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Renewable Energy's Effect on GDP Growth: Results from a Heterogeneous Panel Data Analysis

[1,2] Nasimi Nuriyev, [1] Dundar Murat Demiröz,
[1] Istanbul University, Institute of Social Sciences, Department of Economics, Istanbul, Turkey
[2] Azerbaijan State University of Economic, UNEC Business School, Baku, Azerbaijan

Abstract: Energy is a vital and crucial aspect for the economic advancement of countries and enhancing their living standards. In light of the rapid increase in energy consumption resulting from industrialization activities and technological developments, the limited availability of conventional energy resources has prompted nations to alter their energy production policies and resort to alternative energy sources. Our research, which is based on an extensive literature review, utilizes a heterogeneous panel data model to analyze the data of this study, which covers the period from 1970 to 2019, using real GDP (in million 2017 USD) according to chained PPP, capital stock (in million 2017 USD) according to current PPP, human capital index based on years of schooling and returns to education, and total renewable energy consumption in terawatt-hours (TWh) for each of the 22 European countries. We then calculated the difference between the dependent variable and the classifier-lasso model as suggested by Su, Shi, and Phillips (2016). Our findings indicate a statistically significant econometric relationship between all variables.

Keywords: Renewable energy, Economic growth, Heterogeneous panel and classifier-lasso

1. Introduction

Consequently, the escalating population growth, urbanisation, industrialisation, technological advancements, and improvements in the global economy have resulted in a significant increase in energy demand, and the importance of securing energy supply has become increasingly evident. In response, countries have turned to various measures to utilise new and renewable energy resources to augment their supply and reduce their reliance on imported fossil energy resources. This study examines the short- and long-term effects of renewable resource utilisation on economic growth by considering the renewable energy policies of the European Union (EU). An empirical analysis was conducted using data from EU member countries between 1970 and 2019. Moreover, the study found that the increase in renewable energy production positively impacts economic growth by enhancing GDP per capita in both the short and long run.

The growing energy demand, concurrent with the expansion of production and commercial activities, has increased countries' dependence on energy and a tendency towards external energy deficits. Many countries heavily rely on primary energy inputs, such as oil, natural gas, and coal, which account for a significant proportion of their imports. The instability and sharp rises in the prices of these primary energy inputs can lead to imbalances in the balance of payments for most countries. As a result, there has been a shift towards renewable energy sources to reduce energy dependence and increase energy diversity. This shift is driven by a desire to reduce reliance on energy inputs, increase energy diversity and security, mitigate the risks and shocks associated with sudden price increases in primary energy inputs, address environmental problems at both local and global levels, achieve a low-carbon effect, and create new business opportunities and employment through renewable energy investments. Using solar and wind energy has become a challenge for engineers and technologists as they develop new technologies for the more efficient development of renewable energy sources. (Belev, G. 2021)

This assertion is made by neo-classical and new Keynesian theorists, in contrast to classical theory, which posits that unemployment is a voluntary decision resulting in poverty. Neoclassical and new Keynesian theories propose that government initiatives to provide employment opportunities enable citizens to earn a livelihood and reduce poverty. Furthermore, high inflation rates, substantial government debts, insufficient foreign capital, and the inability of governments to address unemployment contribute to increased poverty levels (Han, Q., Jin, L., Khan, M. A. S., Vitenu-Sackey, P. A., & Obrenovic, B. 2023). The paper organises the subsequent sections: Section 2 reviews relevant studies. Section 3 outlines the methodologies used in the analysis. Section 4 presents the dataset, variables, and empirical results. Lastly, Section 5 offers discussion and policy implications.

2. Literature Review

Following the investigation conducted by Kraft and Kraft (1978) into the connection between energy and gross domestic product, many studies analyzing the causal relationship between energy consumption and economic growth have been carried out in the academic literature. Apergis and Payne (2010) utilized the panel data analysis method and error correction model to examine the relationship between renewable energy consumption and economic growth for 13 Eurasian countries. Based on the annual data collected over the period 1992-2007, their study found that there exists a bidirectional causality relationship between the variables in both the short and long run. In a subsequent study, Apergis and Payne (2011) analyzed the connection between renewable energy consumption and economic growth in six Central American countries using data from 1980-2006.

Moreover, the survival and sustainability of companies have been significantly reduced due to unprecedented financial pressures (Obrenovic, B., Oblakovic, G., & Asa, A. R. 2024). The modernisation perspective is based on a fundamental economic principle that economic growth requires capital investment (Modou, D., & Liu, H. Y. 2017).This section presents prior research investigating the factors that influence the adoption of renewable energy sources, which justifies the identified gap in the literature. Several studies have explored one or more of the four commonly accepted hypotheses regarding the relationship between economic growth and the use of renewable energy sources. The first hypothesis, often referred to as the growth hypothesis, posits that there is a unidirectional causal relationship between economic growth and the use of renewable energy sources. According to this argument, changes in the use of renewable energy sources and associated regulations will have a significant impact on economic growth due to the critical role that energy plays in production. Adams et al. (2018), Shabbir (2021), and Bilgili et al. (2015) empirically supported the growth hypothesis. The conservation hypothesis, which suggests a unilateral causal relationship between the use of renewable energy sources and economic growth, has also been confirmed by several studies (Dong et al., 2018) (Tiwari, 2011). Other studies that emphasize the bidirectional causal relationship between economic growth and the support for renewable energy sources have provided evidence for the feedback hypothesis (Amri, 2017) (Kahia et al., 2017) (Nawaz et al., 2022) (Kahia et al., 2017) (Hayat et al., 2022) (Eren et al., 2019) (Shafi et al., 2023) (Shafi et al., 2019).

