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Energy Consumption, Economic Growth and CO_2 Emissions: Empirical Evidence for EU Countries

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Abstract: This paper explores the relationship between economic growth, energy consumption (from fossil fuels and renewable sources), and CO_2 emissions in the EU, highlighting the causal relationships between these variables. Through a Panel Vector Autoregressive (VAR) model and statistical test, it is found that fossil fuel consumption has a strong positive effect on CO_2 emissions, while renewable energy has a milder negative effect. Granger causality tests confirm the significant causal relationship between fossil fuel consumption and CO_2 emissions, highlight the positive impact of renewables on economic growth, showcase the link between economic growth and both emissions growth and renewable energy consumption. The findings emphasize the urgent need for a more aggressive shift towards renewable energy and enhanced energy efficiency to meet the EU's climate neutrality objectives. This study contributes critical insights for policymakers, emphasizing the importance of balancing economic growth with environmental sustainability by accelerating the transition to cleaner energy sources.

Keywords: renewable energy consumption; CO_2 emissions; panel vector autoregressive (VAR) model; mitigation.

JEL classification: O13; Q43; O44.

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1. INTRODUCTION

Climate change and its impacts have shown the urgent need to take action in mitigation and adaptation to the new conditions it brings. It is well established that the increase in CO_2 emissions has been directly linked to climate change. The greenhouse effect is the main cause of trapping heat in the Earth's atmosphere, thereby blocking it and leading to global warming. Carbon dioxide is considered the most crucial component in the process. Therefore, the reduction of carbon dioxide emissions is central to worldwide efforts to mitigate climate change (IPCC, 2022). On the other hand, economic growth often relies on high levels of energy consumption, a large proportion of which still comes from fossil fuels such as coal, oil, and natural gas. This dependence has directly led to increased carbon dioxide emissions, thus exacerbating global warming (Campbell and Krol, 2023). The European Union has cut emissions in CO_2 as the center theme of its climate policy, ahead of economic stability and growth (European Commission, 2020). Considering these consequences, the European Union has taken significant steps to mitigate emissions while at the same time still providing significant economic growth.

In particular, the EU has set a target of achieving climate neutrality by 2050 and has committed to a 55% reduction in emissions by 2030 under the European Green Deal (European Commission, 2019). It advocates policies that will reduce emissions, enhance energy efficiency, develop renewable sources of energy, and promote clean technology. The European Climate Law (European Commission, 2020) sets legally bound targets for climate neutrality and emission reduction. In other words, through the laws and projects put forward, the EU Member States decided together that reduction in carbon emissions and sustainable development are among the most important concerns. In any case, this means that economic growth will occur with the aim of striking a balance between growth and Environmental Protection.

In accordance with the literature (Lee, 2019; Pejović *et al.*, 2021), this study focuses on investigating the relationship between energy consumption (fossil fuels and renewables), economic growth (GDP per capita) and CO_2 emissions in EU countries. The analysis of these relationships mentioned above is highly relevant because economic growth, energy consumption, and CO_2 emission reduction are at the core of taking action by states in the process of mitigation of climate change. During the past years, EU officials have issued several legislative initiatives related to the development of renewable energy sources and the reduction of CO_2 emissions, such as the Renewable Energy Directive (European Parliament and Council of the European Union, 2023), the Fit for 55 Package (European Commission, 2021), and the REPowerEU Plan (European Commission, 2022). It is, therefore, necessary to further investigate the causality relationship between these factors, based on prior literature, in order to consider their direction of influence. Some studies, for instance, have suggested that re-examination is in order, including Manta *et al.* (2020), Dritsaki and Dritsaki (2014) and Akadiri *et al.* (2019).

This paper provides empirical evidence on the causal nexus of energy consumption, economic growth, and CO_2 emissions within European Union countries. More specifically, it considers the relationships of causality between different types of energy consumption (from both fossil fuel and renewable source) and CO_2 emissions in the EU. Among the key questions this paper tries to answer are to what extent economic growth directly contributes to the increase in CO_2 emissions, and whether the energy use of both fossil fuels and renewable sources plays a significant role in altering these trends.

Another important part of this analysis consists in investigating the direction of causality between the considered variables. Specifically, the aim is to reveal whether higher economic growth results in higher energy consumption, which increases CO_2 emissions. Furthermore, it examines whether the introduction of renewables is helping to decouple growth from environmental damage. This analysis is highly relevant given the EU's target to reach Climate Neutrality by 2050. The critical question it seeks to answer is whether GDP growth and CO_2 emissions can be decoupled through cleaner energy consumption.

Additionally, the study investigates the impact of renewable energy on emission reductions. It assesses whether the increasing share of renewable energy in the energy mix can offset the negative environmental impacts traditionally associated with fossil fuel consumption. By addressing these research questions, the study contributes valuable insights into possible pathways to sustainable economic growth in the EU, helping policy makers to understand the complex dynamics between energy, growth and environmental sustainability.

This study differs from previous research as it applies the Panel VAR model to an extensive sample of EU countries for the period 2000-2020. Furthermore, this analysis focuses on identifying the causality between economic growth and renewable energy consumption, providing new empirical evidence on whether GDP growth can be achieved in parallel with CO_2 emission reductions.

The paper is organized as follows: Section 2 presents a brief literature review, Section 3 develops the methodology applied for the empirical analyses, Section 4 provides details on the data used, Section 5 presents the results of the empirical analyses and their interpretation, and Section 6 offers conclusions, discussion, and suggestions for future research.

