How Does Increasing Renewable Energy and Decreasing Coal-Based Electricity Generation Affect the Future of Unemployment in Developed Countries: A Heterogeneous Panel Data Analysis?

İbrahim Özmen[1]
Mustafa Gerçeker[2]
Mehmet Mucuk[3]

Abstract

This study investigates the net impacts of the transformation from traditional energy generation to renewable energy generation on unemployment in developed countries. In this context, a panel data framework is used to analyze the long-run coefficients and causal relationships for the period of 1990-2021. The long-run results show that increases in renewable energy generation have a reducing effect on unemployment only in Denmark. On the other hand, Germany, Spain, the United Kingdom, and France's results indicate the opposite. Our findings decide the determinants of rising renewable energy generation and take into account its effects on unemployment.

Jel Codes: C13, E24, Q40
Keywords: Renewable energy, green unemployment, heterogeneity, cross-sectional dependency

Artan Yenilenebilir Enerji ve Azalan Kömüre Dayalı Elektrik Üretimi Gelişmiş Ülkelerde İşsizliğin Geleceğini Nasıl Etkiliyor: Heterojen Bir Panel Veri Analizi?

Özet

Bu çalışma, geleneksel enerji üretiminden yenilenebilir enerji üretimine geçen gelişmiş ülkelerde bu dönüşümün işsizlik üzerindeki potansiyel etkilerini araştırmaktadır. Bu bağlamda, 1990-2021 dönemi için uzun dönemli katsayı ve nedensellik ilişkisini analiz etmek için panel veri yöntemlerini kullandık. Sonuçlar, yenilenebilir enerji üretimindeki artışların yalnızca Danimarka' da işsizliği azaltıcı bir etkiye sahip olduğunu göstermektedir. Öte yandan Almanya, İspanya, Birleşik Krallık ve Fransa'nın uzun dönem katsayı tahmin sonuçları bunun aksini göstermektedir. Bulgularımız, politika yapıcıların artan yenilenebilir enerji üretimi politikalarında işsizliğin etkilerini hesaba katılması açısından önemlidir.

Jel Sınıflandırması: C13, E24, Q40
Anahtar Kelimeler: Yenilebilir enerji, Yeşil işsizlik, Heterojen panel, Yatay kesit bağımlılığı

[1] Department of Public Finance, University of Selcuk, 42550, Konya, Turkey. E-mail: ibrahimozmen@selcuk.edu.tr, ORCID: 0000-0003-2632-4217
[2] Department of Economics, University of Selcuk, 42550, Konya, Turkey. E-mail: mustafagerceker@selcuk.edu.tr, ORCID: 0000-0002-2920-255X
[3] Department of Economics, University of Selcuk, 42550, Konya, Turkey. E-mail: mehmetmucuk@selcuk.edu.tr, ORCID: 0000-0002-4341-5236

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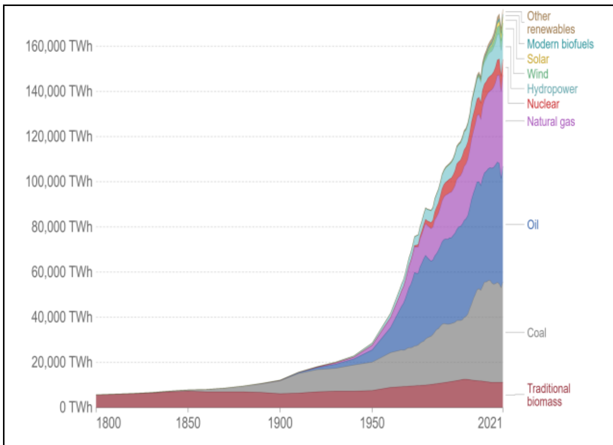
1. Introduction

Global climate change is a significant issue under scrutiny in this century. Climate change means the planet is warming, species are under threat of extinction, weather tends toward disasters, and essential resources such as fresh water and soil are reduced (Özmen and Dündar-Öztaşçı, 2022: 64; Frumkin, 2022; Naqvi et al., 2022). The planet has already warmed by 1.2 ˚C since the Industrial Revolution (Fremstad and Paul, 2022). The policies that can be implemented to reduce the rate of global warming, which the literature agrees is caused by greenhouse gas emissions (Hussain et al., 2022; Naqvi et al., 2022; Raihan and Tuspecova, 2022; Çitak et al., 2022; Özmen et al., 2022), lead to change in energy sources (Saboori et al., 2022; Mostafaeipour et al., 2022).

Transformation away from fossil fuels towards renewable energy has a key role in this regard (Vaughan and Webber, 2020; Steffen and Patt, 2022). This transformation not only plays an active part in tackling global climate change but also strongly affects energy security (Osicka and Cernoch, 2022) and various economic (Borzuei et al., 2022) and political variables (Steffen and Patt, 2022; Krupnik et al., 2022).

Many recent studies argue for the positive effects of renewable energy on economic growth, the reduction of emissions, and public health (Li and Li (2020), Chen et al. (2022), Akadiri and Adebayo (2022), Aslan et al. (2022), Yang et al. (2022), Wang et al. (2022), Wang et al. (2022), Khan et al. (2020), Buonocore et al. (2019), Pata (2021)). Apart from the above, as we focus on in this study, some studies have explored the effects of renewable energy on employment or unemployment; these studies, however, are relatively few. Payne (2009), Tiwari (2010), George and Oseni (2012), Naqvi et al. (2022), Saboori et al. (2022) can be cited as examples of them.



Although the source of energy production and consumption in the world differs according to country, it is predominantly fossil fuels. The most significant share of fossil fuels belongs to coal and oil (OWD, 2022a). However, a major step forward was taken to change this with the United Nations Convention on Climate Change’s 21st Conference of the Parties (COP21) text in Paris, and a global consensus was achieved to reduce fossil-based electricity production (IRENA, 2016).

Figure 1: Global Primary Energy Consumption by source

Source: OWD, 2022a

Renewable energy has been accepted as an alternative to fossil energy sources (Mostafaeipour et al., 2022; Krupnik et al., 2022). In many countries energy policy has been implemented in this direction. Some countries have specific commitments, for instance the European Union (EU) and its member states made a commitment in 2021 to fulfill at least 32% of their total energy needs with renewable energy by 2030 (Krupnik et al., 2022). The International Renewable Energy Agency (IRENA) (2019) estimates that by 2050 renewable energy sources will account for more than 86% of total electricity production.

The transition from conventional sources to renewable energy sources (hence forth CTR) in energy generation can lead to some results for employment (Krupnik et al., 2022) and unemployment. Naqvi et al. (2022) draw attention to the high costs of renewable energy transformation. While renewable energy created new jobs for approximately 12.7 million people all over the world in 2021 (IRENA, 2022), there is no consensus on the effects of CTR on unemployment (Saboori et al., 2022; Naqvi et al., 2022). It can be argued that the transition from conventional production, which can be considered labor-intensive, to technology-intensive renewable energy generation may also result in job losses.