Irandoust (2018). While technological advancements in Denmark and Norway have contributed to the growth of renewable energy certificates (REC), Sweden and Finland have witnessed the opposite due to their distinct energy systems and other factors. (He et al., 2018) Conducted a study on the effects of technological innovation on renewable energy (RE) in China. The research revealed that technological research and development (R&D) is a vital factor influencing REC. The study by Shabbir et al. (Shabbir et al., 2020) explored whether introducing new technology contributes to expanding renewable energy. The findings demonstrated that the advancement of new technologies has a significant effect on REC. However, existing technologies cannot significantly impact renewable energy. Shabbir et al. (2019) emphasized that renewable energy will meet future energy needs, and its production must be efficient. The study highlighted that technical innovation is a crucial element in developing renewable energy, which can help mitigate environmental degradation. Li et al. (2021) found that green energy production hurts innovation.

Apostu et al. (2022) stressed the significance of a rigorous legal and institutional framework in facilitating the shift towards renewable energy for the non-euro countries of Central and Eastern Europe. When examining the growth hypothesis, Balsalobre-Lorente et al. (2018) discuss the energy mix and argue that economic expansion necessitates increased energy consumption, potentially leading to a decrease in the proportion of renewables in the energy mix.
Koçak et al. (2017) view renewable energy sources as a crucial instrument for promoting low-carbon economic growth. In the context of choosing between environmental protection and economic development, developing countries may find that transitioning to renewable energy sources offers advantages, as it safeguards economic activities from the volatility of fossil fuel prices and removes dependence on traditional energy markets.

3. Research Methodology - Materials and Methods

Panel data analysis is a method of estimating economic relations using panel data models constructed with horizontal cross-sectional data that includes a time dimension (Yerdelen Tatoğlu, 2020:37). Unlike a normal horizontal-section or time-series regression, a panel data regression has both unit and time dimensions, which are represented by a pair of subscripts over the variables (Baltagi, 2021:15). The standard panel data regression model is typically depicted in the following manner:

$$y_{it} = \alpha + \sum_{j=1}^{k} \beta_j X_{jit} + u_{it} \tag{1}$$

Here, denote units such as households, individuals, firms and countries and denote time. Therefore, the sub-index indicates the horizontal cross-section dimension and the time series dimension in the data. In the context of equation (1), it is notable that both the fixed parameter and the slope parameters are homogeneous and do not vary across units or time. Models that exhibit this property are known as pooled regression models. The Pooled Least Squares (HEKK) estimator is commonly utilized to estimate these models (Gujarati et al., 2012:). To address the challenges posed by "long" panels with high time dimensionality, researchers developed heterogeneous panel data models. These models have become increasingly popular in empirical research across many fields, including development economics, regional science, and political science (Guliyev.H.,2022). These datasets aggregate many time series from different countries or firms. However, in many applications, the response of a dependent variable to changes in explanatory variables may differ across all units or over time. Accounting for heterogeneity in the interaction between variables in panel data analysis can help advance econometric research and better understand natural economic phenomena. Heterogeneous panel data models, in contrast to classical panels, place emphasis not only on the asymptotics of N but also on the asymptotic convergence of both N and T towards infinity, either sequentially or jointly (Phillips and Moon, 1999). Often, we observe that the individual coefficients of the units can vary across units, resulting in heterogeneous specifications. Therefore, such panels challenge the assumption of parameter homogeneity. In these models, it is theoretically possible to classify parameter heterogeneity as one-way or two-way heterogeneous panel data models.

3.1. Choice Between Homogeneous and Heterogeneous Panel Data Models

When choosing between homogeneous and heterogeneous panel data models, it is critical to first determine whether the panel data structure is appropriate for a homogeneous or heterogeneous structure. Upon detecting heterogeneity in the panel data model through the slopes, the subsequent step involves ascertaining the presence of an inter-unit correlation among the panel's cross-sections. If the panel data model detects no inter-unit correlation, the RCM or MG estimators are the appropriate estimators. On the other hand, if inter-unit correlation is detected in the model, the SUR, CCE, and AMG estimators are more appropriate (Yerdelen Tatoğlu, 2020: 101). It is important to first check the validity of homogeneity based on the slopes and then see if there is a correlation between the units in order to make the right choice of estimator in heterogeneous panel data models.

Panel data models use homogeneity tests to evaluate the homogeneity of the slope parameters. In other words, these tests aim to determine whether the coefficients calculated for each panel are equal to one another. The main hypothesis in homogeneity tests is that the coefficients calculated for all units are equal to each other, whereas the alternative hypothesis is that the coefficients calculated for at least one unit are different from the others (Pesaran, 2015: 734).

H_0: $\beta_i = \beta$ (all i for all units) Parameters for all units are homogeneous

H_1: $\beta_i \neq \beta$ (any i for) Parameters are not homogeneous (heterogeneous)

Swamy's (1970) $\tilde{S}$ Test: Swamy (1970) proposed a test known as the statistic to determine the homogeneity of the slope coefficients. In the $\tilde{S}$ test, the unit dimension N is required to be smaller than the time dimension T, and it is a test resistant to heteroskedasticity across units. To calculate Swamy's (1970) $\tilde{s}$ statistic, follow these steps:

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

In the equation, $\widehat{\beta}_i$ is the pooled OLS estimator, $\widehat{\beta}_{WFE}$ is the pooled estimator of the weighted fixed effect model, M_τ is the unit matrix, and $\hat{\sigma}_i$ is the estimator of σ_i. The test statistic has a Chi-squared distribution with K×(N-1) degrees of freedom. If the calculated $\tilde{s}$ statistic is greater than the critical value, the null hypothesis is rejected, and the slope parameters are heterogeneous for at least one unit (Yerdelen Tatoğlu, 2020: 97).