2. LITERATURE REVIEW

Over the years, there has been increased studies by several researchers on how energy consumption and economic growth are directly related to CO_2 emissions. Particularly, the issues of energy consumption and CO_2 emissions are examined in the context of sustainable development, where countries must find ways to mitigate climate change while fostering economic growth. Furthermore, numerous researchers have examined the relationship between energy consumption and economic indicators, analyzing carbon dioxide emissions to test the hypothesis of a causal relationship between these variables. The relationship between energy consumption and economic indicators has been investigated at the country-specific level by researchers including Ozturk and Acaravci (2010), Ozturk and Al-Mulali (2015) and Shahbaz *et al.* (2013). Additionally, some studies enable the comparison of groups of countries, as outlined by Lee (2005), Halilbegović *et al.* (2023) and Sharma *et al.* (2021).

The relationship between energy consumption and economic growth has been a topic of research, with a particular examination of whether there is a causal link between the two. In the context of neoclassical growth theory, for instance, it is proposed that energy constitutes a crucial element in the production process, exerting a direct influence on output (Stern, 2004). However, empirical studies on the topic indicate a degree of inconsistency in the results obtained with regard to the direction of causality, which has given rise to a heightened interest in further exploration. Some studies, such as those conducted by Ozturk and Acaravci (2010) and Akadiri *et al.* (2019), have found evidence to suggest that energy consumption drives economic growth. However, other studies, including those by Shahbaz *et al.* (2013), have presented arguments that posit a different conclusion, namely that economic growth increases energy demand.

This relationship is of particular importance in the context of the European Union, given that the transition towards climate neutrality requires the overcoming of long-term dependence on fossil fuels, which have historically played a significant role in energy consumption (European Environment Agency, 2022). Research conducted within the European Union has demonstrated the significance of renewable energy sources (RES) in reducing CO_2 emissions and achieving sustainable development goals. As an example, Pejović *et al.* (2021) focus on the utilization of renewable energy sources in the European Union and the Western Balkans. Their findings confirm that an increase in renewable energy usage results in a reduction in CO_2 emissions, thereby contributing to sustainable development. Furthermore, Halilbegović *et al.* (2023) examine the impact of both renewable and non-renewable energy consumption on economic growth in South-Eastern Europe. The findings substantiate the assertion that both types of energy sources have a beneficial impact on economic growth, thereby supporting the view that renewable energy can foster economic growth while simultaneously reducing CO_2 emissions.

In addition, Manta *et al.* (2020) posit that financial growth and CO_2 emissions are mutually reinforcing. The authors present the proposition that governments may implement environmentally focused policies, such as the increased utilization of renewable energy sources and a transition from coal to natural gas as a fuel source, with the objective of reducing energy consumption and CO_2 emissions without negatively impacting economic growth in the short or long term.

Analyzing the nexus of economic growth and CO_2 emission, several studies have taken different theoretical standpoints. Among them, the widely used hypothesis of the Kuznets Environmental Curve posits that with economic growth, initially the degradation of the environment increases, but after reaching an income threshold beyond a certain limit, people start giving priority to environmental quality, leading to a reduction in emissions (Grossman and Krueger, 1995). However, the empirical findings regarding verification of EKC are still not convincing. The EU studies indicate that economic growth has traditionally been related to increased CO_2 emissions, but politico-intervention unveiling has started to decouple growth from emissions in recent years in developed countries (Ozturk and Al-Mulali, 2015; Lee, 2019).

The European Union's policy measures to reduce CO_2 emissions, such as carbon pricing, emissions trading schemes, and promoting renewable energy, have reshaped the trend of emissions. Research by Dritsaki and Dritsaki (2014) points out that the progress in separating economic growth from emissions has varied among member states, with outcomes influenced by each country's energy resources and industrial structure.

Many studies in the current literature do not analyze energy consumption as a whole but instead look at renewable and non-renewable energy separately. Despite strong efforts to shift towards renewable energy, fossil fuels continue to be a major energy source in the EU. Numerous studies, including those by Shahbaz *et al.* (2013) and Rahman and Velayutham (2020), have confirmed a strong positive link between fossil fuel use and CO_2 emissions. Research by Ozturk and Acaravci (2010) further shows that increased fossil fuel consumption directly drives higher CO_2 emissions, worsening the EU's climate challenges. This trend aligns with global patterns showing a connection between higher fossil fuel consumption and greater environmental damage (Sharma *et al.*, 2021).

In contrast, studies indicate that renewable energy sources significantly lower CO_2 emissions, though their economic benefits are not always clear-cut. Rahman and Velayutham (2020) found that while renewable energy does contribute to economic growth, its impact tends to be smaller compared to fossil fuels. This suggests that renewables still represent a smaller portion of the overall energy mix. Additionally, Sharma *et al.* (2021) note that although renewable energy reduces emissions, the extent of this impact varies depending on the technology used and the region.

While most studies have focused on the separate analyses of renewable and non-renewable energy sources, this study contributes to the existing literature by determining their interaction and deriving the overall impact on economic growth and CO_2 emissions. This approach allows for a more holistic understanding of the energy transition in the EU.

3. DATA

The data used in this research is annual for the period from 2000 to 2020 and includes the variables: CO_2 emissions (metric tons per capita), GDP per capita (in constant 2015 US dollars), consumption of renewable energy, and fossil fuels per capita. The data has been transformed to a logarithmic scale. The description of the variables and the data sources are presented in Table no. 1.