IRENA (2020; 2022) states that job losses are expected as a result of the transition from fossil fuels to nuclear energy technologies. If CTR, which is supposed to create new jobs, does not create job opportunities, is it not a simple job replacement? It is important not to underestimate this. In this study, we focus on the *net unemployment* that can be caused by CTR and we search for an answer to that question: If we say there are renewable returns on job opportunities and losses for renewable job loss, are there renewable job returns that can compensate for the losses incurred in abandoning conventional production? By returns, we mean moving toward pure sums from the gross sums.

We conceptualized the theoretical relationship of CTR with unemployment under three headings. These are the *green employment hypothesis* (henceforth GEH), the *green unemployment hypothesis* (henceforth GUH), and the *neutrality* or *green jobs substation* hypothesis. We empirically investigated these hypotheses in six select European countries. For this purpose, we employed panel estimate techniques considering cross-section dependency and slope heterogeneity. We checked the robustness of the findings with novel approaches in the panel literature. Findings show that GEH is acceptable only in Denmark.

Our study differs from the recent literature in three points. i) while recent studies have focused on the relationship between renewable energy consumption and employment, we investigate the effect of the transition from conventional energy to renewable energy on unemployment, known as the net unemployment effect. ii) we focus on six European countries with the highest direct employment (Austria, Denmark, France, Germany, Spain, and the United Kingdom) (Blanco and Rodrigues, 2009). These countries have partially reduced their coal-based electricity production and increased renewable energy generation since 2008 and 2009. iii) our methodological approach includes a second-generation estimator which is called cross-sectional dependency and takes global economic systems into account. To the best of our knowledge, this is the only study in the literature that includes these three elements.

The rest of the paper proceeds as follows: Section 1 presents theoretical knowledge and Section 2 surveys the empirical literature. Section 3 includes the data, methodology, and model. Section 4 contains empirical findings, discussion and conclusion.

2. Theoretical context

Renewable energy creates new jobs (Burke and Stephens, 2018; Lavidas, 2019) via three different channels: Direct jobs, indirect jobs and induced jobs (IRENA, 2011; Van der Zwaan et al., 2013; Hienuki et al., 2015; Ortega et al., 2015). While the jobs that cover the main fields of activity in the industry are referred to as direct jobs, indirect jobs are those created within the supply chain. Induced jobs, on the other hand, are the jobs created as a result of expenses made by people employed in industry-related fields (Blyth et al., 2014). The jobs emerging due to the activities in the field of renewable energy have created the concept of green jobs (Tourkolias and Mirasgedis, 2011). The Bureau of Labor Statistics (BLS) defines green jobs as the jobs that benefit the environment and preserve natural resources (BLS, 2017).

The International Labor Organization (ILO) defines green jobs as works that contribute to the reduction of negative environmental effects. These jobs reduce energy and raw material consumption, decrease greenhouse gas emission, minimize waste and environmental pollution, and preserve and improve ecosystems (ILO, 2017). According to Apergis and Salim (2015), increases in renewable energy investment and utilization capacity may positively affect labor demand. As a result of the utilization of environmentally sensitive energy resources, areas of *green employment* that we call the *green employment hypothesis* (GEH) are gradually expanding. Figure 2 shows green jobs in Germany and other EU countries[4].

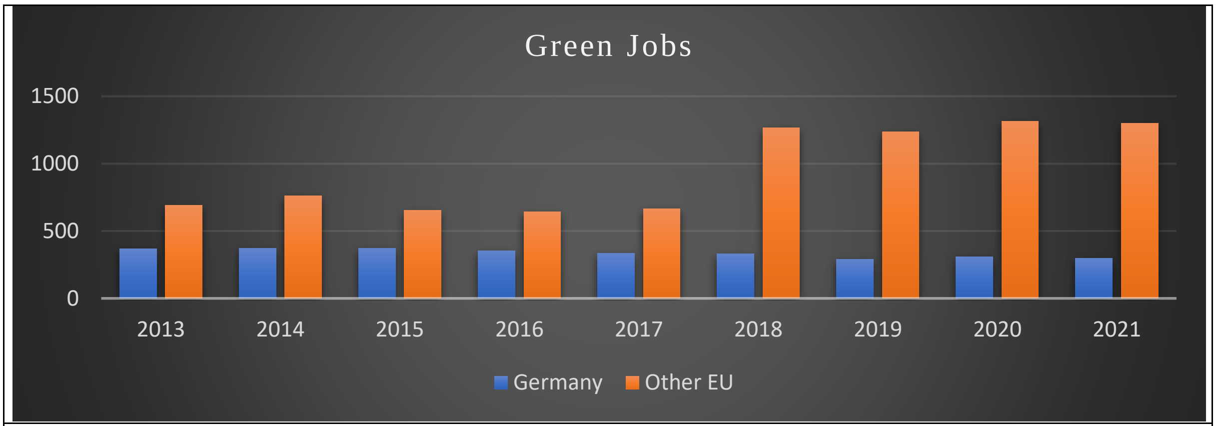


Figure 2: 2013-2021 Green Jobs

Source: IRENA Reports (2011-2022)

Even when the argument in GEH is accepted, this effect can continue until a certain capacity is reached in renewable energy generation. Once full capacity is reached, an increase in unemployment might be expected again. A country that is advantageous in renewable energy technologies, on the other hand, carries on its economic activities without a decrease in employment rate by means of technology exports.

