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Linkages Between Ecological Footprint and Macroeconomic Variables in G7 Countries: MMQR Approach

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G7 Ülkelerinde Ekolojik Ayak İzi ile Makroekonomik Değişkenler Arasındaki Bağlantılar: MMQR Yaklaşımı

Abstract

This study aims to investigate the dynamic causal links among ecological footprint, economic growth, non-renewable and renewable energy consumption and financial development of G7 countries for the 1990-2020 period. In the long run, FMOLS, DOLS and CCR results show that economic growth and non-renewable energy consumption have a positive effect on the ecological footprint, while renewable energy consumption and financial development have an adverse impact on the ecological footprint. According to the MMQR approach, non-renewable energy consumption has the most potent positive effect on the ecological footprint. The impact of renewable energy consumption on the ecological footprint is negative, but its effect is low. Policymakers should focus on increasing renewable energy investment and enhancing financial sector mechanisms for green financing to reduce the ecological footprint in G7 countries.

Keywords : Ecological Footprint, Economic Growth, Renewable Energy, G7 Countries, Quantile Regression Analysis.

JEL Classification Codes : E44, P18, Q43, Q56.

Öz

Bu çalışmanın amacı G7 ülkelerinin 1990-2020 dönemi için ekolojik ayak izi, ekonomik büyüme, yenilenemeyen ve yenilenebilir enerji tüketimi ve finansal gelişme arasındaki dinamik nedensellik bağlantılarını araştırmaktır. FMOLS, DOLS ve CCR sonuçları, uzun dönemde ekonomik büyümenin ve yenilenemeyen enerji tüketiminin ekolojik ayak izini olumlu yönde etkilediğini, yenilenebilir enerji tüketimi ve finansal gelişmenin ise ekolojik ayak izini olumsuz yönde etkilediğini göstermektedir. MMQR yaklaşımına göre ise, yenilenemeyen enerji tüketimi ekolojik ayak izini pozitif yönde ve en güçlü şekilde etkileyen değişkendir. Yenilenebilir enerji tüketiminin ekolojik ayak izi ile negatif yönde ilişkili olmakla birlikte etkisi düşüktür.

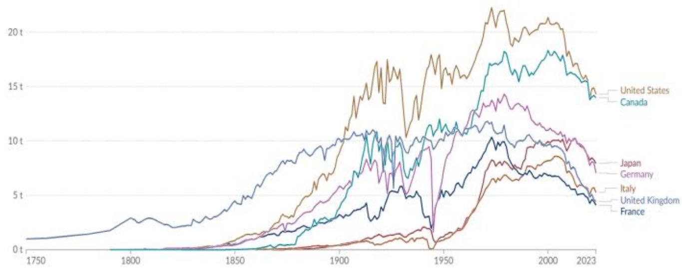
Anahtar Sözcükler : Ekolojik Ayakizi, Ekonomik Büyüme, Yenilenebilir Enerji, G7 Ülkeleri, Quantile Regresyon Analizi.

1. Introduction

In recent years, environmental sustainability and ecological footprint have attracted significant attention and have become an important topic that can be integrated into social distribution, sustainability and economic competitiveness (Lian & Li, 2024). Environmental degradation threatens the sustainability of the global economy as it is associated with the performance of various macroeconomic indicators (Jahanger et al., 2022). In this context, global warming and climate change, which are directly and indirectly linked to human activities that affect the atmospheric structure and the variability of the environment, are among the most critical problems. The acceleration of human activities to provide the necessary transformations due to industrialisation and population growth is one of the leading causes of climate change (Li et al., 2023). Carbon dioxide (CO_2) emissions are the primary greenhouse gas released due to human and economic activities. Carbon emissions are primarily caused by fossil fuels such as oil, coal, natural gas, and cement production (Fatima et al., 2024). G7 countries have an increasing effect on world carbon emissions. These countries are responsible for 18% of global energy sector emissions 2023 (EMBER Energy, 2024). Graph 1 shows the pathway of the per capita CO_2 emissions of the G7. After the Kyoto Protocol in 2002, there was a significant reduction in the per capita CO_2 emissions in the G7 countries (Dritsaki & Dritsaki, 2024). In Canada, France, Germany, Italy, Japan, the USA and the United Kingdom, carbon emissions per capita were 16.7, 6.0, 10.10, 7.77, 9,47, 19,45 and 8,94 metric tons in 2002, respectively, and have gradually decreased since then. The average for 2020, based on seven countries, was 7.88 metric tons. Canada and the United States have recently ranked higher than others. G7 countries must phase out coal by 2030 and fully decarbonise electricity by 2035 to limit global temperature rise to 1.5°C (EMBER Energy, 2024). G7 leaders pledged in June 2021 to achieve net carbon neutrality by 2050 (IEA, 2024). Renewable energy, smart technology, electric vehicles, etc., should be promoted as policy tools to achieve these goals. Currently, the energy sources in G7 countries are as follows: solar 5.7%; wind 10.2%; hydro 10.7%; bioenergy 2.8%; nuclear 17.8%; gas 34.2%; coal 15.9% other fossil 1.7% (EMBER Energy, 2024).

Biological capital is a direct and indirect component of all ecosystems and the biosphere and is vital for maintaining the natural environment and human well-being. Some tools are required to monitor the use and management of biological capital. The ecological footprint is a computational tool that calculates human demands on the biosphere and compares them with the planet's ability to meet them. It helps individuals, businesses and governments track the use and change of biological capital over time. It provides a quantitative input to policymakers’ decision-making processes (Wackernagel & Kitzes, 2008). The ecological footprint is an ecological assessment of sustainable development; in other words, it measures the ecological impact of humans and the ability of nature to absorb these impacts (Li et al., 2022). The ecological footprint, which refers to demand for natural resources, is calculated by comparing it with the biocapacity, which is the supply of natural resources. Both biocapacity and ecological footprint are measured in per capita values using the global hectare (gha) unit. The USA, Japan, Germany and France are among the top 10 countries with the highest ecological footprint. The USA has the world's highest ecological footprint after China (World Population Review, 2024). The average carbon footprint per capita in the G7 countries is 5.1, while the world average is 4 gha per capita (Global Footprint Network, 2024). The values of ecological footprint and biocapacity per capita are shown in Graph 2. The ecological deficit or surplus is the difference between the ecological footprint and the biocapacity. All countries except Canada have ecological deficits. In 1990, the ecological deficits in France, Germany, Italy, Japan, the United States and the United Kingdom were 3.3, 5.2, 4.2, 4.6, 5.6 and 5.7, respectively. In 2020, the ecological deficits in these countries were 1.7, 2.7, 2.8, 3.2, 3.4 and 2.5, respectively. Accordingly, the ecological deficit is gradually decreasing in the G7 countries. This indicates that biocapacity is decreasing and the deterioration in environmental quality is accelerating.