Pesaran and Yamagata (2008) $\tilde{\boldsymbol{\Delta}}$ Test: A standardised version of the Swamy (1970) $\hat{S}$ statistic, which is valid for panels with large unit (N) and time (T) sizes. The first process of this test, called $\tilde{\boldsymbol{\Delta}}$, starts with the calculation of the $\hat{S}$ statistic, and the $\hat{S}$ statistic is adjusted in the next stage (Pesaran, 2015: 738–739).

$$\triangle = \sqrt{N}\left(\frac{N^{-1}\tilde{S}_i - k}{\sqrt{2k}}\right) \tag{3}$$

This test is valid as $(N,T) \to \infty$ provided $\sqrt{N}/T^2 \to 0$ and assumes that the error terms are asymptotically normally distributed $\tilde{\Delta} \sim N$ and uncorrelated across units and time (ε_{it} ile $\varepsilon_{js}, i \neq j$ ve $t \neq s$). The test allows for unit-level heteroskedasticity and is also valid for first-order autoregressive models (dynamic panel data models), but for validity, it is expected that the unit time dimension is close in size ($N/T \to k$) and rapidly converges to infinity at the same time $N, T \to \infty$. In practice, especially when faced with panels of small units (N) size, it is unlikely that N and T will converge to infinity at the same speed, and thus the test loses power. Therefore, Pesaran and Yamagata (2008) proposed a corrected version of the test, the $\tilde{\Delta}_{\mathrm{adj}}$ test:

$$\tilde{\Delta}_{adj} = \sqrt{N}\left(\frac{N^{-1}\tilde{S} - k}{\sqrt{\operatorname{var}(\tilde{z}_{i,T})}}\right) \tag{4}$$

3.2. Cross-Sectional Dependency Tests

If there is a correlation between the units, panel data analysis that accounts for this situation ensures the accuracy and reliability of the findings. However, if the correlation between units is not taken into account, the results of the analyses may be biassed and inconsistent. Since economic units rarely act completely independently of each other, determining the correlation between units is crucial in panel data econometrics. Correlations between units can arise due to spatial proximity, common effects that are not included in the model, and other unobserved pairwise correlations. Different tests, depending on the unit and time dimension, test the existence of correlation between units.

Breusch-Pagan (1980) LM Test - Breusch and Pagan (1980) Lagrange Multiplier (LM) test N when stationary, $T \to \infty$ is a test based on the correlation coefficients of the errors. The LM test statistic is calculated as follows:

$$LM = T\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}^2 \tag{5}$$

It's here, $\hat{\rho}_{ij}$ It shows the instantaneous correlation between i. and j. units and is calculated as follows.

$$\hat{\rho}_{ij} = \hat{\rho}_{ji} = \frac{\sum_{t=1}^{T}\hat{u}_{it}\cdot\hat{u}_{jt}}{\sqrt{\sum_{t=1}^{T}\hat{u}_{it}^2 \cdot \sum_{t=1}^{T}\hat{u}_{jt}^2}} \tag{6}$$

Test statistic $d = \frac{N^*(N-1)}{2}$ has a Chi-square distribution with degrees of freedom. The main hypothesis of the test, H_0: $\operatorname{cov}(u_{it}, u_{jt}) = 0$ (all for t's i ≠ j) There is no correlation between the units. If the calculated LM test statistic is greater than the critical value at the selected significance level, the null hypothesis is rejected and it is concluded that there is correlation between units. This test is appropriate when the time dimension T is larger than the cross-sectional dimension N (Baltagi, 2015: 28).

Pesaran (2004, 2015) CD Test - Breusch and Pagan Lagrange Multiplier (LM) test based on the estimation of the squares of the inter-unit correlation of errors N when stationary, T → ∞ is a valid test. Pesaran's (2004,2015) The CD test, which it proposes when N is greater than T, is based on the average of the correlation coefficients calculated for the residuals of the regression obtained from each unit and the null hypothesis of the CD test statistic,

H_0: cov $(u_{it}, u_{jt}) = 0$("for all t's" i ≠ j) is expressed as. The null hypothesis states that the correlation between the errors of all units is equal to zero. To test the hypothesis, the CD test statistic is calculated as follows (De Hoyos and Sarafidis, 2006: 485):

$$CD = \sqrt{\frac{2T}{N(N-1)}}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij} \tag{7}$$

CD Test statistic N → ∞ as in the Breusch Pagan LM test when the condition is not valid $d = \frac{N(N-1)}{2}$ Chi-square distribution with degrees of freedom, $N, T \to \infty$ in the case of CD test statistic $CD \sim N(0,1)$ normal distribution. If the CD test statistic is greater than the critical value at the chosen significance level, the null hypothesis is rejected and the correlation between the units is concluded to exist. The CD test statistic can be extended for unbalanced panels as follows:

$$CD = \sqrt{\frac{2}{N(N-1)}}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\sqrt{T_{ij}}\hat{\beta}_{ij} \tag{8}$$

Here $T_{ij} \neq (T_i \cap T_j)$ is . Under the basic hypothesis $T_i > k+1$ and $T_{ij} > 3$ in case of CD test statistic is normally distributed $CD \sim N(0,1)$ (Pesaran, 2004:3)

Over the subsequent years, Chudik, Pesaran, and Tosetti (2011) drew attention to the various levels of inter-unit correlation, specifically the weak and strong forms of inter-unit correlation. While the former is usually estimated using spatial methods, the latter is modelled by time-specific factors and factor loadings (Chudik et al., 2015: 4560). In panel data analysis, the strength of common factors that cause inter-unit correlation, known as alpha (α), is referred to as the exponent of CD, with 0 < α < 1 between the two countries. Chudik, Pesaran, and Tosetti (2011) categorised the strength of inter-unit correlation into four categories: weak (α = 0), semi-weak (0 < α < 0.5), half-strong (0.5 < α < 1), and strong (α = 1). They argue that weak or semi-weak inter-unit correlation occurs when the number of common factors remains constant, but the number of units included in the panel increases or decreases. Conversely, semi-strong or strong inter-unit correlation occurs when the number of common factors increases or decreases, while the number of units included in the panel remains constant. Pesaran (2015) investigated the main hypothesis of the standard CD test statistic to identify weak inter-unit correlation in long panels. The modified hypothesis, H_0: α < (2 − δ)/4, which accounts for weakly inter-unit correlated errors, has been modified. In the case where N approaches infinity and 0 < δ ≤ 1, this hypothesis holds (Pesaran, 2015: 1089-1095).