Table no. 1 – Variables description and source

Variable label	Description	Source
CO_2 Emissions	Carbon dioxide emissions are those stemming from the burning of fossil fuels and the manufacture of cement. They include carbon dioxide produced during consumption of solid, liquid, and gas fuels and gas flaring.	World Bank (2023)
GDP per capita (constant 2015 US dollar)	GDP per capita is gross domestic product divided by midyear population. GDP is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without making deductions for depreciation of fabricated assets or for depletion and degradation of natural resources. Data are in constant 2015 U.S. dollars.	World Bank (2023)
Renewables consumption per capita	Measured in kilowatt-hours of primary energy per person, using the substitution method. The category of renewables encompasses hydropower, wind, solar, geothermal, wave and tidal energy, and bioenergy, excluding traditional biofuels.	Energy Institute (2024)
Fossil fuel consumption per capita	Fossil fuel consumption per capita is measured as the average consumption of energy from coal, oil and gas, in kilowatt-hours per person.	Our World in Data (2023)

Source: authors' construct

Table no. 2 presents the descriptive statistics of the variables used in the analysis (CO_2 emissions, GDP per capita, fossil fuel consumption per capita, renewable energy consumption per capita). The number of observations, mean, standard deviation and the maximum and minimum value obtained for each variable are shown in the table. The total number of observations for each variable is 525. The initial goal of the analysis was to include all EU27 countries. However, due to a lack of available energy consumption data, Cyprus and Malta were excluded.

We observe that CO_2 emissions have a mean value of 7.628 and a relatively high standard deviation (3.602), suggesting significant variability between countries or over time. In terms of GDP per capita, it shows large variations which are strongly indicated by the minimum and maximum values (3.72 to 112.41) suggesting that the dataset includes countries at very different stages of economic development. Fossil fuel consumption shows a wide range, reflecting the different dependence of countries on fossil fuels, while renewable energy consumption per capita has a lower average (5.21) but also shows significant variation (6.626 minimum value to 30.217maximum value) which highlights the different energy profiles in the sample.

Table no. 2 – Descriptive statistics

Variable	Obs.	Mean	Std. dev.	Min	Max
CO_2 emissions	525	7.628	3.602	2.927	25.61
GDP per capita (constant 2015 US dollar)	525	29565.52	21517.56	3721.051	112417.9
Fossil fuel consumption per capita	525	32993.59	16497.35	12289.74	111848.4
Renewables consumption per capita	525	5216.57	5710.68	66.26	30217.09

Source: authors' construct

For a better understanding of the sizes of the variables used in the analysis, Figures no. 1, no. 2 and no. 3 are needed. These figures show the trends of the main variables of the analysis (CO_2 emissions, GDP per capita, renewable and fossil fuel consumption per capita) or possible changes in the behavior of the variables over time.

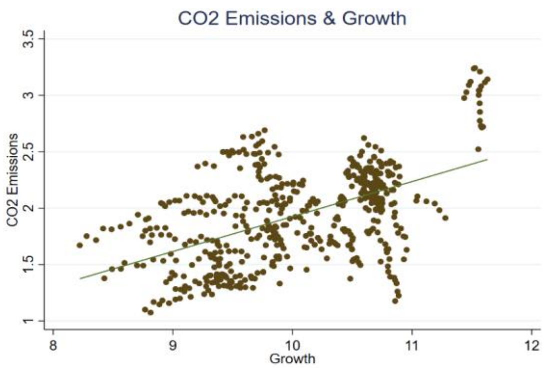

Figure 1 – Relationship between CO_2 Emissions and Economic Growth

Figure no. 1 shows the data for the variables CO_2 emissions and GDP per capita. The regression line shows the linear relationship between growth and CO_2 emissions. The fact that the line is positively sloped suggests that as growth increases CO_2 emissions tend to increase as well. Although there is a general trend for CO_2 emissions to increase with growth, it appears that the data are highly scattered and probably suggests that growth does not fully explain CO_2 emissions. There are obviously other factors that influence CO_2 emissions.

Figure no. 2 shows the relationship between CO_2 emissions and renewable energy consumption. The regression line shows a slightly negative slope, indicating that there is a weak negative relationship between renewable energy and CO_2 emissions. In other words, as renewable energy consumption increases, CO_2 emissions tend to decrease, but the relationship is not very strong. Furthermore, there is a large variation in the data, which means that renewable energy is not the only factor affecting CO_2 emissions.

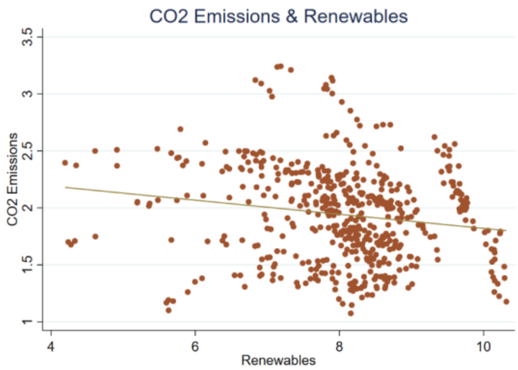

Figure 2 – Relationship Between CO_2 Emissions and Renewable Energy Consumption

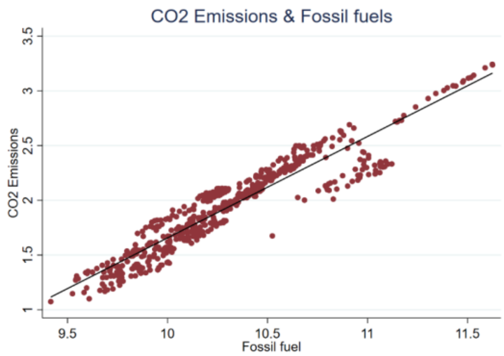

Figure 3 – Relationship Between CO_2 Emissions and Fossil Fuel Energy Consumption

Figure no. 3 illustrates the relationship between CO_2 emissions and fossil fuel use. We observe that there is a positive trend indicating a strong positive correlation between fossil fuel use and CO_2 emissions. This means that as fossil fuel use increases, CO_2 emissions also increase at a steady rate.