Graph: 1
Pathway of the Per Capita CO_2 Emissions of G7 from 1750 to 2023

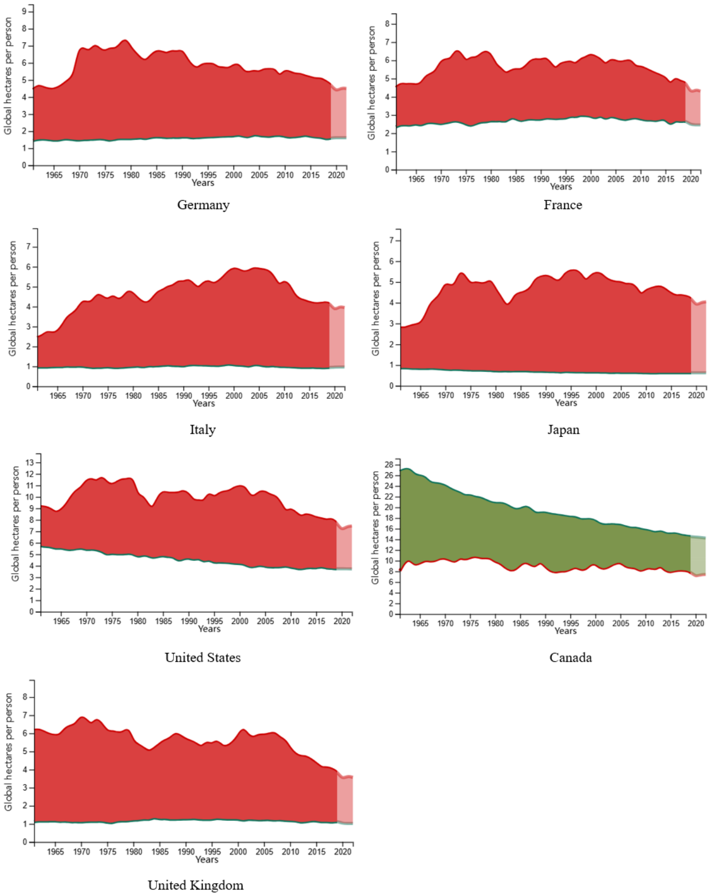


Source: Our World in Data based on the Global Carbon Budget (2024).

Graph 3 shows the trend in ecological footprint in G7 countries for the period 1990-2020. There has been a general downward trend in the ecological footprint of these countries over the last decade. Graph 4 shows that the ecological footprint is concentrated at lower income levels. When income levels increase, the ecological footprint increases. It also shows that the ecological footprint positively relates to non-renewable energy consumption. When renewable energy consumption rises, the ecological footprint decreases. At higher levels of renewable energy consumption, the ecological footprint is lower. With the advancement of financial development, the carbon footprint has generally reduced.

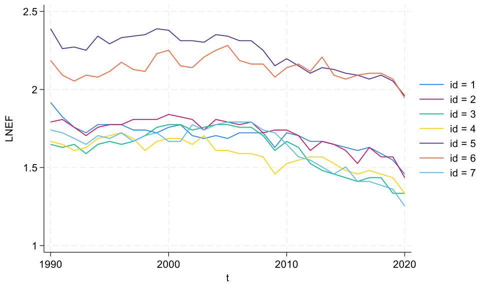
The relationship between environmental degradation and many macroeconomic variables has been analysed in the literature. Financial development, environmental policy implementation, and energy consumption patterns are crucial components in the complex sustainability framework for advanced economies, namely within the G7 consortium (Wang et al., 2024). The financial system provides economic growth through factor accumulation and factor efficiency. Factor accumulation is achieved by mobilising inefficiently used resources in the financial system. Factor efficiency, financial innovations, and the use of technology in the financial system result in reduced information asymmetry, financial liberalisation, improved risk sharing, and reduced equity costs (Sadorsky, 2010). Ensuring the efficiency of the financial system, reducing financial risk and borrowing costs, increasing transparency between borrowers and lenders, and providing greater access to capital and technological advances increase consumption and investment. For households, lower borrowing costs make it easier to purchase durable consumer goods and increase energy demand. For businesses, financing opportunities and financial innovations increase business capacity and employment. In short, financial development increases economic growth and demand, and as a result, energy demand increases (Sadorsky, 2010). It is essential to determine which sources will meet the energy demand. As a result of technological developments and progress in financial markets, transferring resources to renewable energy sources improves environmental quality. Therefore, the financial sector is essential for financing environmentally friendly investments in construction, agriculture, services, technology and renewable energy.

Graph: 2
Ecological Footprint in G7 Countries (per person gha)



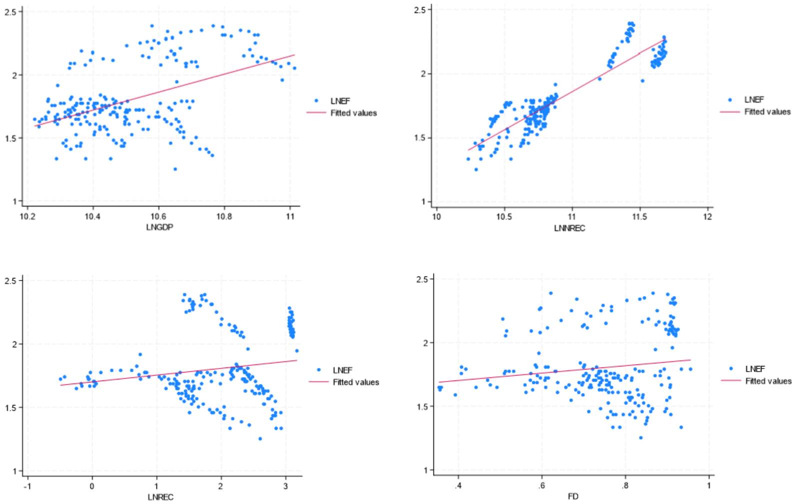
Source: Global Footprint Network.

Graph: 3
Ecological Footprint in G7 Countries



Note: id 1: Germany, id 2: France, id 3: Italy, id 4: Japan, id 5: United States, id 6: Canada, id 7: United Kingdom.
Source: Global Footprint Network

Graph: 4
Scatterplot of Variables of Interest for G7 Countries



Source: Created by the author using Global Footprint Network (GFC), International Energy Agency (IEA), International Monetary Fund (IMF), World Bank (World Development Indicators).

The financial development index has dramatically improved in the G7 countries from 1990 to 2008. Since then, it has maintained a certain level in these countries. However, financial development increases economic growth by stimulating consumption and investment, which may deteriorate environmental quality. The increase in urban population leads to greater energy consumption and use of natural resources (Pata, 2018). Recently, the connections between green growth and the financial sector have begun to be analysed. In this context, Zeng et al. (2024) found that financial technologies (Fin-tech) are negatively affecting green growth (low-carbon sustainable development) in G7 economies. Therefore, it is essential to investigate the impact of the financial sector on growth, energy resources and environmental degradation and update it with new data.

This study investigated the relationships between ecological footprint, economic growth, non-renewable and renewable energy consumption and financial development using DOLS, FMOLS, CCR and MMQR techniques for G7 countries. There are a few studies in which the ecological footprint and macroeconomic variables in the G7 countries are examined using quantile regression analysis. In this respect, the study is thought to contribute to the literature. The ecological footprint is the dependent variable in the study because it measures the carrying capacity of the world and has the power to explain ecological sustainability comprehensively. The rest of the study is designed: The second section covers the literature review, including the variables' connections. The third section contains data, a model, and an econometric analysis. The fourth section consists of findings and discussion. The last section consists of conclusions and policy recommendations.