In general, in panel data analysis, since the correlation between units is more likely to appear in a weak form than in the absence of correlation between units, it is empirically advantageous to modify the test hypothesis in this way and to determine the strength of the correlation between units through this test.

Juodis and Reese (2022) discovered that the Pesaran (2004, 2015) test is sensitive to model specifications, and it shows that deviations in the CD test statistic may occur when the CD test statistic is applied to the residuals of models with a multifactor error structure that includes interacting variables, two-way fixed effects (2WFE), or CCE estimator. In such cases, the Pesaran CD test result is approximately $\sqrt{T}$ as much deviation occurs. Juodis and Reese (2022) also highlighted that the resulting bias can be eliminated by randomly weighting horizontal cross-section covariances using the Rademacher distribution. The Rademacher distribution consists of equally distributed values (ω)-1 and 1. The weighted CDw test statistic is calculated using equation (9).

$$\mathrm{CD}_w = \left(\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\hat{\varepsilon}_{i,t}^2 w_i^2\right)^{-1}\sqrt{\frac{2}{TN(N-1)}}\sum_{t=1}^{T}\sum_{i=2}^{N}\sum_{j=1}^{i-1} w_i\hat{\varepsilon}_{i,t}w_j\hat{\varepsilon}_{j,t} \tag{9}$$

The weighted CD test statistic in panel data models with multifactor error structure is known for its asymptotic normality and favourable dimensionality properties. In their study, the authors also demonstrated that the use of a random weighting process could lead to distortions in test power in high-dimensional panel data models, particularly when N and T are large. To address this, CD_w (2015) proposed an improvement to the test statistic using the power development approach, which resulted in the modified test statistic as follows:

$$CD_{w+} = CD_w + \sum_{i=2}^{N} \sum_{j=1}^{i-1} |\hat{\rho}_{ij}| 1\left(|\hat{\rho}_{ij}| > 2\sqrt{\frac{\ln(N)}{T}}\right) \tag{10}$$

In light of the simulations conducted by the authors, the Two-Way Fixed Effects Model (2WFE) and the CCE model errors have been taken into consideration. The results indicate that the CDw and $CDW+$ tests, provided that $N \geq T$, possess a favorable dimensional property. However, the dimensional property T'' of the N is found to degrade when T is greater than . On the other hand, the power property of the CDw test improves with an increase in T, and the $CDw+$ test shows promising power in the desired scenario.

Pesaran and Xie (2022) $\boldsymbol{CD^*}$ Test - Pesaran and Xie (2022) conclude that the Pesaran (2004|, 2015) test is a valid test in panel data models with weak inter-unit correlations with spatial or network correlations, but based on the discussions made by Juodis and Reese (2022), it tends to over-reject in panel data models with semi-strong or strong inter-unit correlations that need to be modelled with time-specific factors and factor loadings (2WFE model or CCE estimator). At the same time, Pesaran and Xie (2022) use the model developed by Juodis and Reese (2021). CDw and $CDw+$ Although they state that their test has good power and dimension properties in panel data models with strong inter-unit correlation, the developers of the test did not provide evidence on the performance of the test in panel data models with spatial and network relationships. In addition, the test has good power and dimension properties in cases with weak inter-unit correlation such as spatial effects, and especially in cases with weak interunit correlation such as spatial effects. $CDW+$ test N in T that he's travelling too far away from ($N \gg T$) They prove that errors tend to over-reject regardless of whether they are normally or non-normally distributed. Therefore, Pesaran and Xie (2022) show that under the null hypothesis regardless of whether the latent common factors are weak or strong. N (0,1) with asymptotic distribution $C*$ (CD star) test is suggested. The CD* test statistic is calculated as follows:

$$CD^*(\theta_n) = \frac{CD+\sqrt{\frac{T}{2}}\theta_n}{1-\theta_n} \tag{11}$$

here $\theta_n = 1 - \frac{1}{n}\sum_{i=1}^{n} a_{i,n}^2$ and it is equal to θn refers to factor loadings. Pesaran and Xie (2022) use a weak or semi-weak form of inter-unit correlation ($\alpha < 0.5$) in the case where CD^* test CD test is equal to the test, but in strong form ($0.5 < \alpha \leq 1$) in the case of inter-unit correlation CD^* test should be used. So in practice, C^* When choosing between the CD or CD test, it would be useful to determine the strength of the inter-unit correlation using the Pesaran (2015) test. If the test shows that the correlation between the units is strong, then this time CD^* test CD is preferable to the test. CD* statistic $\mathrm{N,T} \rightarrow \infty$ or $N/T \rightarrow k$ (k is a constant), the asymptotic normal distribution $CD^* \sim N(0,1)$ fits.

3.3. Classifier-Lasso Estimator for Heterogenous Panel

In the work of Huang et al. (2024), we present a novel approach, the classify lasso method, which employs the c-lasso method to fit panel data models with concealed group structures. This method uses a post-estimation technique to showcase and visualise the estimated results. There are several ways to enhance the existing classify lasso method. One potential enhancement is to extend the prediction framework to include profile likelihood estimation and the generalised moment estimation approach, as suggested by Su, Shi, and Phillips (2016). Another potential improvement is to increase the speed of the estimation procedure, as computational time can be a concern when working with vast financial datasets. This paper utilises the classifier-lasso method, executed with the classify lasso method, to investigate panel data models by concurrently detecting and estimating unobservable parameter heterogeneity. Experts employ penalised least squares estimation to identify group-specific coefficients and classify unidentified group membership into a predetermined number of groups. This allows for comprehending the distinct behaviours exhibited by the various groups in the dataset. (Initial estimates) The classify lasso method starts with the initial (Huang W. et al., 2024)

$$\widehat{\boldsymbol{\alpha}}^{(0)} = \left(\boldsymbol{\alpha}_1^{(0)'}, \dots, \widetilde{\boldsymbol{\alpha}}_K^{(0)'}\right)' = \mathbf{0}_{pK\times 1} \text{ and } \widehat{\boldsymbol{\beta}}^{(0)} = \left(\widetilde{\boldsymbol{\beta}}_1^{(0)'}, \dots, \widehat{\boldsymbol{\beta}}_N^{(0)'}\right)' \tag{12}$$

