energy research and development is essential to foster the emergence of more efficient and affordable technologies, which could in turn accelerate their large-scale deployment. Finally, the introduction of regulations favorable to the use of clean energy, such as stricter emissions standards or requirements for the use of renewable energy in the energy sector, could incentivize companies and industries to adopt more sustainable practices. By combining these different approaches, policymakers can create an environment conducive to the transition to a greener and more sustainable economy, while boosting economic growth and mitigating the adverse effects of climate change.

Indeed, it's important to acknowledge the limitations of this study. The constrained temporal scope, reaching only until 2021, might hinder a comprehensive understanding of recent developments in the intricate relationships between the utilization of renewable energies, CO_2 emissions, and economic growth. Given the rapidly evolving landscape of environmental policies, technological innovations, and global events, newer data could provide valuable insights into how these dynamics have evolved in the most recent years. Furthermore, while this study meticulously analyzed various factors, certain external influences like political shifts, technological breakthroughs, or major global events were not fully accounted for. These factors could potentially impact the observed relationships and might merit consideration in future research endeavors to provide a more holistic understanding of the subject matter. Therefore, it's imperative for future studies to address these limitations by incorporating more recent data and accounting for a broader range of influencing factors to enhance the robustness and applicability of the findings.

To pave the way for further exploration, expanding this study's scope could yield valuable insights. One avenue could involve examining other groups of countries beyond the G7 or delving into the dynamics within emerging economies. By doing so, researchers could gain a more comprehensive understanding of how different socio-economic contexts influence the relationship between renewable energy adoption, CO_2 emissions, and economic growth. Additionally, investigating the impact of specific policies on the adoption of renewable energies and CO_2 emissions could shed light on the effectiveness of various regulatory approaches and incentives in promoting sustainability. Moreover, delving into the short-term mechanisms underlying these relationships presents another promising area for future research. By exploring how immediate factors such as policy changes, market dynamics, and technological disruptions affect the dynamics between renewable energy utilization, CO_2 emissions, and economic growth, researchers can offer more nuanced insights into the temporal aspects of these interactions. Furthermore, conducting in-depth analyses of the socio-economic implications of energy policies could prove instrumental in guiding policymakers towards more effective and equitable strategies. Understanding how energy policies impact employment, income distribution, and overall societal well-being can help ensure that sustainability initiatives not only mitigate environmental degradation but also foster inclusive economic development. By embarking on these avenues of research, scholars can contribute to a deeper understanding of the complex interplay between renewable energy adoption, CO_2 emissions, and economic growth, ultimately informing more informed and impactful policy decisions in the pursuit of a sustainable future.

6. ACKNOWLEDGEMENT

This work was supported and funded by the Deanship of Scientific Research at Imam Mohammad Ibn Saud Islamic University (IMSIU) (grant number IMSIU-DDRSP2502).

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