2. Literature Review

Many studies in the literature explain the relationships between ecological footprint and variables such as economic growth, human capital, urbanisation, energy consumption, financial development, population, trade openness, savings, economic complexity and globalisation. In this context, studies have reached the following conclusions: Energy consumption, economic growth, imports, natural resources consumption, and urbanisation increase environmental degradation. However, eco-innovation, economic complexity, export, foreign direct investment, financial globalisation, financial development, improving human capital, energy efficiency, renewable energy consumption, fintech, trade openness, technological innovations, and ecological governance reduce environmental degradation (Pata, 2018; Wang & Dong, 2019; Ahmed et al., 2020; Wang et al., 2020; Ahmad et al., 2021; Usman et al., 2021; Ansari, 2022; Jahanger et al., 2022; Miao et al., 2022; Radmehr et al., 2022; Luo et al., 2023; Yapraklı et al., 2023; Xia & Liu, 2024).

2.1 Nexus Between Economic Growth And Environment

Studies investigating the relationship between economic growth and environmental degradation have increased considerably since Grossman and Krueger's (1991) survey. Studies supporting the Environmental Kuznets Curve hypothesis (EKC) have shown that countries become more sensitive to environmental degradation when they reach high-income levels. Economic growth occurs through energy consumption as countries move towards growth, and environmental quality gradually deteriorates. After a certain threshold level of economic growth, with the development of environmental awareness, policymakers begin to take measures to improve environmental quality. It is assumed that this technological progress will be made through technology transfer. As energy solutions from renewable energy sources are preferred, the ecological footprint decreases (Destek & Sinha, 2020). Tamazian et al. (2009) supported the EKC hypothesis for BRIC countries. In that study, where panel data analysis was carried out for 1992-2004, it was concluded that higher economic and financial development levels in the BRIC countries reduced environmental degradation. Omri et al. (2015) examined the relationship between financial development, CO_2 emissions, trade and economic growth using simultaneous equation panel data models for 12 MENA countries from 1990 to 2011. Their empirical results verified the existence of the environmental Kuznets curve. Ike et al. (2020) conducted panel data analysis for G7 countries. The results confirmed the validity of the environmental Kuznets curve hypothesis at both panel and country-specific levels. Destek and Sinha (2020) conducted a study using second-generation panel data methodologies for 24 OECD countries covering 1980-2014. The group-average results show that the inverted U-shaped Environmental Kuznets Curve hypothesis does not hold for OECD countries because a U-shaped relationship was found between economic growth and ecological footprint.

2.2. Nexus Between Non-Renewable And Renewable Energy Consumption And The Environment

Economic growth patterns can explain the relationship between energy consumption and ecological footprint. In the first stage of economic development, countries use energy obtained from fossil fuels to carry out production. When growth reaches a certain level, policymakers and industries turn to renewable energy sources, and there is a decrease in environmental degradation (Destek & Sinha, 2020). While the consumption of renewable energy sources such as solar, hydropower, geothermal, wind, and biomass improves environmental quality, the increase in the consumption of non-renewable energy sources such as oil, natural gas, and coal increases environmental degradation. (Khan et al., 2019; Akram et al., 2021; Destek & Sinha, 2020; Wang et al., 2022; Luo et al., 2023). Jebli et al. (2020) analysed the situation using the Generalised Method of Moments system and the Granger causality test in countries classified according to their income levels from 1990 to 2015. They found that for upper-income countries, renewable energy consumption leads to decreased carbon emissions. However, in low-income countries, the reducing effect of increasing renewable energy consumption on environmental degradation is greater than in high-income countries. Lian and Li (2024) conducted panel data analysis in G7 countries from 1990 to 2022 and found a negative correlation between green growth and environmental degradation. Accordingly, using renewable energy sources and accelerating technical innovation can help achieve stable economic growth and less environmental impact. However, Pata (2018) concluded that renewable energy consumption increasingly affects carbon emissions in Türkiye. This is because renewable energy consumption is constantly decreasing, and sufficient steps have not been taken. It has been argued that raising public awareness, developing carbon capture and storage technologies and implementing carbon taxes will be effective as a suggestion. Ike et al. (2020) verified the pollution reduction effect of renewable energy consumption for the entire panel in G-7 countries, but reached different results on a unit basis. As a policy, a tax program has been proposed in which the tax applied to fossil fuels is proportional to renewable energy sources. Accordingly, the use of renewable energy should be increased until it becomes affordable compared to fossil fuels.

2.3. Nexus Between Financial Development And Environment

Financial development has a vital role in economic growth and efficiency. Various studies have investigated the environmental impact of financial development. There is no consensus on the effects of financial development on the environment. Studies that draw attention to the negative aspects of financial development indicate that income increases with financial development, production, and consumption levels increase, and therefore energy consumption increases (Dasgupta et al., 2001). As a result, environmental quality deteriorates. On the other hand, some studies support that environmental quality is better in economies with developed financial markets. A developed banking sector is generally expected to facilitate financial reform and increase efficiency in financial markets by weeding out low-yield financial instruments. Tamazian et al. (2009) used panel data from 1992 to 2004 in BRIC economies and pointed out the effect of financial development on reducing carbon emissions. Ensuring financial development for foreign direct investments based on R&D improves environmental quality. Capital markets and banking sector improvements can help reduce per capita carbon emissions by improving energy efficiency. Using the Johansen cointegration theory, Zhang (2011) investigated the long-run equilibrium relationship between financial development and carbon emissions. According to a study, financial development improves environmental quality by promoting R&D expenditures and environmentally friendly enterprises. Omri et al. (2015) examine the relationship between financial development, CO_2 emissions, trade and economic growth using simultaneous equation panel data models for 12 MENA countries from 1990 to 2011. They argue that higher levels of financial system development and trade openness support technological innovation by increasing energy conservation and R&D expenditures, which in turn result in energy efficiency and can therefore reduce carbon emissions. Miao et al. (2022) used the Method of Moments Quantile Regression (MMQR) technique to assess the role of financial globalisation and renewable energy consumption on the ecological footprint in newly industrialised countries using annual data from 1990 to 2018. They found that financial globalisation reduces the ecological footprint in all quantiles in newly industrialised countries. Jahanger et al. (2022) aimed to check whether technological innovation, natural resource consumption, globalisation, economic growth, human capital development and financial development affect ecological footprint figures in 73 developing countries from 1990 to 2016 through long-run cointegration tests. They argue that increasing the productivity of natural resources through technological innovation will improve environmental quality. In addition, investment in human capital and financial development is also compatible with environmental development goals. Zhang (2023) investigates the impact of China's Green Finance Innovation and Reform Pilot Zones on corporate finance. He used the Differences-in-Differences (DID) approach for certain provinces of China. According to this study, financial innovations can drive financial sector growth and influence environmental sustainability. Xia and Liu (2024) used the nonlinear moments quantile regression (MMQR) method for empirical research to assess the asymmetric impact of Fintech, natural resource rent, and ecological regulations on the ecological footprints (EF) for G7 countries from 2000 to 2020. According to this study, fintech and ecological governance significantly reduce the ecological footprint. Differences in the impact of financial markets on environmental quality are due to different countries and country groups being examined. For example, Tamazian (2009)’s findings cover BRIC economies, while Zhang (2011) studied China. Omri et al. (2015) reached findings on 12 MENA countries, while Miao et al. (2022) studied newly industrialising countries. Studies also suggest financial development positively impacts environmental quality, particularly in developing countries.