Here $\mathbf{0}_{pK\times 1}$ denotes a $pK \times 1$ zero matrix, and

$$\tilde{\boldsymbol{\beta}}_i^{(0)} = \begin{cases} \left(\mathbf{X}_i'\mathbf{X}_i\right)^{-1}\mathbf{X}_i'\mathbf{y}_i, & \text{if } \mathbf{y}_i'\mathbf{y}_i > 0.0001N \\ \left(\mathbf{X}'\mathbf{X}\right)^{-1}\mathbf{X}'\mathbf{y}, & \text{if } \mathbf{y}_i'\mathbf{y}_i \leq 0.0001N \end{cases} \tag{13}$$

where $\mathbf{y}_i$ and $\mathbf{X}_i$ are a $T \times 1$ vector and a $T \times p$ matrix that denote the dependent and independent variables of individual i and $\mathbf{X} = \left(\mathbf{X}_1', \ldots, \mathbf{X}_N'\right)'$, $\mathbf{y} = \left(\mathbf{y}_1', \ldots, \mathbf{y}_N'\right)'$. If the variation of the dependent variable of individual i is large enough, the initial value is set to its time-series estimation result; otherwise, the pooled panel one is used. (Conditional minimization) Suppose we have obtaine d $\widehat{\boldsymbol{\alpha}}^{(r-1)}$ and $\widehat{\boldsymbol{\beta}}^{(r-1)}$ at the r th iteration, $r \geq 1$. Let $Q_{NT}^{\text{ols}}(\boldsymbol{\beta}) = 1/(NT)\sum_{i=1}^{N}\sum_{t=1}^{T}\left(\tilde{y}_{it} - \boldsymbol{\beta}_i'\tilde{\mathbf{x}}_{it}\right)^2$, and (Huang W. et al., 2024)

$$\begin{cases} \left(\boldsymbol{\beta}^{(r,1)}, \hat{\alpha}_1^{(r)}\right) = \underset{\beta,\alpha_1}{\arg\min}\left(Q_{NT}^{\text{ok}}(\boldsymbol{\beta}) + \frac{\lambda}{N}\sum_{i=1}^{N}\|\boldsymbol{\beta}_i - \boldsymbol{\alpha}_1\|\prod_{k\neq 1}^{K}\|\boldsymbol{\beta}_i^{(r-1)} - \hat{\boldsymbol{\alpha}}_k^{(r-1)}\|\right) \\ \left(\boldsymbol{\beta}^{(r,2)}, \hat{\alpha}_2^{(r)}\right) = \underset{\beta,\alpha_2}{\arg\min}\left(Q_{NT}^{\text{ok}}(\boldsymbol{\beta}) + \frac{\lambda}{N}\sum_{i=1}^{N}\|\boldsymbol{\beta}_i^{(r,1)} - \hat{\boldsymbol{\alpha}}_1^{(r)}\|\|\boldsymbol{\beta}_i - \boldsymbol{\alpha}_2\|\prod_{k\neq 1,2}^{K}\|\boldsymbol{\beta}_i^{(r-1)} - \hat{\boldsymbol{\alpha}}_k^{(r-1)}\|\right) \\ \ldots\ldots \\ \left(\hat{\boldsymbol{\beta}}^{(r,K)}, \hat{\boldsymbol{\alpha}}_K^{(r)}\right) = \underset{\beta,\alpha_K}{\arg\min}\left(Q_{NT}^{\text{olv}}(\boldsymbol{\beta}) + \frac{\lambda}{N}\sum_{i=1}^{N}\prod_{k=1}^{K-1}\|\hat{\boldsymbol{\beta}}_i^{(r,k)} - \hat{\boldsymbol{\alpha}}_k^{(r)}\|\|\boldsymbol{\beta}_i - \boldsymbol{\alpha}_K\|\right) \end{cases} \tag{14}$$

We hence obtain $\widehat{\boldsymbol{\alpha}}^{(r)} = \left(\widehat{\boldsymbol{\alpha}}_1^{(r)}, \ldots, \widehat{\boldsymbol{\alpha}}_K^{(r)}\right)$ and $\widehat{\boldsymbol{\beta}}^{(r)} = \widehat{\boldsymbol{\beta}}^{(r,K)}$. (Convergence criterion) The iterative algorithm ends if $r = R_{\max}$ or (Huang W. et al., 2024)

$$\frac{\sum_{i=1}^{N}\|\tilde{\boldsymbol{\beta}}_i^{(r)} - \tilde{\boldsymbol{\beta}}_i^{(r-1)}\|}{\sum_{i=1}^{N}\|\tilde{\boldsymbol{\beta}}_i^{(r)}\| + 0.0001} < \epsilon_{\text{tol}} \text{ and } \frac{\sum_{i=1}^{N}\|\tilde{\boldsymbol{\alpha}}_i^{(r)} - \hat{\boldsymbol{\alpha}}_i^{(r-1)}\|}{\sum_{i=1}^{N}\|\hat{\boldsymbol{\alpha}}_i^{(r)}\| + 0.0001} < \epsilon_{\text{tol}} \tag{15}$$

where $R_{\max}$ is the maximum number of iterations and ϵ_{tol} is the tolerance level. Let R be the largest number that meets the above criterion, so $\widehat{\boldsymbol{\beta}} = \widehat{\boldsymbol{\beta}}^{(R)}$ and $\widehat{\boldsymbol{\alpha}} = \widehat{\boldsymbol{\alpha}}^{(R)}$. (Huang W. et al., 2024)

4. Variables, Dataset and Empirical Results

4.1 Variables and Dataset

Drawing upon the discourse above and the pertinent theoretical framework, this research examines lnY represents the real GDP at chained PPPs, expressed in millions of 2017 US dollars. lnK denotes the capital stock at current PPPs, expressed in millions of 2017 US dollars. lnL signifies the human capital index, determined by years of schooling and returns to education. lnREC represents the total renewable energy consumption in terawatt-hours (TWh), with the subscript i denoting each of the 22 European countries and t indicating time. All variables are expressed in logarithmic form, with the abbreviation "ln" representing the logarithmic form. This study utilized annual panel data from 1970 to 2019. The energy consumption information was obtained from the Our World in Data (OWID) database. In contrast, the data on real GDP, capital stock, and human capital index were obtained from the Penn World Table (10.01) database. Table 1 provides a comprehensive description of the variables and their definitions.