4. METHODOLOGY

The methodology of the study was based on the Panel VAR (Vector Autoregressive VAR) model and the analysis of the causal relationship between CO_2 emissions, GDP per capita, renewable energy consumption per capita and fossil fuel consumption per capita. In particular, this model was chosen to investigate the dynamic relationships between multiple endogenous variables. Panel VAR enables these interactions to be studied without requiring the assumption of unidirectional causality, thus allowing for a more comprehensive understanding of the complex relationships that develop between the variables being examined. Prior to the application of the basic Panel VAR Model, panel-appropriate tests were carried out and a panel regression was performed to show simple correlations of the variables.

4.1 Panel Regression

Before estimating the main model, we conducted a simple panel regression estimation, which is defined as follows:

$$CO_2\ Emissions_{it} = \alpha + \beta_1 GDP\ per\ capita_{it} + \beta_2 Renewables\ consumption\ per\ capita_{it} + \beta_3 Fossil\ fuel\ consumption\ per\ capita_{it} + \varepsilon_{it} \tag{1}$$

where:

- $CO_2\ Emissions_{it}$ is the dependent variable representing CO_2Emissions for observation i at time t,
- $GDP\ per\ capita_{it}$ is GDP per capita (in constant 2015 US dollars),
- $Renewables\ consumption\ per\ capita_{it}$ is the renewables consumption per capita,
- $Fossil\ fuel\ consumption\ per\ capita_{it}$ is the fossil fuel consumption per capita in 2023,
- α is the constant term of the model,
- $\beta_1,\ \beta_2, \beta_3,$ are the coefficients representing the effect of each independent variable on the dependent variable,
- ε_{it} is the error term.

The theoretical background of the tests, the results of which are presented in the next section, is outlined below.

4.2 Cross-Sectional Dependence Tests

Cross-sectional dependence on panel data is an important issue that can affect the validity of estimates. When residuals from one cross section are related to those of other cross sections, conventional estimates may lead to biased estimates and erroneous conclusions (Pesaran, 2004). For this reason, it is necessary to carry out cross-sectoral dependency tests so that, based on the results, the necessary actions can be taken in subsequent analyses. To test intersectional dependence, we performed four Tests which are represented below:

4.2.1 Pesaran's Test for Cross-Sectional Dependence

Pesaran (2004) test is based on the average of the correlations between the cross-sectional residuals. It is suitable for large panels where the time (T) is significantly greater than the number of cross sections (N). The statistic test is calculated as follows:

$$P_{test} = \sqrt{\frac{2T}{N(N-1)}}(\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij}) \quad (2)$$

where T is the time dimension, N is the number of sections, $\hat{\rho}_{ij}$ is the correlation of residuals between sections i and j. It is proved that under the null hypothesis of no cross-sectional dependence, P_{test} approaches the normal distribution N(0,1) for N→∞ and for sufficiently large T (De Hoyos and Sarafidis, 2006).

4.2.2 Breusch-Pagan LM Test

The Breusch-Pagan LM test (1980) proposed a Lagrange Multiplier (LM) statistic for detecting inter-layer dependence in order to examine the correlation of errors (residuals) between different layered units in a panel of data. The LM statistic follows an asymptotic χ^2 distribution and is mainly used when T (the number of time observations) is significantly larger than N (the number of stratified units). The LM test is particularly useful for testing correlation errors, as its existence can cause problems with the reliability of the estimates. The test is expressed by the following equation:

$$LM_{BP} = T * (\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij}) \quad (3)$$

where $\hat{\rho}_{ij}$ is the sample estimate of the pairwise correlation of the residuals:

$$\hat{\rho}_{ij} = \hat{\rho}_{ji} = \frac{\sum_{t=1}^{T} \hat{u}_{it}\hat{u}_{jt})}{(\sum_{t=1}^{T} \hat{u}_{it}{}^{2})^{\frac{1}{2}} (\sum_{t=1}^{T} \hat{u}_{jt}{}^{2})^{\frac{1}{2}}} \quad (4)$$

where $\hat{u}_{it}$ is the estimate of the main model. The null hypothesis is that there is no dependence between sections and it is rejected if the LM statistic is significant, indicating the existence of dependence (Breusch and Pagan, 1980; De Hoyos and Sarafidis, 2006).

4.2.3 Friedman's Test

The test of Friedman (1937) is often used when there is a hypothesis of cross-sectional dependence. More specifically, the test proposed by Friedman is a non-parametric test based on the correlation coefficient of Spearman rankings. The Spearman correlation coefficient is obtained from the equation:

$$\hat{r}_{ij} = \hat{r}_{ji} = \frac{\sum_{t=1}^{T}(\hat{r}_{i,t} - \frac{T+1}{2}) (\hat{r}_{j,t} - \frac{T+1}{2})}{\sum_{t=1}^{T}(\hat{r}_{i,t} - \frac{T+1}{2})^{2}} \quad (5)$$

Friedman's test is based on Spearman’s mean correlation and is given by the equation:

$$R_{ave} = \frac{2}{N(N-1)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{r}_{ij} \quad (6)$$

where $\hat{r}_{ij}$ is the estimated correlation coefficient and large values of R_{ave} indicate the existence of non-zero cross-sectional correlations. Friedman showed that:

$$FR_{test} = (T-1)\{(N-1)R_{ave}^2 + 1\} \tag{7}$$

asymptotically follows the x[2] distribution with $T-1$ degrees of freedom, for constant T as N increases (Friedman, 1937; De Hoyos and Sarafidis, 2006).