This study is one of the few studies that apply the MMQR approach to assessing environmental quality in G7 countries. It aims to examine the periodic effects of the variables. In addition, while the literature about environmental quality intensively analyses developing countries, the number of studies analysing industrialised countries is relatively low. In these aspects, the study is expected to contribute to the literature.

The following hypotheses were developed based on the literature:

H_1: Economic growth that does not follow a green, sustainable growth path increases the ecological footprint

H_2: Non-renewable energy consumption increases the ecological footprint due to environmental degradation

H_3: Renewable energy consumption reduces ecological footprint by providing green growth

H_4: Financial development affects the ecological footprint, depending on its role in green financing and investment

3. Data and Model Specification

3.1. Data

This study employs data from G7 countries from 1990 to 2020 to evaluate the impact of economic growth, non-renewable and renewable energy consumption and financial development on ecological footprint. The dependent variable is ecological footprint (EF), and the independent variables include economic growth (GDP), non-renewable energy consumption (NREC), renewable energy consumption (REC) and financial development (FD). The dependent variable selected to assess environmental quality is ecological footprint, which is quantified as per person gha, GDP per capita income at 2015 prices, non-renewable energy consumption as kilowatt-hours per capita, renewable energy consumption as a percentage of total energy consumption and financial development as financial development index. The variables except FD are in logarithmic form. Ecological footprint variable obtained from the Global Footprint Network. Economic growth variable obtained from the World Bank, World Development Indicator statistics (WDI). Non-renewable and renewable energy consumption variables are received from the International Energy Agency (IEA). The financial development variable is obtained from the International Monetary Fund (IMF) databases. Measurement units and data sources are shown in Table 1. Statistical descriptive analysis of variables is given in Table 2. It provides descriptive details of all the variables. The LNREC variable has the highest standard deviation of 0.866. The FD variable has the lowest mean of 0.750. Jarque-Bera (JB) statistics show that not all the variables are normally distributed.

Table: 1
Variables Description

Variables	Description	Unit of Measurement	Role	Sources
EF	Ecological Footprint	Per person (gha)	Dependent	GFN
GDP	Gross domestic product	GDP per capita (constant 2015 US$)	Independent	WDI
NREC	Non-renewable energy consumption	Primary energy consumption per capita (kWh/person)	Independent	IEA
REC	Renewable energy consumption	Renewable energy consumption (% of total final energy consumption)	Independent	IEA
FD	Financial development	Financial development index	Independent	IMF

Table: 2
Descriptive Analysis of G7 Countries

Variables	LNEF	LNGDP	LNNREC	LNREC	FD
Mean	1.804	10.516	10.903	1.937	0.750
Std. dev.	0.271	0.184	0.412	0.866	0.134
Min	1.253	10.222	10.231	-0.494	0.354
Max	2.389	11.014	11.688	3.172	0.956
Variance	0.734	0.034	0.169	0.751	0.018
Skewness	0.556	0.683	0.680	-0.692	-0.797
Kurtosis	2.329	2.756	2.186	3.081	3.221
Jarque Bera test	15.66	13.22	24.76	13.34	16.80
Probability	0.000***	0.013**	0.000***	0.013**	0.000***
Observations	217	217	217	217	217

3.2. Model Mpecification

$$EF_{it} = f(GDP_{it}, NREC_{it}, REC_{it}. FD_{it},) \quad (1)$$

$$LNEF_{it} = \beta_0 + \beta_1 LNGDP_{it} + \beta_2 LNNREC_{it} + \beta_3\, LNREC_{it} + \beta_4 FD_{it} + \mu_{it} \quad (2)$$

The general quantile conditional function for quantile τ is given as:

$$Q_{LNEF_{it}} = (\tau|\lambda_i, \delta_t, X_{it}) = \lambda_i + \delta_t + \beta_{1,\tau} LNGDP_{it} + \beta_{2,\tau} LNNREC_{it} + \beta_{3,\tau} LNREC_{it} + \beta_{4,\tau} FD_{it} + \mu_{\tau,it} \quad (3)$$

where τ shows quantiles such as 10th, 20th, 30th, 40th, 50th, 60th, 70th, 80th, and 90th $i = 1, \ldots \cdot\cdot N$ is for cross-sections and t for the time-period starting from $t = 1, \ldots\ldots T$. The term β denotes the coefficients of parameters and μ_{it} is the error term. $LNEF_{it}$ is the dependent variable.

4. Econometric Methodology

The CD test is performed before panel data analysis. Pesaran's (2004) test is used in the current research. The slope homogeneity test developed by Pesaran and Yamagata (2008) is used. After determining the cross-sectional dependency, the second-generation unit root tests are performed, as Pesaran (2007) suggested. Westerlund's (2007) test is used to determine the existence of a long-term relationship between the parameters. Then, this study uses DOLS (Dynamic Ordinary Least Squares), FMOLS (Fully Modified Ordinary Least Squares) and CCR (Canonical Cointegration Regression) methodologies to investigate the potential long-term relationship among variables. DOLS was developed by Stock and Watson (1993), FMOLS was developed by Phillips and Hansen (1990), and CCR was created by Park (1992). Then, an assessment of the impact of GDP, NREC, REC, and FD on the ecological footprint was conducted in each quantile. The current research used MMQR to examine and analyse the interaction of variables. Finally, the Dumitrescu and Hurlin (2012) test determines causality relationships between variables.

4.1. Cross-Sectional Dependence Test

Traditional econometric approaches may lead to misleading and ineffective results because they do not consider cross-sectional dependence (CD). Therefore, it is essential to determine the CD. Three tests measure cross-sectional dependence in panel data analysis. Breusch & Pagan (1980) state that the LM test is appropriate if T>N. Pesaran et al. (2008) is an appropriate test if T<N. Pesaran (2004) is a proper test of T≈N. In all tests, the null hypothesis and alternative hypothesis are as follows:

$H_0 = Cov(\mu_{it}, \mu_{jt}) = 0$ for all t and $i \neq j$

$H_1 = Cov(\mu_{it}, \mu_{jt}) \neq 0$ for at least one $i \neq j$

CD statistics for Breusch & Pagan (1980) are expressed as follows:

$$LM_{BP} = T.\sum_{i=1}^{T-1}\sum_{j=i+1}^{N}\hat{\theta}_{ij} \sim \chi^2 N(N-1)/2 \quad (4)$$

CD statistics for Pesaran (2004) are expressed as follows:

$$CD = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{J=i+1}^{N}\hat{\rho}_{ij}\right) \sim N(0,1) \quad (5)$$

$$T = 1,2,3,4,\ldots\ldots 15\ldots\ldots N$$

$$M = \sqrt{\frac{2T}{N(N-1)}\left(\sum_{i=1}^{N-1}\sum_{J=i+1}^{N}\hat{\rho}_{ij}\right)\frac{(T-k)\hat{\rho}_{ij}^2 - E(T-k)\hat{\rho}_{ij}^2}{Var(T-k)\hat{\rho}_{ij}^2}} \quad (6)$$

CD test is valid for N and T tending to infinity in any order, where $\hat{\rho}_{ij}^2$ denotes the residual pairwise correlation coefficient sample estimates obtained through the OLS-ordinary least squares. In the presence of CD, the alternative hypothesis must be accepted against the null hypothesis. Westerlund cointegration test and most of the second-generation Cross-sectional Augmented IPS (CIPS) tests assume dependency between the sections (Ahmad et al., 2021).