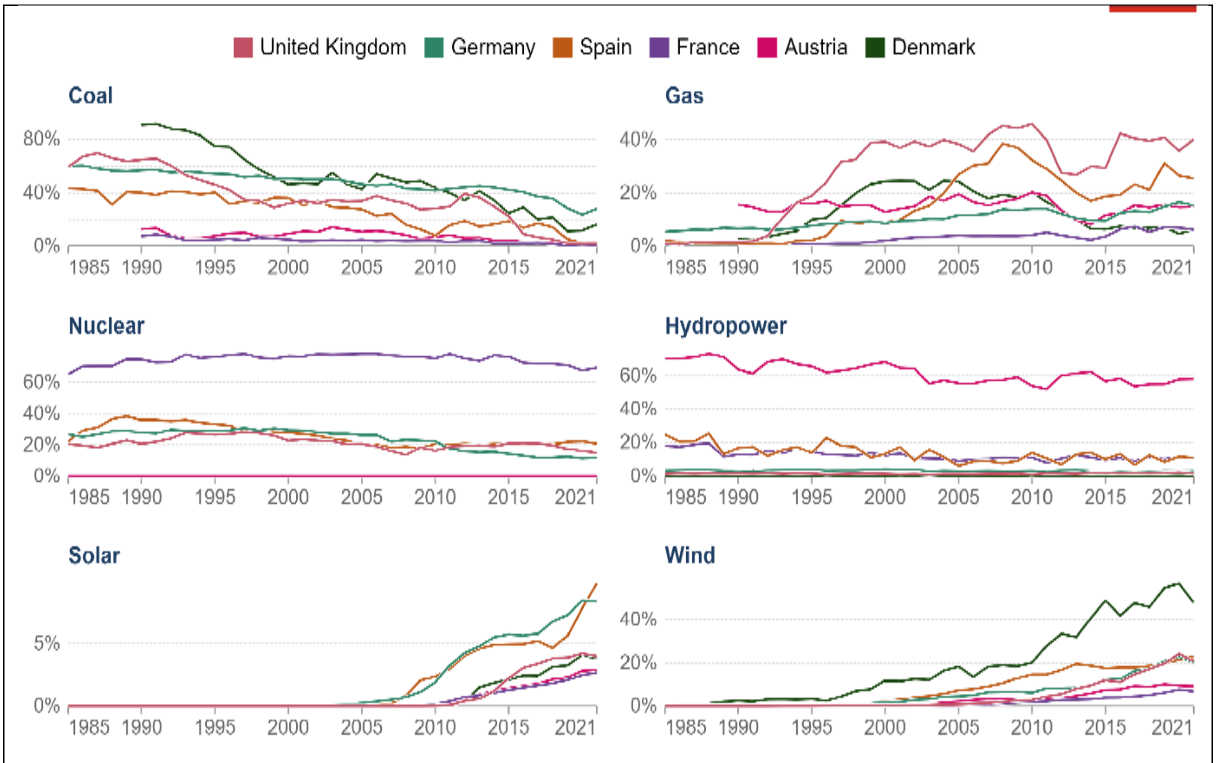


Figure. 3: Electricity generations by country

[4] In the EU countries, the most stable data on Green Jobs belonged to Germany, and we have provided statistics of Germany to give the reader a perspective. These variables can be taken back to 2009, but they are not steady.

Source: OWD, 2022b

The countries which cut down fossil fuel production (as we see in Figure 3) due to cost or environmental factors and tend towards renewable energy generation may initially face unemployment problems, namely *green unemployment*. Furthermore, while technological development creates new jobs, it may bring the possibility of the emergence of the newly unemployed (Zhao and Luo, 2017).

Apergis and Salim (2015) list the adverse effects of CTR on the labor market under three headings. Firstly, in the transition phase, investments can crowd out other sectors, and a change in imports can reduce consumption. Second, structured production processes may need to be changed to reduce pollution and ensure efficient use of resources, which also affects the labor market. Lastly, green jobs can change the employment structure of labor-intensive sectors by reducing environmental pressures. Hillebrand et al. (2006) argue that long-run increases in energy prices can reduce demand, and investment can be made in other sectors. As a result, these processes can create net job losses. Saboori et al. (2022) indicate that new jobs created by green jobs require green skills. As a result, the labor market may experience some uncertainty in the short run.

In addition, the decrease in the coal-based energy production of thermal power plants has an effect that may lead to an increase in unemployment. In our study, we exclude these discussions and call the aforementioned phenomenon the *green unemployment hypothesis* (GUH). It is argued that renewable energy technologies are more labor-intensive compared to fossil fuel technologies and that they create more employment areas particularly in construction, installation, and production processes (Bowen 2012). Because the long-term effects are not focused on in earlier studies, these effects are unclear.

Based on the approaches we have mentioned above and our arguments about CTR, we can summarize our possible main hypotheses as follows;

i) $\beta_{1_{it}} + \beta_{2_{it}} > or \geq 0$, GUH is effectual,

ii) $\beta_{1_{it}} + \beta_{2_{it}} < or \ \leq 0$, GEH is effectual,

iii) $\beta_{1_{it}} + \beta_{2_{it}} = 0$, neutrality or green jobs substation hypothesis (so opportunities and possibilities are equivalent) effectual.

where $\beta_{1_{it}}$ and $\beta_{2_{it}}$ represent our long-run coefficient estimates for each unit in the sample.

3. Empirical Literature

In this section, we present some studies on the relationship between renewable energy and unemployment. Although renewable energy consumption and employment variables were used in these studies, Apergis and Salim (2015), Rafiq et al. (2018), Yılancı et al. (2020), Ibrahiem and Sameh (2020) and Naqvi et al. (2022) preferred unemployment instead of employment as the variable. The studies examining the impact of renewable energy on employment vary in terms of the techniques and variables. We can say that three different approaches, employment-based analytical methods, input-output analysis (I-O), and econometric analysis, are preferred in the literature.

Moreno and Lopez (2008) investigated the impact of renewable energy on employment for the period of 2005 to 2010 in Asturias (Spain). Their findings indicated that the development of renewable energy has a notable effect on employment. The authors pointed out that renewable energy gradually compensates for the loss of employment in the traditional mining industries. Wei et al. (2010) investigated the impact of renewable energy investments on employment in the U.S. They focused on the net impact of renewable energy on employment for the period of 2009-2030 by using an excel-based analytical model. They found that all renewable energy and low-carbon resources create more employment than the fossil fuel industry. Barros et al. (2017) used an analytical model based on input-output analysis to determine the relationship between renewable energy and direct employment. While non-renewable energy generation plants directly contribute to employment by 0.1 - 2.4 man-year per GWh, this range for renewable energy generation plants is 0.1 - 4 man-year. Rivers (2013) investigated the relationship between renewable energy and unemployment by general equilibrium analysis for the U.S. and found that reducing emissions in electricity production by 10% with support policies for renewable energy increased the rate of unemployment equilibrium by about 0.1-0.3 points. Fragkos and Paroussos (2018) investigated the net employment impacts resulting from the projected transformation of the European Union energy sector towards Renewable Energy Sources. They used the general equilibrium model (GEM-E3) based on the CGE (Computable General Equilibrium). Their results show that renewable energy expansion has a positive net impact on employment. The authors estimated that the expansion in renewable energy sources creates approximately 200,000 additional direct jobs in 2050. Nagatomo et al. (2021) investigated the relationship between renewable energy and employment in Japan by constructing a simulation using a mathematical method called MARKAL. They found that renewable energy technologies have a positive effect on employment in rural areas by 2050. Nasirov et al. (2021) constructed three different energy scenarios for Chile using the SWITCH method, which assumes an increase in renewable energy technologies. Their findings indicate that the increase in renewable energy technologies has a more positive contribution to employment compared to fossil energy sources.

Lambert and Silva (2012) stated that it is difficult to measure the impact of renewable energy on employment and that the model should be chosen carefully. It is also emphasized that different methods should be used depending on the size of the scale of the studies. According to Lambert and Silva (2012), the input-output analysis is more suitable for studies conducted at the national level to determine the relationship between renewable energy and employment. On the other hand, it is not easy to conduct regional or provincial-based studies by using Input-Output analysis. Therefore, the questionnaire-based analytical study method for small samples may reveal better results. However, with the increasing number of studies in the literature on renewable energy and employment, it has become more evident over time that there is no consensus on the best way to measure the potential of renewable energy to create jobs (Lambert and Silva, 2012). Hillebrand et al. (2006) examined the contribution of renewable energy investments to employment by using the input-output model for Germany. Findings show that policies devoted to renewable energy investment in Germany positively contribute to employment in the short run but this effect turns negative in the medium run. Lehr et al. (2008) obtained different results for Germany by using the same technique. According to energy investment scenarios created for the years 2010, 2020, and 2030, the impact of renewable energy support policies on employment is positive. In addition, the unemployment rate decreases in the long run. Tourkolias and Mirasgedis (2011) examined the relationship between renewable energy technologies and employment in Greece by using input-output analysis. The results show that renewable energy technologies have a positive and significant impact on employment. Hienuki et al. (2015) investigated the impact of geothermal energy investments on employment in Japan. They found that geothermal energy can generate employment of 0.89 person-year per GWh within the period of five phases of the life cycle. Lehr et al. (2016) investigated the sample of Tunisia by using the input-output model. The authors stated that while investments in solar heaters have positive impacts on employment, investment in wind energy doesn’t increase employment to a great extent. Hondo and Moriizumi (2017) identified the job creation potential of renewable energy technologies for Japan. The results show that nine different renewable energy technologies increase employment, each at different levels.