Table 1: Description of variables and data sources

Variables	Symbol	Definition	Measure	Data sources
Real GDP at chained PPPs	lnY	Represents the real GDP at chained PPPs	millions of 2017 US dollars	Penn World Table (10.01)
Capital stock at current PPPs	lnK	Capital stock at current PPPs, expressed in millions of 2017 US dollars	millions of 2017 US dollars	Penn World Table (10.01)
Human capital	lnL	Human capital index, which is determined by years of schooling and returns to education	index	Penn World Table (10.01)
Renewable energy consumption	lnREC	Represents the total renewable energy consumption in terawatt-hours (TWh)	terawatt-hours	Our World in Data (OWID) database

The rationale underpinning the choice of these countries is that there is no loss of data. Table 2 presents an summary of the countries categorised by group.

Table 2: Selected countries

UE Economies
Austria, Belgium, Bulgaria, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Luxembourg, Netherlands, Norway, Poland, Portugal, Romania, Spain, Sweden, Switzerland, Turkey, United Kingdom.

$$\ln Y_{it} = \beta_0 + \beta_1 \ln K_{it} + \beta_2 \ln L_{it} + \beta_3 \ln REC_{it} + \varepsilon_{it} \quad (16)$$

The heterogeneous panel data model is commonly utilized to evaluate the influence of lnY (real GDP) on lnREC (total renewable energy consumption in terawatt-hours (TWh)) across a selection of countries, with annual data spanning the period between 1970 and 2019.

Table 3: Assessment of the Slope Parameter's Homogeneity in the Panel Data Model

	Swamy (1970) S testi	Pesaran ve Yamagata (2008) Delta Testi	Pesaran ve Yamagata (2008) Delta adj. Testi
Test statistic	16052.49***	44.322***	46.719***
Probability value	0.00	0.00	0.00
Note: ∗∗∗, ∗∗, and ∗, denotes statistical significance at the 1%, 5%, and 10% level, respectively.			

Table 4 displays a variety of tests employed by Swamy (1970) and Pesaran and Yamagata (2008) to evaluate the homogeneity of slope coefficients in a panel data model. Swamy (1970) used the $\tilde{S}$ test, while Pesaran and Yamagata (2008) implemented the $\tilde{\Delta}$ test and its small sample bias-corrected version, $\tilde{\Delta}adj$. These tests were utilized to test whether the null hypothesis of homogeneity of slope parameters could be rejected at the 5% confidence level, indicating that the slope coefficients differ from unit to unit and are, therefore, heterogeneous. However, it should be noted that these tests are not immune to potential issues such as heteroskedasticity and autocorrelation, as highlighted in the existing literature. Therefore, it is essential to take these factors into account when interpreting the results of these tests.

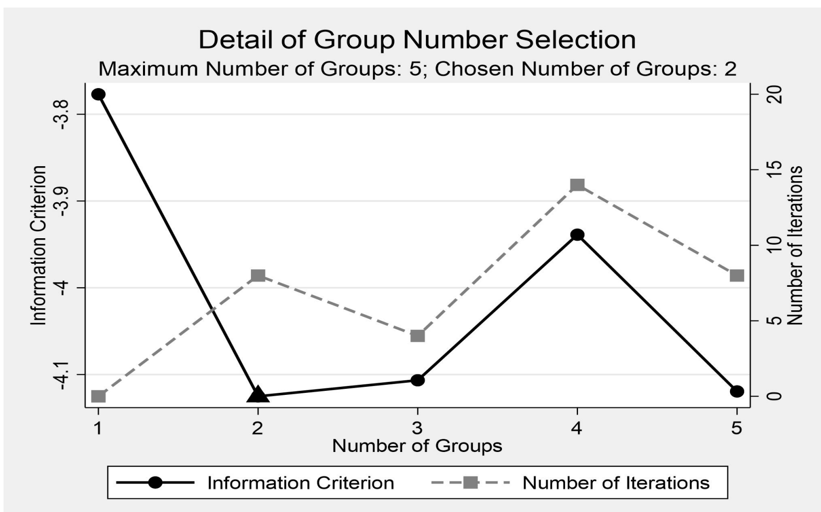
The outcomes of the CD test conducted by Pesaran (2004, 2015) and the CDw+ test with the power augmentation method proposed by Fan et al. (2015) are illustrated in Table 4. It is important to take into account the size of the panel when selecting an inter-unit correlation test. Given that the data set used has N=22 and T=50, and N is smaller than T, the results of the LM adj*- Pesaran et al. (2008) Bias-adjusted scaled Lm adj*, Pesaran (2004, 2015) CD test, and Fan et al.'s (2015) CDw+ test with power augmentation approach are more trustworthy. All tests and the test results of the aforementioned methods reject the null hypothesis of no correlation between units at the 5% significance level for all variables.