4.2. Slope Homogeneity Test

Pesaran and Yamagata (2008) developed the method of Swamy (1970) to test for the slope homogeneity phenomenon, as described in equations:

$$\bar{\Delta}= \sqrt{N}\left[\frac{N^{-1}\tilde{S}-k}{\sqrt{2k}}\right] \tag{7}$$

$$\bar{\Delta}_{adj}= \sqrt{N}\left[\frac{N^{-1}\tilde{S}-k}{\sqrt{\frac{2k(T-k-1)}{T+1}}}\right] \tag{8}$$

$$\tilde{S} = \sum_{\mathrm{i}=1}^{N}(\hat{\beta}_i - \tilde{\beta}_{WFE})' \frac{X_i' M_\tau X_i}{\vartheta_i^2}(\hat{\beta}_i - \tilde{\beta}_{WFE}) \tag{9}$$

$\bar{\Delta}$ and $\bar{\Delta}_{adj}$ are the standardised dispersion and the biased-adjusted statistics. $\hat{\beta}_i$ indicates the pooled OLS regression coefficients for each individual i, ranging from 1 to N, and $\tilde{\beta}_{WFE}$ represents the weighted fixed effect (WFE) pooled estimator. Besides, M_τ, ϑ_i^2 and k are respectively the identity matrix, estimate of ϑ_i^2 and the number of independent variables (Le & Bao, 2020). The $\bar{\Delta}$ test statistic is used for large samples, and the $\bar{\Delta}_{adj}$ test statistic is used for small samples. The null hypothesis is that the slope parameters are homogeneous.

4.3. Unit Root Analysis

Before examining the cointegration between variables, it is essential to determine their unit root properties (Ahmed et al., 2020). Pesaran (2007) developed cross-sectional augmented Dickey-Fuller (CADF) and cross-sectional augmented Im-Pesaran-Shin (CIPS) tests, which account for the cross-sectional dependence and heterogeneity in panel data.

The regression equation of the CADF test is as follows:

$$\Delta y_{it} = a_i + b_i y_{i,t-1} + c_i \bar{y}_{t-1} + d_i \Delta \bar{y}_t + \mu_{it} \tag{10}$$

where $\bar{y}_{t-1}$ refers to the cross-sectional average of the series’ lagged value and $\Delta\bar{y}_t$ refers to the cross-sectional average of the first difference of the series. The arithmetic mean of these test statistics is then calculated, and the CIPS statistics are computed for the entire panel. The CIPS statistics are shown in the equation (Pesaran, 2007).

$$CIPS = N^{-1}\sum_{i=1}^{N} CADF_i \tag{11}$$

The asymptotic null distribution of the individual $CADF_i$ and the associated Equation 11 statistics are investigated as $N \to \infty$ followed by $T \to \infty$, as well as jointly with N and T tending to infinity such that $N/T \to k$, where k is a fixed finite non-zero positive constant. If the test statistic value is greater than the absolute value of the critical values, the null hypothesis is rejected and the series is considered stationary (Pesaran, 2007).

4.4. Cointegration Tests

Westerlund's (2007) cointegration analysis is applied to estimate the long-run relationship between the variables. It is expressed in Equation 12 as follows:

$$\Delta y_{it} = \acute{\delta}_i d_t + \tau_i\left(y_{i,t-1} - \acute{\beta}_i x_{i,t-1}\right) + \sum_{j=1}^{p_i} \tau_{ij}\Delta y_{i,t-j} + \sum_{j=0}^{p_i} \gamma_{ij}\Delta x_{i,t-j} + \mu_{it} \tag{12}$$

where d_t denotes the deterministic component, $\grave{\delta}_i$ holds the vector of coefficients, and τ_i presents the convergence term that drives the adjustment speed convergence from short-run to long-run equilibrium. Westerlund (2007) proposed four new panel cointegration tests designed to test the null hypothesis of no cointegration. Two tests are designed to test the alternative hypothesis that the panel is co-integrated as a whole, while the other two test the alternative hypothesis that there is at least one cointegrated individual. The test's null hypothesis is no cointegration, tested by four statistics, including two group statistics (G_t and G_a) and two panel statistics (P_t and P_a). The four statistics consider the error correction model's heterogeneous short and long-run parameter coefficients. The generalised form of the test is as follows:

$$G_t = \frac{1}{N}\sum_{i=1}^{N}\frac{\acute{a}i}{SE(\acute{a}i)} \tag{13}$$

$$G_a = \frac{1}{N}\sum_{i=1}^{N}\frac{T\acute{a}i}{\acute{a}i(1)} \tag{14}$$

$$P_t = \frac{\acute{a}}{SE(\acute{a})} \tag{15}$$

$$P_a = T\acute{a} \tag{16}$$

4.5. Long-Term Estimation Techniques

Three cointegration techniques are used to evaluate this study's long-run relationship between variables. These cointegration techniques include DOLS (Dynamic Ordinary Least Squares) developed by Stock and Watson (1993), Fully Modified Ordinary Least Squares (FMOLS) developed by Phillips and Hansen (1990), and Canonical Cointegration Regression (CCR) developed by Park (1992). These forecasts exhibit higher levels of reliability in their long-term predictions because of their ability to effectively deal with endogeneity and serial correlation problems. They estimate the cointegration relationship when variables are cointegrated at level I (1). FMOLS, DOLS and CCR methods are used to prove the accuracy of the results obtained and to increase the reliability of the findings. In addition, these methods can produce reliable findings in small samples. The FMOLS estimator is asymptotically unbiased and efficient because it uses a semiparametric method to eliminate estimation problems arising from the long-run correlation between the cointegration equation and stochastic shocks. The FMOLS method is a modified version of the least squares method that considers the presence of endogeneity in the independent variables and the effects of serial correlation associated with cointegration (Phillips & Hansen, 1990). The CCR estimator is procedurally completely related to FMOLS, and estimators are fully efficient and have an unbiased, normal asymptotic distribution, but CCR focuses only on data transformation, while FMOLS focuses on both data and parameter transformation (Park, 1992). The DOLS technique integrates both lagged and leading values of the explanatory variable. Thus, the error term in the symmetric cointegration equation includes trends in the random regression. The DOLS estimator can be obtained from the least squares estimates, and these estimators are unbiased and asymptotically efficient even in the presence of endogeneity problems. It also adjusts for possible autocorrelation and residual non-normality (Stock & Watson, 1993).