Payne (2009) is one of the first to investigate causality with macroeconomic models (energy consumption and employment). Furthermore, the studies of Tiwari (2010), George and Oseni (2012), Apergis and Salim (2015), Nakıpoğlu-Özsoy and Özpolat (2020), and Çelik (2021) investigating the causality relationship between renewable energy and employment can be cited as examples. Apergis and Salim (2015) examined the relationship between renewable energy consumption and unemployment. They used 80 countries' data between the period of 1990-2013. Findings show that renewable energy consumption has a positive effect on unemployment in the EU and African countries. In addition, they found that an increase in renewable energy consumption decreases unemployment in Asian and Latin American countries. Nakıpoğlu-Özsoy and Özpolat (2020) investigated the causal relationship between renewable energy consumption and employment for BRICS and MIST countries using by Bootstrap Granger Causality Test. They found bi-directional causality for Russia, Indonesia, and India and one-way causality for Brazil, Turkey, and South Africa. Çelik (2021) investigated the relationship between renewable energy generation and employment by using Spectral Granger Causality in the USA for the period of February-1973 and September- 2019. Findings indicate that there is no causal relationship between the two variables.

Moyo et al. (2017) examined the relationship between renewable energy consumption and unemployment in South Africa for the period of 1990-2014 by using the Autoregressive Distributed Lag (ARDL) model. The findings show that renewable energy consumption has a negative impact on employment in the long run. The authors argued that the production and consumption of renewable energy should be increased to increase the level of employment. Osei et al. (2022) examined the relationship between renewable energy production and employment using the System Generalized Method of Moments for 40 Asian, and 50 European Countries for the period of 2000-2018. Their findings show that renewable energy production has a positive impact on employment in both European and Asian countries. Yılancı et al. (2020) examined the relationship between renewable energy production and employment using the Fourier ADL Cointegration Test and Fully Modified OLS for selected OECD countries. Empirical results show that renewable energy consumption has a positive impact on the unemployment rates of Austria, Portugal, and Spain, while it has a negative impact on Australia, Chile, France, Germany, and Japan. Rafiq et al. (2018) investigated renewable energy consumption and unemployment in 41 countries from 1980 to 2014. The authors used both linear and non-linear panel and time series estimation techniques. The findings show that renewable energy consumption increases unemployment. Ibrahiem and Sameh (2020) examined the relationship between clean energy sources and unemployment by using Johansen and Juselius Cointegration, ARDL, and VECM methods for Egypt in the period from 1971 to 2014. Empirical results stated that clean energy resources have an adverse effect on unemployment. Naqvi et al. (2022), examined whether renewable energy production has asymmetric effects on unemployment by using Panel NARDL-PMG methods in Europe for the period from 1991 to 2019. They found that renewable energy production in European countries significantly reduced unemployment for the aforementioned period. Swain et al. (2022) investigated the renewable energy transformation impact on employment by using the panel VAR method in 28 European Countries and Norway for the period from 2000 to 2018. Empirical results suggest that renewable energy has a positive but small net impact on employment.

On the other hand, the number of studies addressing the relationship between unemployment and renewable energy generation on the basis of economic growth is quite high.

Chang et al. (2001), Sari and Soytas (2004), Narayan and Smyth (2005), Apergis and Payne (2010a), Apergis and Payne (2010b), Menegaki (2011), Pao and Fu (2013) could be cited as examples. These studies focused on the indirect impact of renewable energy on employment.

4. Data, Model and Methodology

4.1. Data and Model

We used data from 1990 to 2021 from the six selected developed countries. The data include renewable energy generation (REG), the measured share of electricity production from renewables, coal-based energy generation (CEG), the measured share of electricity production from coal and the unemployment rate (UNP). Reg and Ceg data were obtained from the Our World in Data (OWD, 2022c, d). Unp was obtained from World Development Indicators (WDI, 2022).

Various modeling approaches have been used in the literature to model the relationship between renewable energy and employment. However, as we mentioned in the theoretical context, we focused on the net unemployment, so our benchmark of the function and econometric model can be expressed as follows:

Unp = f (Ref, Ceg) (1)

The econometric model in which double-log is created by adding β constant term and $\varepsilon_{\mathrm{it}}$error term to the function (1) is given in equation (2).

$$\mathrm{lnUnp_{it}} = \beta_0 + \beta_{1\mathrm{i}}\mathrm{lnReg}_{it} + \beta_{2\mathrm{i}}\mathrm{lnCeg}_{it} + \varepsilon_{\mathrm{it}} \quad (2)$$

where $i = 1, \ldots, N$ shows each country in the panel and $t = 1, \ldots, T$ shows cross section and *ln* refers to the natural logarithm of the series.

Coal-based electricity production tends to decrease in all units in the panel. In this context, the decreased employment in thermal power plants may lead to increased unemployment. Accordingly, a decrease in variable Ceg is expected to have an increasing impact on variable Unp. The increase in Reg may also decrease unemployment via direct, indirect, and induced impacts or increase unemployment with possible technological effects.

a. Methodology

We employed the long-run estimators and panel non-causality tests to investigate the possible theoretical relationships among the Ceg, Reg, and Unp. We also took the presence of cross-section dependence and slope homogeneity into account in unit root and cointegration tests.

4.2.1. Cross-sectional dependence and slope homogeneity tests

First, cross-sectional dependence of the series and model are tested to accurately determine relationships between the variables and coefficients of countries. Cross-sectional dependence is particularly important in two aspects. The first involves determining the economic relationships between countries and arranging the model based on this interaction. The second involves determining the power and correct tests for unit root and cointegration analyses. Cross-sectional dependence (CD) analysis is used to investigate whether shocks occurring in the series of each panel units affect others or not. We used CD tests developed by Breusch and Pagan (1980), Frees (1995), Pesaran (2004) and Pesaran (2015). Findings are presented in Tables 2 and 3.

Another pioneer test in panel data analysis is the slope homogeneity test. We apply slope heterogeneity test suggested by Pesaran and Yamagata (2008). This test, considering cross-section dependency in panel data, suggests two different methods based on sample size. While

$\tilde{\Delta}$ test is valid for big samples, $\tilde{\Delta}_{adj}$ test is recommended for small samples. The findings can be seen in Table 2.