4.2.4 Frees' Test

The Free's test (1995), takes into account common characteristics of real data, such as heteroscedasticity and non-normality. Specifically, Free's test is based on the sum of the squares of the correlation coefficients of scores and is given by the equation:

$$R_{ave}^2 = \frac{2}{N(N-1)} \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \hat{r}_{ij}{}^2 \tag{8}$$

where N is the number of cross-sectional units, $\hat{r}_{ij}$ is the rank correlation coefficient between the residuals of the i and j cross-sectional units.

$$F_{test} = N\{R_{ave}^2 - (T-1)^{-1}\} \xrightarrow{d} Q = a(T)\{x_{1,T-1}^2 - (T-1)\} + b(T)\{x_{2,T(T-3)/2}^2 - T(T-3)/2\} \tag{9}$$

where $x_{1,T-1}^2$ and $x^2_{2,\frac{T(T-3)}{2}}$are independently x[2] random variables with $T-1$ and $\frac{T(T-3)}{2}$ degrees of freedom, respectively, $a(T) = \frac{4(T+2)}{5(T-1)^2(T+1)}$ and $b(T) = \frac{2(5T+6)}{5T(T-1)(T+1)}$. Thus thenull hypothesis is rejected if $R_{ave}^2 > (T-1)^{-1} + \frac{Q_q}{N}$, where $Q_q$is the appropriate quantile of the Q distribution.

4.3 Unit root tests

Applying a panel VAR model, is necessary that the variables are stationary and for this reason unit root tests are performed. In our analysis, we performed both first- and second-generation unit root tests, taking cross-sectional dependence into account. The methods we used are Levin-Lin-Chu (LLC) and Im-Pesaran-Shin (IPS) tests for the first generation and Pesaran's CADF and CIPS for the second generation.

4.3.1 Levin-Lin-Chu (LLC) Test

The Levin-Lin-Chu test (2002) is based on the assumption that the autoregressive coefficient, ρ, is common across all cross-sectional units. The equation of the test can be expressed as:

$$\Delta_{y_{it}} = \varphi_{y_{i,t-1}} + z'_{it}\,\gamma_i + \sum_{j=1}^{p} \vartheta_{ij} \Delta_{y_{i,t-j}} + \varepsilon_{it} \quad (10)$$

where y_{it} is the variable under control, $\Delta_{y_{it}}$ is the first difference of the variable, φ is the common coefficient that determines whether a unit root exists, $z'_{it}\,\gamma_i$ are the panel-specific features, which include constants and trends, ϑ_{ij} are the coefficients of the lagged first differences, and ε_{it} is the white noise term. The null hypothesis of the test is that a unit root exists, meaning the series is not stationary. If the value of the test statistic is significant, the null hypothesis is rejected in favor of stationarity.

4.3.2 Im-Pesaran-Shin (IPS) Test

The Im-Pesaran-Shin (IPS) test (2003) allows for differentiation in the autoregressive coefficient χ between panels, in contrast to the Levin-Lin-Chu test which assumes a common coefficient. The IPS test tests for the existence of a unit root in the panel data and is based on separate Dickey-Fuller (ADF) regressions for each panel. The basic equation for each cross section i is as follows:

$$\Delta_{y_{it}} = \varphi_i y_{i,t-1} + z'_{it}\,\gamma_i + \varepsilon_{it} \quad (11)$$

where y_{it} is the variable under control, $\Delta_{y_{it}}$ is the first difference of the variable, φ_i is the panel-specific coefficient, which determines whether there is a unit root, $z'_{it}\,\gamma_i$ includes constants and trends and ε_{it} is the noise term.

The IPS test allows for heterogeneity in the coefficients φ_i between cross sections. This test calculates the average of the t-statistics from the ADF regressions for each cross-section and then tests whether this average deviates significantly from zero. If the value is sufficiently small, then the null hypothesis that all series contain a unit root is rejected.

4.3.3 Cross-sectionally Augmented Dickey-Fuller (CADF) test

The CADF test (Pesaran, 2007) is a second-generation test that takes into account cross-sectional dependence in panel data. This test adapts the traditional Dickey-Fuller test by incorporating a common term for cross-sectional dependence. The model equation used is as follows:

$$\Delta_{y_{it}} = \alpha_i + \gamma y_{i,t-1} + \delta \bar{y}_{t-1} + \sum_{j=1}^{p} \vartheta_j \Delta_{y_{i,t-j}} + \varepsilon_{it} \quad (12)$$

where $\Delta_{y_{it}}$ is the first difference of the variable y , $\alpha_i$is the constant for each cross-section, $\gamma$is the coefficient of the lag of the variable $y_{i,t-j}$,t- , $\Delta_{y_{i,t-j}}$ is the average of the y values for all cross-sections at $t-1$, $\sum_{j=1}^{p} \vartheta_j \Delta_{y_{i,t-j}}$ are the lagged differences of the variable and ϵit is the error term.

CADF takes into account the interactions between the cross-sections through the $\bar{y}_{t-1}$ which represents the cross-sectional averages. The null hypothesis (H_0) is that there is a unit root, while the alternative hypothesis (H_1) is that the series are stationary.