Table 4: Cross-sectional dependency test results

	CD+	***p*-value**	**CDw+**	***p*-value**
Model	**34.81*** **	0.000	696.36***	0.00
CD - Pesaran (2015, 2021)				
CDw+ with power enhancement from Fan et al. (2015)				
$\alpha = 0$ is weak, $0 < \alpha < 0.5$ is semi-weak, $0.5 < \alpha < 1$ is semi-strong and $\alpha = 1$ is strong correlation between units.				
Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively				

Figure 1 presents information about the selection of the optimal number of groups. The figure comprises two y-axes: the left axis represents the 'Information Criterion', while the right axis denotes the 'Number of Iterations'. The x-axis corresponds to the 'Number of Groups' with values 1, 2 and 3. Grey dots on the dashed line represent the number of iterations for each group. The black dots on the solid line indicate the values of the information criterion for each group. A black triangle marks the minimum value of the information criterion above Group 2, signifying the optimal number of groups selected.

Figure 1: Selection of number of groups



Consequently, evidence suggests that the model exhibits heterogeneity across countries. To maintain consistency in the results of the various control variables, we established two groups for subsequent analyses. Table 5 enumerates thirteen countries in Group 1 and nine in Group 2.

Table 6 shows the Hausman test results (chi2(3) = 9.84, Prob > chi2 = 0.0200). According to the test results, the null hypothesis H_0, which states that the fixed-effects model is valid, is accepted, and the fixed-effects model will give more efficient and consistent results.

Table 6 shows the heteroskedasticity test results of the Modified Wald test (chi2 (13) = 561.68, Prob>chi2 = 0.0000). According to the test result's statistical value, the hypothesis H_0, which expresses heteroskedasticity and constant variance (homoskedasticity), is accepted, indicating that there is heteroskedasticity in the model.

Table 6 shows two test values calculated as a result of the Durbin-Watson and Baltagi-Wu tests. The fact that these two test statistics are less than 2 indicates that autocorrelation is significant in the model.

In Table 6, Pesaran and Friedman's tests were used to test the correlation betw1111111een units in the estimated random effects model. According to both tests, there is a correlation between units in the estimated model.

Table 5: Classifier-lasso Estimator Results

Group 1	**Group 2**
Austria	Belgium
Finland	Bulgaria
France	Denmark
Germany	Greece
Ireland	Hungary
Luxembourg	Italy
Netherlands	Portugal
Norway	Turkey
Poland	United Kingdom
Romania	
Spain	
Sweden	
Switzerland	

Table 6: Group 1 Estimation Results

Variables	**FE**		**RE**	
	coef	**Driscall-Kraay standart error**	**Coef**	**Driscall-Kraay standart error**
lnL	1.544639***	.1363095	1.239448***	.1304487
lnK	.543481***	.0224613	.5968505***	.0215106
lnREC	.0717199***	.0105275	.0697429***	.0105576
Constant	3.108504***	.1879135	2.703781***	.1941519

N= 13 T=50
Hausman test - chi2(3) = 9.84, Prob > chi2 = 0.0200
Heteroskedasticity test (Modified Wald test for groupwise heteroskedasticity) - chi2 (13) = 561.68, Prob>chi2 = 0.0000
Autocorrelation test - Modified Bhargava et al. Durbin - Watson = .12052175, Baltagi - Wu LBI = .16335215
Pesaran's test of cross sectional independence = 22.402, Pr = 0.0000, Friedman's test of cross sectional independence = 264.353, Pr = 0.0000
Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

As observed by Su, Shi and Phillips (2016), the classifier-lasso method emphasises the significance of all variables in the estimation results for the 13 countries selected for group 1. A 1% increase in K (representing the capital stock in current PPP terms, in millions of 2017 US dollars) leads to a 0.543481% increase in Y (representing real GDP in chained PPP terms, in millions of 2017 US dollars), a 1% increase in L (representing the human capital index determined by years of schooling and returns to education) leads to a - 1.544639, and REC (total renewable energy consumption in terawatt-hours (TWh)) increased by 1%, and Y (representing real GDP in chained PPPs, in millions of 2017 US dollars) increased by - 0.0717199%.

Table 7 shows the Hausman test results (chi2(3) = 1053.68, Prob > chi2 = 0.0000). According to the test results, the null hypothesis H_0, which states that the fixed effects model is valid, is accepted and the fixed effects model will give more efficient and consistent results.

Table 7 shows the heteroskedasticity test results of Modified Wald test (chi2 (8) = 366.54, Prob>chi2 = 0.0000). According to the statistical value of the test result, the hypothesis H_0, which expresses heteroskedasticity and constant variance (homoskedasticity), is accepted, indicating that there is heteroskedasticity in the model.

Table 7 shows that there are two test values calculated as a result of Durbin-Watson and Baltagi-Wu test. The fact that these two test statistics are less than 2 indicates that autocorrelation is significant in the model.

Pesaran and Friedman tests were used to test the correlation between the units in the random effects model estimated in Table 7. According to the Pesaran test result, there is no correlation between the units in the model, while according to the Friedman test, there is correlation between the units in the model.

Table 7. Group 2 Estimation Results

Variables	FE		RE	
	coef	Driscall-Kraay standart error	Coef	Driscall-Kraay standart error
lnL	2.061266***	.1099185	1.911308***	.1100443
lnK	.1884661***	.0216943	.2165662***	.0217803
lnREC	.0476691***	.006032	.0498328***	.0062159
Constant	7.876378***	.2139115	7.62461***	.2569452

N= 9 T=50
Hausman test - chi2(3) = 1053.68, Prob > chi2 = 0.0000
Heteroskedasticity test (Modified Wald test for groupwise heteroskedasticity)- chi2 (8) = 366.54, Prob>chi2 =0.0000
Autocorrelation test - Modified Bhargava et al. Durbin–Watson = .12411842, Baltagi - Wu LBI = .17661185
Pesaran's test of cross sectional independence CD= 0.790, Pr = 0.4296, Friedman's test of cross sectional independence = 66.202, Pr = 0.0000,
Note: ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7 shows the Hausman test results (chi2(3) = 1053.68, Prob > chi2 = 0.0000). According to the test results, the null hypothesis H_0, which states that the fixed effects model is valid, is accepted and the fixed effects model will give more efficient and consistent results.