For the robustness of slope homogeneity, we applied two novel approaches. The first is modified Wald (Mwald) test developed by Okui and Yanagi (2019). This method is a heterogeneous modern dynamics technique (Sarkodie and Owusu, 2020) and includes two aspects, cumulative distribution function (CDF) and kernel density. The second is the HAC version of the slope homogeneity test developed by Blomquist and Westerlund (2013). These tests deepen our empirical findings. The findings can be seen in Table 4 and Figures 3 and 4.

4.2.2. Panel unit root tests

After determining the existence of both cross-sectional dependence and slope heterogeneity (CDHT), we used second-generation panel unit root tests for stationary analysis. We employed two second-generation unit root tests developed by Pesaran (2007). These are cross-sectional augmented IPS (CIPS) and Pesaran cross-section augmented Dickey Fuller (PESCADF) panel unit root tests. CIPS is efficient in terms of heterogeneity. The PESCADF test provides efficient results in the cross-section dependency (Ali et al., 2020). The critical values for the CIPS and PESCADF tests are given in Pesaran (2007). The findings can be seen in Table 5.

4.2.3. Panel cointegration tests

Before estimating the long-run coefficients of non-stationary series, it is necessary to determine whether there is a long-run relationship between the series. For this purpose, we employed two tests. The first includes four different test statistics calculated for the panel cointegration test developed by Westerlund (2007), which takes CDHT into account. Two for group means statistics (G_α and G_τ) and two for panel statistics (P_α and P_τ). G_α and G_τ check cointegration relationship for the whole group, whereas the P_α and P_τ check each unit of cross section (Westerlund, 2007). Westerlund (2007) uses the bootstrap technique to cope with cross-sectional dependence (Aydın and Bozatlı, 2022).

The second is the feasible generalized least squares (FGLS) method. The FGLS method is used to estimate panels with heteroskedasticity and contemporaneously correlated error matrix (Mumini and Mwimba, 2022), and it can also be used as a robustness check for the cointegration test (Addai et. al., 2022). In addition, we used FGLS regression to get rid of the heteroskedasticity and autocorrelation problems in the panel sample as mentioned by Awan et al. (2020). Tables 6 and 7 show these findings, respectively.

4.2.4. Long run coefficient estimators and bias corrected

We employed two different long-run coefficient estimators. The first is the Augmented Mean Group (AMG) estimator developed by Eberhardt and Bond (2009) and Eberhardt (2012). This method can procure the long-run coefficients both for each country constituting the panel and for the panel as a whole. The second is the Common Correlated Effects Mean Group (CCE-MG) developed by Pesaran (2006). Both estimators emphasize variable non-stationarity, cross-section dependence as well as parameter heterogeneity. Table 8 shows the findings of AMG and CCE-MG estimators.

For the bias-corrected model in Equation 2, we used two tests, LM (k) and Q (p), developed by Born and Breitung (2016). LM (k) tests are for autocorrelation of order *k*, whereas Q (p) looks for autocorrelation up to order *p*. The results of these tests alone may not tell which estimates are more reliable, but they are still among the factors that can guide this decision and a model with explicit statistical results of this test is more reliable than a model determined as ceteris paribus “correct”. These tests act on the fixed effected assumption and are based on the residual of its regression (Wursten, 2018: 82).

4.2.5. Panel Granger non-causality test

Finally, we used the panel Granger non-causality test developed by Dumitrescu and Hurlin (2012). They developed non-causality techniques for heterogeneous panels. This technique, which is based on specific Wald statistics of Granger non-causality testing, can procure all panels or a single unit for findings. The test is applicable to stationary series (Dumitrescu and Hurlin, 2012). This method allows different lag numbers to be selected manually and is compatible with cross-sectional dependence thanks to the bootstrap approach. Table 9 shows the causality findings from the Reg/Ceg to Unp.

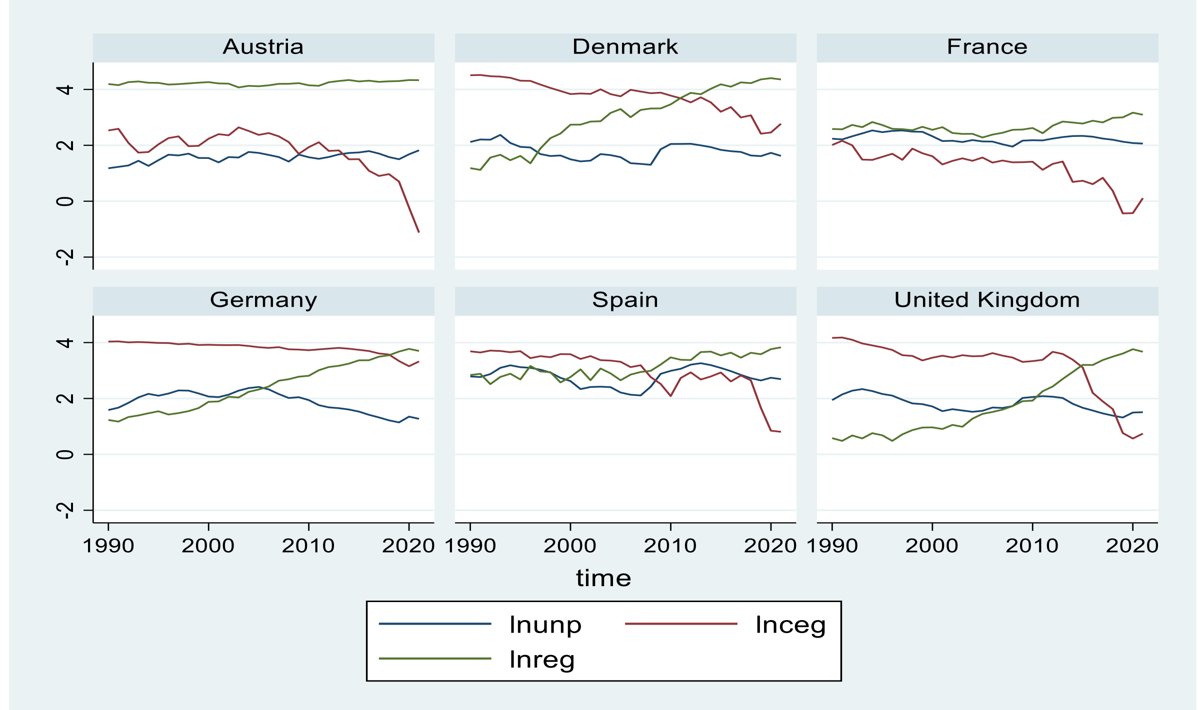
5. Empirical Findings

Let us start with descriptive statistics. Table 1 presents summary statistics of variables. Results show that Reg and Ceg means are higher than Unp, respectively.

Table 1. Descriptive statistics

	Unp	Reg	Ceg
Mean	8.50	27.70	27.12
Median	2.05	2.68	3.53
Maximum	26.09	81.61	91.52
Minimum	3.14	1.62	0.32
Std. Dev.	4.84	23.78	21.67
Skewness	0.57	0.87	0.64
Kurtosis	5.61	2.38	2.79
Observations	192	192	192

The standard divisions of Unp are the lowest. The skewness shows that each variable skewed positively. Moreover, the kurtosis value revealed that Unp is a leptokurtic distribution and Reg and Ceg are a platykurtic distribution. Accordingly, Unp is farther from the normal distribution than Ceg and Reg.