4.3.4 Cross-sectionally Augmented IPS (CIPS) test

Pesaran's Cross-sectionally Augmented IPS (CIPS) Test is an extension of the IPS test that takes into account cross-sectional dependence. Unlike traditional first-generation tests, CIPS adjusts the IPS statistic by including cross-sectional averages of lagged levels. The equation of the CIPS test is:

$$CIPS = \frac{1}{N}\sum_{i=1}^{N} CADF_i \tag{13}$$

where $CADF_i$ is the CADF statistic for each cross-section. The CIPS test is ideal for panel data with a large number of cross-sections (N) and a relatively small number of time observations (T), and takes into account cross-sectional dependence, which makes it suitable for panels with cross-sectional dependence.

4.4 Panel Vector Autoregressive (VAR) model

The key empirical results of this paper were obtained using the main panel VAR model. This model allows simultaneous analysis of different endogenous variables and the study of their interactions. The specification of a basic VAR model can be described by the following equations:

$$Y_{it} = \alpha_1 + \sum_{p=1}^{P} \beta_{1p} Y_{i,t-p} + \sum_{p=1}^{P} \gamma_{1p} X_{i,t-p} + \varepsilon_{it}^{(Y)} \tag{14}$$

$$X_{it} = \alpha_2 + \sum_{p=1}^{P} \beta_{2p} Y_{i,t-p} + \sum_{p=1}^{P} \gamma_{2p} X_{i,t-p} + \varepsilon_{it}^{(X)} \tag{15}$$

where:

- Y_{it} and X_{it} are the endogenous variables for observation i at time t,
- α_1 and α_2 are the constant terms of the equations,
- β_{1p} and β_{2p} are the coefficients of the lags of the variables Y_{it} and X_{it},
- γ_{1p} and γ_{2p} are the coefficients of the lags of the variables Y_{it} and X_{it} respectively,
- P is the number of lags included in the model,
- $\varepsilon_{it}^{(Y)}$ and $\varepsilon_{it}^{(X)}$ are the error terms of the equations.

5. EMPIRICAL RESULTS

The results of the analysis are presented in the tables below. In the first stage a panel regression considers seeing the correlations between the variables. In the panel regression the variables were used in logarithmic form to see the percentage variables. In more detail, the results of the regression are presented in Table no. 3. The results for GDP per capita show that a 1% increase in GDP per capita increases CO_2 emissions by 0.028%, however this variable is not statistically significant. For fossil fuel energy consumption per capita it appears that a 1% increase in renewable energy consumption per capita is associated with a 1.036% increase in CO_2 emissions (statistically significant at the 1% level). Finally, with respect to renewable energy consumption per capita, a 1% increase in fossil fuel consumption per capita is associated with a 0.038% decrease in CO_2 emissions (statistically significant at the 1% level). The model, according to the R^2 result, explains 88.1% of the variation in CO_2 emissions, indicating a good fit.

Table no. 3 – Regression Results (Fixed effect model with robust std errors)

Variable	CO_2 Emissions
GDP per capita (constant 2015 US dollar)	0.028
	(0.025)
Fossil fuel consumption per capita	1.036***
	(0.027)
Renewables consumption per capita	-0.038***
	(0.006)
Constant	-8.711***
	(0.236)
Number of observations	525
R^2	0.881

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%; standard errors in parentheses
Source: authors' calculations

Subsequent to the analysis it was considered necessary to test for cross-sectoral dependence. In panel data it is common for observations to be independent of each other, i.e. changes in one cross-section may affect the others. The existence of cross-sectional dependence indicates that alternative estimation methods (e.g. standard error correction or models that take cross-sectional dependence into account) may need to be applied. As cross-sectional dependence can lead to inaccurate estimates, we have made the necessary tests to identify and account for it.

The tests performed are Pesaran's test, Breusch-Pagan LM, Frees' test and Friedman's test are specifically designed for different situations and assumptions about the distribution of the data. The results of the cross-sectional dependence tests are presented in Table no. 4. We observe that cross-sectional dependence exists in all variables and the results are significant at the 1% level of significance.

Table no. 4 – Cross-sectional independence tests

Test	Statistic
Pesaran's test	12.038***
Breusch-Pagan LM	904.641***
Frees' test	2.150***
Friedman's	86.722***

Source: authors' calculations

Since after the above tests it was shown that there is cross-sectoral dependence, we proceeded to unit root tests. Due to the cross-sectional dependence, it was considered necessary to carry out both first- and second-generation unit root tests. The difference between first- and second-generation tests is that first generation tests assume that there is no cross-sectional dependence between observations, while second generation tests allow and often correct for cross-sectional dependence.

The results of the unit root tests in Table no. 5 show that all variables (CO2 Emissions, GDP per capita, Fossil fuel consumption per capita, Renewables consumption per capita) are stationary at the first differences and do not have a unit root, according to the results of both the first- and second-generation tests. The results are statistically significant at the 1% level, as indicated by asterisks.