4.6. Theory of the Quantile Regression Model

In the quantile regression approach, the variable series doesn't need to conform to a normal distribution, and regression is performed on the independent variable using the conditional quantiles of the dependent variable (Xu & Lin, 2020). Quantile regression captures all significant variation between the predicted and observed variables, so spurious regression coefficients are not derived. Traditional regression does not provide consistent results without a normal distribution, while the panel quantile approach does not follow distributional assumptions (Akram et al., 2021). The typical formulation of MMQR is based on a linear data generation process in which the heterogeneity of random factors is introduced. In addition, non-linear quantitative effects are considered, as well as location and scale effects (Guan et al., 2023). The MMQR model can produce accurate results in heteroscedasticity, endogeneity and autocorrelation problems.

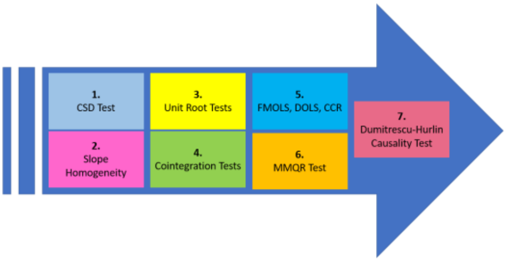
4.7. Dumetriscu-Hurlin Causality Test

Dumitrescu and Hurlin (2012) concluded that the causality valid for any country in panel data analysis is also valid for other countries. Their study considered CD and heterogeneity to determine the direction of causality and reached consistent results when T>N or T<N. Dumitrescu and Hurlin's equation is given as:

$$y_{i,t} = \partial_i + \sum_{i=1}^{p} \partial_i^p \, y_{i,t-n} + \sum_{i=1}^{p} \pi_i^p \, x_{i,t-n} + \mu_{it} \tag{17}$$

The intercept and coefficient ∂_i and $\pi_i = (\pi_i^1, \ldots \pi_i^p)$ are fixed. The autoregressive parameter and regression coefficient are, respectively, ∂_i^p and π_i^p. Dumitrescu and Hurlin's (2012) null hypothesis is that all units have no homogeneous Granger causality relationship. The alternative hypothesis is that this relationship exists in at least one unit. The econometric procedure followed in the study is given in Graph 5.

Graph: 5
Methodological Framework



5. Results and Discussion

In the first step of the study, preliminary prediction tests consisting of multicollinearity, cross-sectional dependency, slope homogeneity and unit root tests were used. Table 3 shows the correlation analysis between variables and results for multicollinearity. The correlation of ecological footprint with non-renewable energy consumption is positive and strong, while the correlation between ecological footprint and financial development is very weak. The variance inflation factor (VIF) test is used to determine the presence of multicollinearity. If the VIF value is less than 10, it is concluded that there is no multicollinearity. Since the VIF values are less than 3 in this study, there is no multicollinearity problem. Investigating cross-sectional dependency is a vital unit root test preference issue in panel data analysis. The second-generation unit root test is used in the presence of cross-sectional dependency. This study uses the CD test developed by Pesaran (2004) and the slope homogeneity test developed by Pesaran and Yamagata (2008). The cross-sectional dependency and slope homogeneity test results are reported in Table 4. Both delta and adjusted delta statistics reveal slope heterogeneity among G7 countries. The cross-sectional dependency test results show that cross-sectional dependency exists by rejecting the null hypothesis of no cross-sectional dependency. Due to cross-sectional dependency, CADF and CIPS tests from the second generation unit root tests were performed. These tests consider both the heterogeneity and cross-sectional dependency of the series. All variables must be cointegrated at the I(1) level in long-run panel estimations. Table 5 shows the CADF and CIPS unit root test results. According to the CADF unit root test results, the variables are cointegrated at the I(1) level, while the CIPS unit root test results gave mixed results at the I(0) and I(1) levels. Since the data are heterogeneous, not normally distributed, and have cross-sectional dependence, quantile regression analysis is appropriate for these series.

Table: 3
Correlation Analysis of G7 Countries

Variables	LNEF	LNGDP	LNNREC	LNREC	FD
LNEF	1.0000				
LNGDP	0.4846	1.0000			
	(0.0000)				
LNNREC	0.9043	0.4680	1.0000		
	(0.0000)	(0.0000)			
LNREC	0.1706	0.1581	0.3519	1.0000	
	(0.0118)	(0.0198)	(0.0000)		
FD	0.1437	0.7410	0.2062	0.0891	1.0000
	(0.0344)	(0.0000)	(0.0023)	(0.1911)	
Multicollinearity test					
VIF		2.88	1.51	1.14	2.35
1/VIF		0.347	0.425	0.663	0.875
Mean VIF		1.97			

Table: 4
Test of Cross-Section Dependency and Slope Homogeneity

Variable	CD-test	p-value
LNEF	19.78	0.000
LNGDP	22.11	0.000
LNNREC	20.71	0.000
LNREC	16.48	0.000
FD	21.70	0.000
	Test Statistics	p-value
LM	73.52	0.000
LM adj*	21.21	0.000
LM CD*	5.955	0.000
Slope Homogeneity Test		
Δ	6.664 p-value: 0.000	
Adj. Δ	7.421 p-value: 0.000	

Table: 5
CADF and CIPS Panel Unit Root Analysis

	CADF				CIPS			
	with constant and trend				with constant and trend			
Variables	Level	First Difference	Level	First Difference	Level	First Difference	Level	First Difference
LNEF	-2.099	-3.364***	-2.604	-3.488***	-3.298***	-5.982***	-3.660***	-6.094***
LNGDP	-1.335	-3.786***	-2.645	-3.958***	-1.538	-4.321***	-2.764*	-4.342***
LNNREC	-2.148	-4.594***	-2.545	-4.646***	-2.885**	-5.797***	-3.535***	-5.956***
LNREC	-1.084	-3.826***	-2.036	-4.290***	-1.431	-5.774***	-2.437	-5.956***
FD	-1.841	-3.930***	-2.637	-3.929***	-2.006	-5.372***	-2.958**	-5.527***

*Note: CADF and CIPS tests with demean 10%, 5%, 1% critical values -2.21, -2.33, -2.55, respectively. CADF and CIPS tests with demean and trend 10%, 5%, and 1% critical values -2.73, -2.84, and -3.06, respectively. ***, ** and * denote significance at the 1%; 5% and 10% significance levels.*

Westerlund's (2007) cointegration test was developed to test the existence of a long-term relationship between variables. According to the results obtained from Gτ, Ga, Pτ and Pa statistics in Table 6, there is long-run cointegration between variables. According to the results of FMOLS, DOLS and CCR analyses in Table 7, all variables affect the ecological footprint in the long run. According to these tests, economic growth and non-renewable energy consumption have a positive effect on the ecological footprint, while renewable energy consumption and financial development have a negative impact on the long run. According to the FMOLS test results, a 1% increase in GDP and NREC variables leads to a rise of 0.329% and 0.573% in the ecological footprint, respectively. A 1% increase in REC and FD variables leads to a decrease of -0.043% and -0.425% in the ecological footprint. According to the DOLS test, a 1% increase in GDP and NREC variables increases the ecological footprint by 0.455% and 0.545%, respectively. A 1% increase in REC and FD variables decreases the ecological footprint by 0.040% and 0.420%, respectively. According to the CCR test, a 1% increase in GDP and NREC variables increases the ecological footprint by 0.325% and 0.575%, respectively. A 1% increase in REC and FD variables decreases the ecological footprint by 0.043% and 0.424%, respectively. All three test results contain similar coefficients.