Graph 1. Graphs by countries

Graph 1 represents the variables of each cross-section. While Austria has high renewable energy production, Germany and UK have higher coal-based production. Austria and the UK seem competent to drop lnCeg. On the other hand, the graph shows that other countries except Germany have turned their production processes in favor of lnReg from lnCeg. Although an increasing trend of lnReg and a decreasing trend of lnCeg can be seen in all countries, this transition is relatively low in Germany. Additionally, Spain and France have higher unemployment rates than the rest of the samples.

Table 2. Results of cross-sectional dependence and homogeneity tests for model

Cross-sectional dependence tests:	Statistic	d.f	p-value
Breusch-Pagan chi-square	130. 763[a]	15	0.0000
Pearson LM normal	20.039[a]		0.0000
Pearson CD normal	-2.218[c]		0.8267
Friedman chi-square	58.064[a]	31	0.0023
Frees normal	0.996[a]		0.0000
Pesaran (2015) CD	3.343[a]		0.0008
Slope Homogeneity tests:			
Δ	6.634[a]		0.000
adj Δ	7.092[a]		0.000
Δ^{HAC}	7.450[a]		0.000
adj Δ^{HAC}	7.965[a]		0.000

Notes: Based on the results, the null hypothesis of cross-sectional independence in the panel data is rejected at [a]1%, and [c] 10% levels of significance.
Source: Authors' estimation

Table 2 shows the results of cross-section dependence and slope homogeneity tests. The findings indicate that there is cross-section dependence and heterogeneity of the slopes in the models.

Table 3. Results of cross-sectional dependence tests for series (Pesaran (2004).

Variable	CD-test	p-value	mean	mean abs
lnUnp	4.00[a]	0.000	0.182	0.390
lnReg	15.36[a]	0.000	0.701	0.701
lnCeg	19.43[a]	0.000	0.887	0.887

Note: [a] indicates statistical significance at 1%.
Source: Authors' estimation.

Table 3 shows cross-section dependence for all variables. Table 4 presents moment estimations for the robustness check parameter heterogeny. These results confirm that the slope coefficient parameters of the countries are heterogeneous.

Table 4. Moment estimations for model.

Parameters	Estimate	S. E	Low[δ]	High[δ]
Mean of Mean	2.55	0.078	2.401	2.716
Mean of Autocovariance	0.952	0.135	0.653	1.228
Mean of Autocorrelation	-0.417	0.021	-0.459	-0.380
Variance of Mean	0.119	0.034	0.050	0.181
Variance of Autocovariance	0.266	0.085	0.102	0.442
Variance of Autocorrelation	0.005	0.003	-0.000	0.011
Correlation between Mean and Autocovariance	-0.166	0.259	-0.705	0.357
Correlation between Mean and Autocorrelation	0.246	0.365	-0.367	0.980
Correlation between Autocovariance and Autocorrelation	-0.333	0.235	-0.735	0.214

Notes: [δ] indicates %95 confidence intervals for moments based on each unit of sample. S. E typifies standard errors of estimates depending on bootstrapped unit of the sample.
Source: Authors' estimation

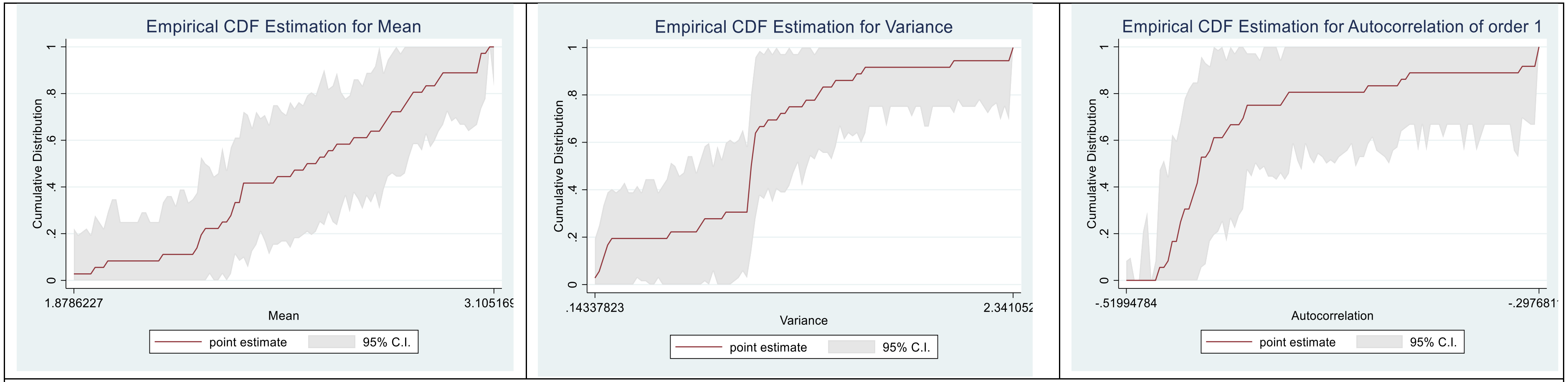


Figure 3. CDF estimations

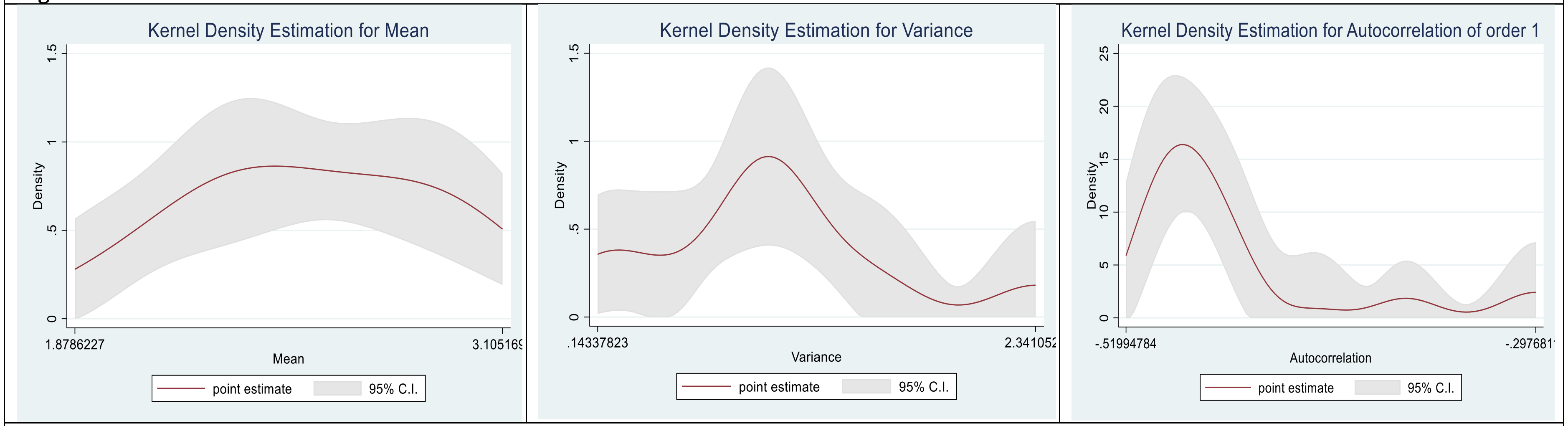


Figure 4. Kernel Density estimations

According to the results in Figure 3 and 4, it is in the range of 95% strength. Accordingly, both results show that cross countries are heterogeneous. These pioneer test findings guide us in deciding on the fit methods for the rest of the analysis.