Table 7 shows the heteroskedasticity test results of Modified Wald test (chi2 (8) = 366.54, Prob>chi2 = 0.0000). According to the statistical value of the test result, the hypothesis H_0, which expresses heteroskedasticity and constant variance (homoskedasticity), is accepted, indicating that there is heteroskedasticity in the model.

Table 7 shows that there are two test values calculated as a result of Durbin-Watson and Baltagi-Wu test. The fact that these two test statistics are less than 2 indicates that autocorrelation is significant in the model.

Pesaran and Friedman tests were used to test the correlation between the units in the random effects model estimated in Table 7. According to the Pesaran test result, there is no correlation between the units in the model, while according to the Friedman test, there is correlation between the units in the model.

As Su, Shi and Phillips (2016) observe, the classifier-lasso method emphasises the importance of all variables in the estimation results for the nine countries selected for group 2. A 1% increase in K (representing the capital stock in current PPP terms, in millions of 2017 USD) corresponds to a 0.1884661% increase in Y (representing real GDP in chained PPP terms, in millions of 2017 USD). Moreover, a 1% increase in L (representing the human capital index determined by years of schooling and returns to education) results in an increase of 2.061266%, while a 1% increase in REC (total renewable energy consumption in terawatt-hours (TWh)) corresponds to a 0.0476691% increase in Y (representing real GDP in chained PPP terms, in millions of 2017 US dollars).

Table 6-7 exhibits the Classifier-lasso method's estimation results and assumption tests (Su, Shi, and Phillips, 2016). The primary objective of this technique is to detect unobserved parameter heterogeneity in panel data models using penalised techniques and to determine group-specific coefficients, classify unknown group membership, and establish the number of groups based on an information criterion. In the table above, the results of the Classifier-lasso estimation reveal that all variables in Groups 1 and 2 possess statistical significance at the 1%, 5%, and 10% significance levels. Moreover, the z- statistic calculated for the significance of the regression models of the countries within these groups is also statistically significant.

5. Conclusion and Policy Implications

The use of renewable energy sources has been demonstrated to offer numerous advantages, including increased access to and affordability of energy and the promotion of economic growth. Numerous empirical investigations have been undertaken across diverse nations and regions to explore the interrelationship between energy production, consumption, and economic growth. Swamy's (1970) $\tilde{S}$ Test and Pesaran and Yamagata's (2008) $\tilde{\Delta}$ Test are applied to evaluate the appropriate econometric model between Homogeneous and Heterogeneous Panel Data Models (HPDMs and HPDMS, respectively). The results of these tests indicate that the null hypothesis, which posits that the slope parameters are homogeneous, is rejected at the 5% confidence level. Consequently, this finding implies that the slope coefficients vary across different units, demonstrating that the panel data model possesses a heterogeneous structure.

When evaluating the Breusch-Pagan (1980) LM Test, the Pesaran (2004, 2015) CD Test, and the Pesaran, Ullah and Yamagata (2008) Adjusted LM Test, it is concluded that the null hypothesis of no correlation between units is rejected for all variables at a significance level of 5%. Furthermore, the alpha values obtained from the Pesaran (2015) CD test indicate a strong inter-unit correlation for all variables. In general, it is concluded that the analysed panel structure is heterogeneous concerning both inter-unit correlation and slope coefficients. In this case, it would be appropriate to use heterogeneous estimators that consider inter-unit correlation. These estimators control for inter-unit correlation with the help of common factors.

The empirical analysis shows that energy production from renewable resources positively impacts economic growth in both groups of countries. These findings show that renewable energy resources are essential to economic growth. It is seen that the studies in the literature mainly address the relationship between the two variables with causality and cointegration tests. However, in this study, the effects of the amount of renewable energy consumption on GDP and the main component of neoclassical economic growth with the heterogeneous panel model have been revealed and contributed to the literature. According to the results of the analysis, the amount of renewable energy consumption has a positive effect on GDP for both groups of countries.

It has made it necessary to determine a new energy policy based on domestic resources that will cause the least minor environmental damage and maximise the economy's contribution. Countries' orientation towards renewable and domestic energy resources with the least harmful environmental impacts will reduce dependence on foreign energy consumption and the current account deficit. The fact that renewable energy production is costly and that it takes long periods to reach the desired level of production may have prevented renewable energy production from reaching the desired level.

This situation is one of the most important reasons for the positive relationship between renewable energy production and economic growth. However, the finding of a long-run relationship between the parameters shows that although renewable energy production is difficult and costly, the continuity of policies for renewable energy production is essential, considering the damage caused by using fossil energy resources to the environment and the economy. For this purpose, incentive policies, especially tax incentives and subsidies to reduce renewable energy production costs, and the provision of investment loans to ensure the sustainability of production are the priority policies that can be implemented to increase renewable energy production. In addition, alternative policies should also be implemented in order to increase competitiveness in renewable energy production in the long term. For this purpose, it is also essential to develop and implement policies that ensure the continuity of renewable energy production by providing the necessary physical and economic infrastructure, such as following the developments in energy technologies, making technological investments and preparing the necessary facilities for production.

As a result, studies show that energy demand will increase both on a national and global scale. Domestic and renewable energy resources should be produced using appropriate and efficient technologies for a cleaner environment in terms of energy consumption. More importance should be given to research and development activities in this direction. In addition, bureaucratic difficulties and deficiencies related to the electricity transmission network should be reduced, more contributions from the private sector to renewable energy investments should be ensured, and individuals should be made aware that renewable energy resources can substitute non-renewable energy resources.

Most of the analyses carried out in these studies indicate a positive correlation between renewable energy consumption and economic growth in both the short and long run. This suggests that renewable energy resources are as adequate a factor of production for economic growth as other natural resources, labour, and capital. The substantial evidence that renewable energy resources contribute to economic growth underscores the significance of supporting these resources in the fight against global warming.These results are valid only for 22 European countries. The same methodology needs to be checked in other country groups to ensure the reliability of the results.

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