The hypotheses were established that economic growth and non-renewable energy consumption would increase the ecological footprint, while renewable energy consumption would decrease the ecological footprint. The effect of financial development was expected to be positive or negative. Since the G7 countries are developed economies and have developed financial markets, they can make investments to meet the demand for renewable energy and organise credit distribution mechanisms to support renewable energy investments by integrating technological developments with financial markets. Therefore, financial markets work effectively in these countries in increasing environmental quality. The fact that economic growth deteriorates environmental quality shows that although carbon emissions have decreased in recent years in these countries, renewable energy consumption is not yet at the desired level. Therefore, it is necessary to support energy efficiency. In recent years, using natural resources beyond their capacities has led to the deterioration of environmental quality and increased economic growth.

Table: 6
Cointegration Test Results

Westerlund (2007) Panel Cointegration Test				
Statistics	Value	Z value	P-value	Robust P-value
Gt	-3.056	-1.691	0.045	0.060
Ga	-12.843	0.039	0.516	0.040
Pt	-8.916	-2.983	0.001	0.000
Pa	-14.092	-1.670	0.047	0.010
Westerlund variance ratio: -1.7411 p-value: 0.0408				

Table: 7
Cointegration Regression Tests

Variables	FMOLS		DOLS		CCR	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-+value
LNGDP	.3292719**	0.011	.4550922**	0.015	.325671**	0.016
LNNREC	.573231***	0.000	.5453149***	0.000	.5751477***	0.000
LNREC	-.0432758**	0.012	-.0407405*	0.091	-.0434227**	0.013
FD	-.4257548***	0.008	-.420486*	0.074	-.4244082**	0.011
_cons	-7.496736***	0.000	-8.531276***	0.000	-7.48059***	0.000

*Note: ***, **, and * denote significance levels at 1%, 5%, and 10% levels.*

The MMQR model can produce accurate results in heteroscedasticity, endogeneity and autocorrelation problems. MMQR approaches are particularly suitable for situations where the model contains endogenous explanatory parameters and panel data exhibit individual-specific effects. Moreover, MMQR can produce reliable estimates, especially when the underlying model is nonlinear (Fatima et al., 2024). This study's data are heterogeneous, not normally distributed, and contain cross-sectional dependence; therefore, quantile regression analysis is appropriate. The null hypothesis of the Wooldridge test, which tests the existence of autocorrelation, is based on the assumption that the variance in the series is constant. Since the null hypothesis of the Wooldridge test is rejected in this study, there is a heteroskedasticity issue in the series. Tables 8 and 9 show the quantile regression results. According to the MMQR approach, economic growth and non-renewable energy consumption have a positive effect on the ecological footprint, while renewable energy consumption and financial development have a negative impact on the ecological footprint. In addition, non-renewable energy consumption positively and most strongly affects the ecological footprint. The effect of renewable energy consumption on the ecological footprint is negative, but its impact is low. This is because renewable energy consumption is less than non-renewable energy consumption, thus reducing the impact on the ecological footprint. The effect of economic growth increased across quantiles. Bootstrap

Quantile Regression was used as a robustness test to validate the econometric findings. Results supporting MMQR and long-run tests were obtained.

Table: 8
Outcomes of the MMQR

	Location	Scale		Lower Quantile		
Variables				0.10	0.20	0.30
LNGDP	0.370417***	0.02422		0.33434***	0.34429***	0.35071***
LNNREC	0.585006***	-0.03295***		0.63408***	0.62055***	0.61182***
LNREC	-0.05086***	0.003522		-0.05610***	-0.05466***	-0.05372***
FD	-0.42594***	0.051382		-0.50248***	-0.48137***	-0.46775***
	Middle Quantile			Higher Quantile		
	0.40	0.50	0.60	0.70	0.80	0.90
LNGDP	0.35746***	0.36578***	0.37461***	0.38463***	0.39425***	0.41917***
LNNREC	0.60264***	0.59131***	0.57930***	0.56567***	0.55258***	0.51868***
LNREC	-0.05274***	-0.05153***	-0.05025***	-0.04879***	-0.04739***	-0.04377***
FD	-0.45344***	-0.43577***	-0.41704***	-0.39579***	-0.37538***	-0.32250***

*Note: ***, **, and * denote significance levels at 1%, 5%, and 10% levels.*

Table: 9
Simultaneous Quantile Regression With Bootstrapped Standard Errors

Variables	Quantiles										
	0.10			0.20			0.30			0.40	
	Coefficient	S.E.		Coefficient	S.E.		Coefficient	S.E.		Coefficient	S.E.
LNGDP	.3073642***	[0.407]		.4113327***	[0.067]		.4170431***	[0.089]		.4895723***	[0.074]
LNNREC	.6476253***	[0.257]		.6249053***	[0.032]		.6050161***	[0.027]		.5768024***	[0.030]
LNREC	-.0654953***	[0.008]		-.0566562***	[0.011]		-.0490566***	[0.008]		-.0459272***	[0.012]
FD	-.4051206***	[0.065]		-.5226556***	[0.091]		-.5522641***	[0.109]		-.613834***	[0.097]
_cons	-8.175003***	[0.381]		-8.918202***	[0.551]		-8.733032***	[0.871]		-9.123291***	[0.683]
Pseudo R^2	0.65			0.62			0.61			0.61	
Variables	Quantiles										
	0.50			0.60			0.70			0.80	
	Coefficient	S.E.		Coefficient	S.E.		Coefficient	S.E.		Coefficient	S.E.
LNGDP	.5141888***	[0.067]		.528396***	[0.094]		.5982357***	[0.130]		.5874353***	[0.186]
LNNREC	.5555059***	[0.039]		.5302641***	[0.042]		.4897131***	[0.047]		.5100948***	[0.047]
LNREC	-.0407082***	[0.015]		-.0351723**	[0.017]		-.0231176	[0.021]		-.0512422	[0.032]
FD	-.6278028***	[0.059]		-.547698***	[0.095]		-.543245***	[0.114]		-.442249***	[0.160]
_cons	-9.125139***	[0.620]		-9.042384***	[0.906]		-9.33525***	[1.074]		-9.41969***	[1.503]
Pseudo R^2	0.62			0.64			0.66			0.65	
Autocorrelation test (Wooldridge) F (1,6) 11.910 Prob>F 0.0136											
Heteroskedasticity test statistics: 18.11 p-value: 0.000											

*Note: ***, **, and * denote significance levels at 1%, 5%, and 10% levels. Bootstrap standard errors in [].*

In the MMQR approach, a 1% increase in economic growth positively affects the ecological footprint, ranging from 0.334% to 0.419%. In simultaneous quantile regression, a 1% increase in economic growth positively affects the ecological footprint, ranging from 0.307% to 0.587%. Conversely, the effect of non-renewable energy consumption generally decreased across quantiles. At higher quantiles, the impact of non-renewable energy consumption on the ecological footprint is low. Two tests create a positive effect ranging from 0.634% to 0.518% and 0.647% to 0.489% respectively. Renewable energy is the variable that has the least impact on the ecological footprint. A 1% increase in renewable energy consumption reduces the ecological footprint between 0.056% and 0.043%; between 0.023% and 0.065% in two tests. In the MMQR approach, the effect of financial development decreases towards the higher quantiles. This effect is 0.502% in the 10^{th} and decreases to 0.322% in the 90^{th} quantile. In simultaneous quantile regression, the negative impact of financial development on the ecological footprint increases up to the 60^{th} quantile and decreases after this quantile. It took values between -0.405% and -0.627%. After verifying the relationship between dependent and independent variables, short-term relationships between variables must be known in policy making (Akram et al., 2021). The Dumetriscu-Hurlin (2012) test results for causality relationships between variables are given in Table 10. Accordingly, there is a one-way causality relationship from the EF to the GDP and a two-way causality relationship between the EF and the NREC and REC variables.