After observing the presence of slope heterogeneity and the cross-dependency of the variables and model, we employed the second-generation unit root test, CIPS and PESCADF and the Westerlund (2007) panel cointegration test that take into account our two pioneer tests' findings.

Table 5. Panel unit root tests results

Variable	CIPS		PESCADF	
	Level	First Difference	Level	First Difference
InUnp	-1.489	-3.76[a]	-1.547	-1.835
InReg	-2.037	-6.190[a]	-1.367	-2.914[a]
lnCeg	-2.509	-4.451[a]	-2.095	-3.420[a]

Notes: [a] indicates statistical significance at 1%. CIPS' H_0 (homogeneous non-stationary). PESCADF the null hypothesis presumes all series are non-stationary in a heterogeneous panel with cross-sectional dependence.
Source: Authors' estimation.

Table 5 shows the panel unit root findings. These findings show that while all variables have unit roots at the level, they are stationary at first differences. That is to say, variables are same order integration I (*1*). These findings indicate that the mean and variance of the variables used changed over time.

Table 6. Panel cointegration tests results

Test	Test sta.	p-value
G_τ	-2.027[c]	0.070
G_α	-6.377[b]	0.040
P_τ	-4.245[c]	0.090
P_α	-5.368[c]	0.080

Notes: [b] the rejection of the null hypothesis at 5% significance level. [c] the rejection of the null hypothesis at 10% significance level. The bootstrap used is 1000 for Westerlund (2007).
Source: Authors' estimation.

The findings show that there is a cointegration for each test. In other words, unemployment moves together with explanatory variables in the long run. Table 6 shows panel cointegration test results. We used different cointegration approaches for robustness. FGLS findings are reported in Table 7.

Table 7. Cross-sectional time-series FGLS regression- Dependent variable: lnUnp

Series	Coef.	Std. error	t-sta.	p-value
c	2.893[a]	0.019	-6.45	0.000
lnReg	-0.216[a]	0.026	-8.12	0.000
lnCeg	-0.125[a]	0.019	-6.45	0.000

Note: [a] indicates 1% levels of significance.
Source: Authors' estimation

This test deals with heterogeneous panels and verifies errors. The findings of the FGLS indicate that the null hypothesis of no cointegration is rejected at 1% levels, respectively.

For the estimate of the long-run coefficients of the model, we employed two different long-run estimators for more robustness. Table 8 shows the long-run estimate of AMG and CCE-MG methods.

Table 8. Results of AMG and CCE-MG estimations

Countries	AMG		CCE-MG		Valid Hypothesis
	lnReg	lnCeg	lnReg	lnCeg	
Austria	-0.559	-0.116[b]	-0.764	-0.020	None/None
Denmark	-0.087	-0.285[c]	-0.437[a]	0.008	None/GEH
France	0.231[c]	0.024	0.287[b]	-0.131	GUH
Germany	-0.153	0.727	1.141[b]	-0.269	None/GUH
Spain	0.555[a]	0.014	0.478[a]	0.238[a]	GUH
UK	-0.007	0.033	0.317[b]	0.485[a]	None/GUH
Panel	-0.003	-0.32	0.170	0.052	None

Note: [a], [b], and [c] indicate statistical significance at 1%, 5%, and 10 % respectively.
Source: Authors' estimation.

Equation 2 in levels might be mis-specified, and unemployment might have strong trends. If these are correlated to lnCeg and lnReg, this might imply bias in their coefficient estimates. We can control serial correlation in the residuals

Table 9. Results of bias-corrected tests

Variable	Q (p)-test				LM (k)-test			
	Q (p)-stat	p-value	N	Max T	LM (k)-stat	p-value	N	Max T
Post Estimation	17.38	0.000	6	32	4.17	0.000	6	32

Notes: N is the number of cross-sections, and Max T is the time of each cross-section. 1 lag model was reported. We checked robustness of our estimates with two lags and since our findings did not change, we did not report them.
Source: Authors' estimation

Table 9 shows the LM and Q test results. The test findings strongly reject the null hypothesis, indicating the residuals are serially correlated.

The long-run coefficient estimation results in Table 8 can be divided into two groups on a country basis. The first is the countries where the GEH hypothesis is acceptable and the second is the countries where the GUH hypothesis is effective. Let's start the findings with CCE-MG. CCE-MG findings show that the GEH hypothesis is acceptable for only Denmark, but we cannot check robustness of these findings with AMG. We have some proof for the GUH hypothesis in the rest of the countries. CCE-MG findings indicate that the GUH hypothesis is valid in France, Germany, Spain, and the UK. In addition, the estimation coefficient of both explanatory variables for Spain and the UK is positive.

AMG findings provide evidence supporting the GUH hypothesis for France and Spain. Apart from that, the coefficient of lnCeg is negative in Austria and Denmark. That's to say, coal-based electricity generation is decreasing unemployment in each country. We have shown this as "none" in the last column of Table 8 because we have not discussed it theoretically. It can be said that these findings may give clues about the labor-intensive functioning of lnCeg, but we do not have strong evidence for this.

AMG findings for France and Spain show that REG has an increasing effect on unemployment, meaning that a 1% increase in REG leads to an increase of 0.23% and 0.55% in UNP. The CCE-MG coefficient estimator confirms that these findings vary with slight differences. Apart from these, there is no common finding of both estimators. Finally, we have no statistical evidence from the pool panel for both hypotheses. We showed it as "none" in Table 8.

Finally, we checked non-causality for variables. Table 9 shows panel non-causality test findings.

Table 10. Panel Granger non-causality results

Causality	K	$\overline{W}$	$\bar{Z}$	p-value	$\tilde{Z}$	p-value
lnReg => lnUnp	1	3.1842	3.7831[a]	0.0002	3.1953[a]	0.0014
	2	2.1416	0.1734	0.8624	-0.0334	0.9733
lnCeg => lnUnp	1	1.6234	1.0798	0.2802	0.8287	0.4073
	2	3.2184	1.4922	0.1356	1.0787	0.2807

Notes: [a] indicates statistical significance at 1%. K indicates the lag length. => symbols the direction of causality. The maximum lag length is determined as 2 with AIC, HQ, and SC information criteria.
Source: Authors' estimation.

The results indicate that there is a unidirectional causality running from renewable energy generation to unemployment. These findings confirm each other (Z-bar and Z-bar tilde). It may be a clue that our findings indicate the GUH hypothesis for the sample.