Table no. 5 – Unit root tests

	First generation		Second generation	
Variables	**Levin–Lin–Chu**	**Im–Pesaran–Shin**	**Pesaran's CADF test**	**Pesaran's CIPS test**
CO_2 Emissions	-4.017***	-9.229***	-8.383***	-4.406***
GDP per capita (constant 2015 US dollar)	-3.775***	-5.566***	-2.741***	-2.88***
Fossil fuel consumption per capita	-3.262***	-9.334***	-9.912***	-4.814***
Renewables consumption per capita	-10.886***	-11.497***	-9.302***	-4.611***

Source: authors' calculations

After the unit root tests and since all variables are stationary at the level of first differences, we proceeded to apply the main model. More specifically, we run a model VAR panel to look at the interactions between variable CO_2 emissions, GDP per capita, renewable consumption per capita, and fossil fuel consumption per capita. The results of the model are shown in Table no. 6. We observe how CO_2 emissions are negatively affected by their past emissions, but positively by fossil fuel consumption. In addition, CO_2 emissions are negatively affected by their past emissions, but positively by fossil fuel consumption. GDP per capita has a positive and significant effect on CO_2 emissions and renewable consumption, but a negative effect on fossil fuels. Finally, renewable consumption appears to have little effect on the remaining variables, while fossil fuel consumption leads to an increase in CO_2 emissions.

Table no. 6 – Panel Var Model

	CO_2 Emissions	GDP per capita	Renewables consumption per capita	Fossil fuel consumption per capita
L1. CO_2 Emissions	-0.749**	-0.047	-0.389*	0.898**
	(0.298)	(0.107)	(0.210)	(0.445)
L2. CO_2 Emissions	-0.813**	-0.356***	-0.495*	0.504
	(0.346)	(0.125)	(0.263)	(0.465)
L1. GDP per capita	0.719***	0.728***	0.628***	-1.025**
	(0.236)	(0.143)	(0.192)	(0.421)
L2. GDP per capita	0.495***	-0.015	0.423***	0.971***
	(0.165)	(0.110)	(0.140)	(0.339)
L1. Renewables	0.413	-0.023	0.074	-0.650
consumption per capita	(0.284)	(0.114)	(0.220)	(0.459)
L2. Renewables	0.463	0.329**	0.217	-0.327
consumption per capita	(0.319)	(0.135)	(0.258)	(0.477)
L1. Fossil fuel	0.075**	0.021*	0.053**	-0.013
consumption per capita	(0.034)	(0.012)	(0.024)	(0.085)
L1. Fossil fuel	0.055**	0.007	0.038*	-0.110*
consumption per capita	(0.028)	(0.011)	(0.021)	(0.058)
Observations	425	425	425	425

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%; standard errors in parentheses
Source: authors' calculations

For a better understanding of the results, performed the extraction of graphical representations of the impulse responses of each variable (CO_2 emissions, GDP, fossil fuel and renewable energy consumption) to possible shocks, using a Panel VAR system over time. The representations of these impulse responses are shown in Figure no. 4.

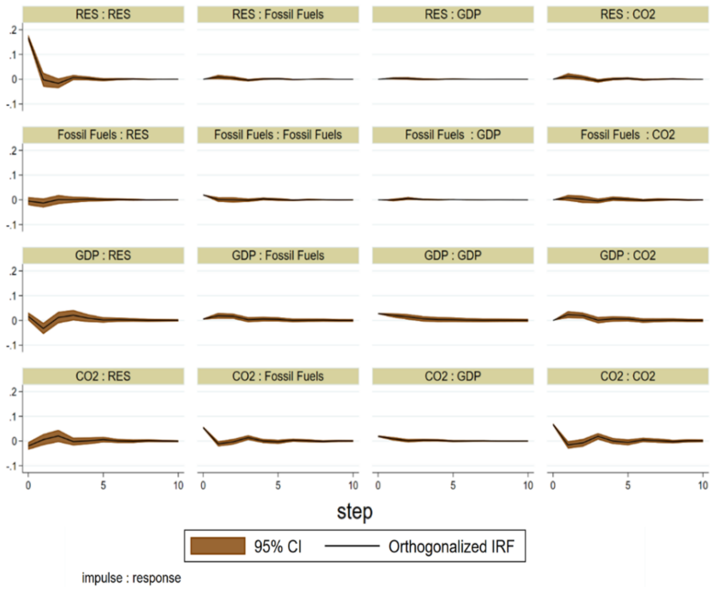

Figure 4 – Impulse Response Functions (IRFs) derived from the Panel VAR model
Source: authors' calculations

More specifically, Figure no. 4 shows that a shock to renewable energy consumption directly and negatively affects fossil fuel consumption, suggesting that an increase in renewable energy use leads to a reduction in fossil fuel dependence. Also, the effect on CO_2 emissions from increased renewable energy consumption is relatively mild, indicating that renewables do not affect emissions as strongly as fossil fuels.

In contrast, fossil fuel consumption causes a significant increase in CO_2 emissions. While the effect on economic growth (GDP) is small, it reveals that fossil fuel consumption is related to economic activity. In terms of GDP, the shock to CO_2 emissions appears to have a positive but weak effect, while the relationship with renewable energy shows little response. Finally, it is observed that a shock to CO_2 emissions has a negative effect on renewable energy consumption, but no significant effect on other variables such as GDP per capita or fossil fuel consumption.

Table no. 7 presents the results of the Wald test for Granger causality testing and examines whether one variable can predict the other. In more detail, we see that important Granger causalities are observed between CO_2 emissions and GDP, fossil fuel consumption and GDP, as well as between CO_2 and renewable energy sources. Fossil fuel consumption significantly affects CO_2 emissions, GDP and renewable sources. CO_2 affects renewable sources and all variables overall and finally renewable consumption affects GDP and all variables overall.