These results are consistent with the literature. Ansari (2022) supports that non-renewable energy consumption increases the ecological footprint while renewable energy consumption reduces it. Ahmed et al. (2020), Usman et al. (2021), and Yapraklı et al. (2023) support the positive impact of non-renewable energy consumption and economic growth on the ecological footprint. Tamazian et al. (2009) found that financial openness decreases environmental degradation. Zhang (2011) suggests financial development can contribute to environmentally friendly initiatives. According to Omri et al. (2015), technological innovation, Miao et al. (2022), financial globalisation and Zhang (2023) financial innovation increase environmental quality. Guan et al. (2023) concluded that economic growth in G7 countries has deteriorated environmental quality. Graph 6 demonstrates the impact of independent variables on the explained variable across different quantiles. GDP and NREC variables are in the positive region and increase the ecological footprint, while REC and FD variables are in the negative region and decrease the ecological footprint. While the effect of the GDP variable increases slightly in forward quantiles, the impact of the NREC variable decreases. For example, the value of the GDP variable is 0.334 in the first quantiles, while it was 0.419 in the higher quantiles. The value of the NREC variable is 0.634 in the first quantiles and 0.518 in the higher quantiles. REC variable oscillates within a specific range, and its effect is relatively low. REC variable coefficients are between -0.056 and -0.044. The reducing effect of the FD variable decreases in high quantiles. FD variable oscillates from -0.502 to -0.322.

Graph: 6
Graphical Representation of the Trends of Explanatory Variables of the Ecological Footprint

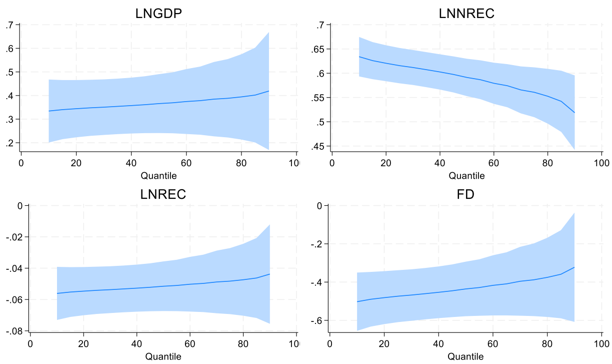


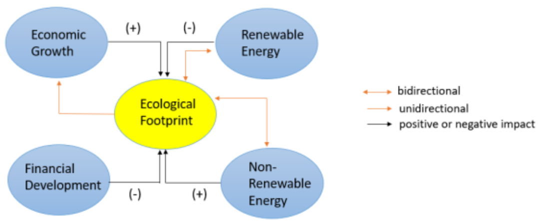
Table: 10
Panel Dumetriscu-Hurlin (2012) Causality Test Results

No	Hypothesis	W-Statistic	Z-bar Statistic	Probability	Decision of Causality
1	LNEF≠LNGDP	4.7974	7.1042	0.0000	LNEF → LNGDP
2	LNGDP≠LNEF	1.1978	0.3700	0.7114	
3	LNEF≠LNNREC	5.0194	7.5195	0.0000	LNEF⇔LNNREC
4	LNNREC≠LNEF	3.6631	4.9821	0.0000	
5	LNEF≠LNREC	6.4252	10.1495	0.0000	LNEF ⇔ LNREC
6	LNREC≠LNEF	2.0369	1.9398	0.0524	
7	LNEF≠FD	1.8113	1.5178	0.1291	
8	FD≠LNEF	0.9307	-0.1296	0.8968	

6. Conclusion and Policy Implications

This study investigates the relationship between economic growth, non-renewable and renewable energy consumption, financial development and ecological footprint for a panel of G7 countries. Graph 7 summarises the effects and causalities of variables. According to the results, economic growth positively affects ecological footprint, and a one-way causality relationship was found between ecological footprint and economic growth. Non-renewable energy consumption has a powerful positive effect on the ecological footprint. A two-way causality relationship was found between non-renewable energy consumption and the ecological footprint. The findings show that renewable energy consumption negatively impacts the ecological footprint in G7 countries, but its impact is lower than that of other variables. A bidirectional causality relationship was determined between the renewable energy consumption and the ecological footprint. Financial development has a negative effect on ecological footprint, but there is no causal relationship between the two variables. Economic growth has been found to have a negative impact on environmental quality. It exhibits a positive relationship with the ecological footprint at levels of 0.3%-0.4% in all quantiles. The excessive consumption of non-renewable energy resources such as coal, oil, natural gas and the inability to benefit from renewable energy resources at the desired level have effectively achieved this result. Economic growth means more production and consumption, and therefore more use of resources. Exceeding the carrying capacity of the environment causes environmental degradation. To prevent this situation, environmentally friendly energy sources such as solar and wind energy should be used, and policy practices aimed only at increasing economic growth should be abandoned. Policies should be developed to improve the efficiency of renewable energy consumption. Developing policies to increase the efficiency of renewable energy consumption involves a multifaceted approach. Key strategies include updating energy efficiency standards, implementing financial incentives like feed-in tariffs, promoting household adoption of renewables, investing in R&D, and integrating circular economy practices. These measures can lead to significant economic and environmental benefits, supporting a transition to a sustainable energy future. With the implementation of specific policies such as increasing the production of green products (electric vehicles, recycled products, etc.) and providing green credit support, especially for businesses in the construction, agriculture, and heavy industry sectors, businesses can be enabled to switch to green investment and green production. Technological and financial investments are necessary for the sustainability of energy efficiency. Financial products can be effective in the production of green technology products and their transfer between G7 countries. Strict environmental policies must be implemented so banks can conduct environmentally friendly projects. Environmental footprint can be reduced by protecting ecosystems and ensuring the sustainability of natural resources. Development of eco-tourism, protection of primary forests and forest planting can ensure the sustainability of natural resources. The independent variables considered in the study significantly explain the ecological footprint. This study included macroeconomic variables impacting environmental quality, such as GDP, financial development, and renewable and non-renewable energy consumption. In future studies, using different variables such as technology, population, environmental taxes, green investment and choosing different modelling techniques in measuring the environmental quality of G7 countries will enrich the literature.

Graph: 7
The Direction of Causality Relations Among Variables



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Appendix

Table: 11
List of Sample Countries

Canada	France	Germany	Italy
Japan	United Kingdom	United States	