Table no. 7 – Panel VAR-Granger causality Wald test

			X^2				X^2
CO_2	→	GDP	18.540***	Fossil	→	CO_2	5.344*
CO_2	→	Fossil	4.080	Fossil	→	GDP	21.671***
CO_2	→	Renewables	6.021**	Fossil	→	Renewables	5.975**
CO_2	→	All	25.248***	Fossil	→	All	27.519***
GDP	→	CO_2	8.753**	Renewables	→	CO_2	4.089
GDP	→	Fossil	7.143**	Renewables	→	GDP	12.707***
GDP	→	Renewables	2.994	Renewables	→	Fossil	2.051
GDP	→	All	10.652	Renewables	→	All	19.343***

Notes: * significant at 10%; ** significant at 5%; *** significant at 1%

Source: authors' calculations

Ensuring the stability of the panel VAR model used to analyze the relationship between CO_2 emissions, GDP per capita and energy consumption (both fossil fuels and renewables) is the focus of the eigenvalue stability condition in Figure no. 5.

Stability is crucial for interpreting impulse response functions (IRFs), which show how variables such as CO_2 emissions react over time to shocks in energy consumption or economic growth. If the model was not stable, these IRF's would not return to their initial value, leading to possibly misleading conclusions about the long-term effects of these shocks. The eigenvalue stability results in Figure no. 5 confirm that the model is stable, allowing valid conclusions to be drawn from the empirical analysis.

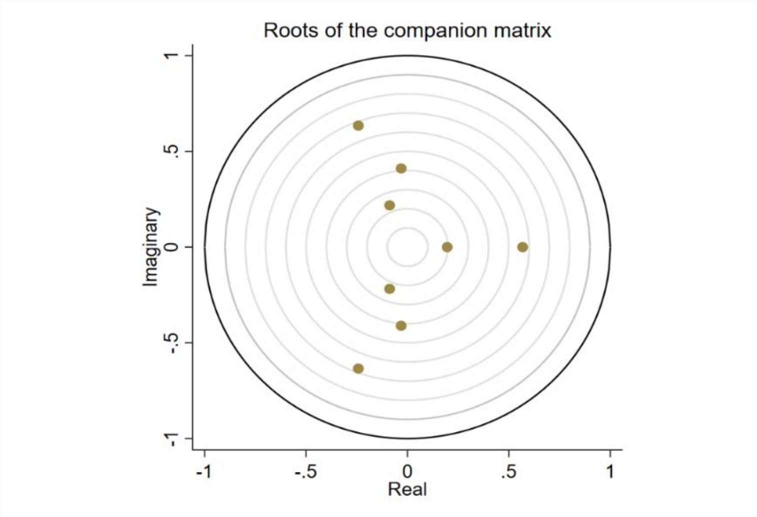

Figure no. 5 – Eigenvalue stability condition

6. CONCLUSION REMARKS

To conclude, exploring the relationship between economic growth, energy consumption and CO_2 emissions in Europe is crucial for climate change mitigation. This paper focuses on the relationship between economic growth, energy consumption and CO_2 emissions for European Union countries. Analyzing the causal relationships between these factors can play a key role in the decision-making process and contribute to the broader effort to reduce CO_2 emissions and achieve sustainable development. The main findings show that fossil fuel consumption has a strong positive effect on CO_2 emissions, indicating that an increase in fossil fuel consumption leads to a significant increase in emissions. This result underlines the need to reduce their consumption, in line with the European Green Deal's targets to reduce emissions by 55% by 2030 and achieve climate neutrality by 2050 and the urgent need to accelerate the transition to cleaner energy sources, as set out in the agreement. At the same time, renewable energy consumption has a negative effect on CO_2 emissions, although its effect remains weaker than that of fossil fuels. GDP per capita also shows a positive effect on CO_2 emissions, confirming the close link between economic growth and increased energy consumption and emissions. It is also apparent that the consumption of fossil fuel contributes much to both the level of emissions and GDP, which evidences that economic activity in the EU still depends greatly on fossil fuel. Logically, therefore, consumption of renewable energy sources has contributed relatively little to economic activity to date, a proxy for the fact that transition to renewable energy sources has so far not managed to replace the dependence on fossil fuels.

Our analysis indicates that there is bidirectional causality between renewable energy consumption and economic growth. The reasoning for this evidence is verified by the conclusions of Apergis and Payne (2010) and Apergis and Payne (2012). Similar results in our analysis indicate that, as in both considered studies, bidirectional causality exists in both short- and long-run frameworks. Also, while the findings of Asiedu *et al.* (2021) showed the strong efficient effect of renewable energy on reducing CO_2 emissions, our results tend to show it to be milder in the EU, meaning economic growth is still highly dependent on the use of non-renewable energy sources. Also, Al Araby *et al.* (2019) explores the impact of renewable energy on the decrease of CO_2 emission and finds a positive impact; hence supporting our analysis.

The findings indicate that policymakers in the European Union should place greater emphasis on increasing investment in renewable energy and improving energy efficiency. The strong link between fossil fuel consumption and CO_2 emissions highlights the urgent need to reduce fossil fuel use. Likewise, the relatively limited impact of renewables on emissions suggests that more efforts are needed to expand their share in the energy mix. In general, speeding up the transition to a cleaner energy model through innovative policies, green technologies, and energy efficiency is crucial for achieving sustainable economic growth.

Future research will look at how new renewable energy solutions can reduce CO_2 emissions and speed up the transition to a cleaner energy mix. As economic growth has been heavily dependent on fossil fuels, a key issue for investigation will be whether a transition to full decarbonization is possible for individual sectors of the economy or for different EU countries. Further studies should also explore the dynamics of the deployment of technologies, such as energy storage and smart grids, in order to increase the contribution of renewables to energy demand. These findings could help policymakers achieve the 2050 climate neutrality target.

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