6. Discussion

Our key findings are as follows: Green Unemployment hypothesis applies to countries other than Denmark, and the Green Employment hypothesis applies to Denmark. I-O studies in the CTR literature have findings on the positive effects of renewable energy on employment. Of these, only Hillebrand et al. (2006)'s findings are consistent with our findings for Germany. As mentioned above, all I-O analysts, except Hillebrand et al. (2006), have evidence of the job creation capacity of renewable energy for developed countries. Most of the analytical papers also provided evidence of the job creation potential of renewable energy for developed countries.

However, the results of econometric methods differ from those above and provide evidence that different options are possible in this discussion. For example, the study of Apergis and Salim (2015) is one of them and their findings indicating that CTR positively affects unemployment in EU countries are consistent with our results. On the other hand, Çelik (2021) found no significant causality between the variables, contrary to our causality findings. Osei et al. (2022) findings are inconsistent with our findings. Yılancı et al. (2020) confirm our results for Austria and Spain but have opposite results for France and Germany. Our findings are consistent with the results of Rafiq et al. (2018) However, we are not confirmed by the results of Naqvi et al. (2022) and Swain et al. (2022) for the EU.

It is worth noting that most of these studies have not focused directly on CTR and their models are different from ours. We focused on the net effects of CTR. In addition, among these studies, ours is the only paper investigating panel data with cross-section analysis. We can say that these differences affect our findings.

7. Conclusion

Scarcity of fossil fuel reserves and current ecological problems caused by fossil fuel consumption increase the usage of renewable energy on a global scale. Besides, the increased renewable energy generation brings along significant debates due to its impacts on macroeconomic indicators. In the framework of panel data models, this study aims at testing the impact of the transition from coal-based to renewable energy-based electricity production on unemployment in six European countries (Austria, Denmark, France, Germany, Spain, and United Kingdom) which have decreased their coal-based electricity production.

For the panel framework, we focused on the net employment impact, which is the transition of traditional energy sources to the renewable energy generation for the period of 1990-2021. We examined the green employment hypothesis, green unemployment hypothesis and neutrality or green jobs substation hypothesis.

We can explain the main findings in five headings. Firstly, the findings of our pioneer tests, which are cross-section dependency and slope homogeneity tests, have strong evidence for cross-sectional dependence and slope heterogeneity for the model and variables. Besides, we checked robustness of all pioneer test findings with novel approaches and they supported the results. Secondly, we employed second-generation unit root tests considering pioneer test results for stationary. Since all of our series are stationary at the first difference I (1), we have to investigate cointegration before estimating long-run relationships. Therefore, we investigated whether the series cointegrated or not in the long run. Our cointegration test results show that series act together in the long run. We also have robustness for cointegration test results with a novel approach, and they support each other. This process was our third main finding. The other one is the coefficient estimation for each unit of the sample. But before coefficient estimation, we needed to check for the bias-correction of our model. For this, we preferred a new method, and our findings strongly rejected the null hypothesis, showing that the bias in the model was invalid. In other words, empirical results show that our model is a fit.

Long-run coefficient estimation findings show that while the Green Employment Hypothesis is effective in Denmark, the Green Unemployment Hypothesis is effective in France, Germany, Spain, and the United Kingdom. The strongest of these findings is for the effectiveness of the Green Unemployment Hypothesis for France and Spain. Others are relatively weak compared to this evidence. We base this argument on the fact that the proof for the Green Unemployment Hypothesis as opposed to the Green Employment Hypothesis is confirmed by both tests for France and Spain. Apart from these, we do not have statistically significant findings for Austria in any hypotheses. Finally, our causality test shows that there is causality from renewable energy generation to unemployment.

Green jobs are in many different parts of Denmark, thereby supporting geographically inclusive growth (Denmark's Integrated National Energy and Climate Plan, 2019). Denmark was among the first European countries to support wind energy in the 1980s. Denmark is a good example of how a small country can become a world player in new energy technology by mastering the commercialization process (Lund, 2009: 61). In 2018, Denmark-based wind turbine manufacturer Vestas had a global market share of around 20.3 percent and ranked first in the world. Denmark is also the leading country in the field of electricity generation from wind energy (OWD, 2022e). Approximately 48 percent of the electricity produced in Denmark in 2021 was produced by wind energy. Employment in the Wind Energy sector involves many skills similar to those of oil and gas workers. Besides, the Danish social welfare state's power reduces the risks of workers in energy transition. Social and employment support can help reduce injustices and lessen inequalities in the transition (Krawchenko, 2022).

Global systems continue to produce energy from fossil sources. The International Energy Agency (IEA) (2022) report shows that fossil energy investments excluding coal are around 40% of the total investments and renewable energy investments are around 20% of the total. This report indicates that volatility for both investment types between 2015-2022 indicates a 13% decrease in fossil fuels, while the increase in renewable energy investments is around 70%. There's also the risk of a crowding out effect. Under current conditions, we do not have strong evidence that renewable energy production reduces unemployment. It seems that we have not yet reached the desired or promising point regarding unemployment and climate change.

So, despite all this, is unemployment, which appears to be a possible opportunity cost clash with the climate crisis, acceptable? It's hard to answer because we have no evidence for this argument. The global system has been exploiting and destroying nature up to now. The current generation seems to be paying the price for this. The effects of renewable energy generation on net unemployment have not sufficiently been investigated in the literature. We also suggest that empirical studies on this issue should turn to nonparametric methods and quantile approaches because the variables seem asymmetrical, and effects can differ in the short, middle, and long run.

References

Addai, K., Serener, B., and Kirikkaleli, D. (2022). "Environmental Sustainability and Regulatory Quality in Emerging Economies: Empirical Evidence from Eastern European Region". *Journal of the Knowledge Economy*, 1-37. https://doi.org/10.1007/s13132-022-01000-2

Akadiri, S. S. and Adebayo, T. S. (2021). "Asymmetric nexus among financial globalization, non-renewable energy, renewable energy use, economic growth, and carbon emissions: impact on environmental sustainability targets in India," *Environmental Science and Pollution Research*, 29, 16311–16323, https://doi.org/10.1007/s11356-021-16849-0.

Ali, S., Doğan, E., Chen, F. and Khan, Z. (2020), "International trade and environmental performance in top ten-emitters countries: The role of eco-innovation and renewable energy consumption," *Sustainable Development*, 29(2):378-387. DOI: 10.1002/sd.2153.

Apergis, N. and Payne, J. E. (2010a). "Renewable energy consumption and economic growth: Evidence from a panel of OECD countries," *Energy Policy*, *38*(1), 656–660. https://doi.org/10.1016/j.enpol.2009.09.002

Apergis, N. and Payne, J. E. (2010b). "Renewable energy consumption and growth in Eurasia," *Energy Economics*, *32*(6), 1392–1397. https://doi.org/https://doi.org/10.1080/00036846.2015.1054071

Apergis, N. and Salim, R. (2015). "Renewable energy consumption and unemployment: evidence from a sample of 80 countries and nonlinear estimates," *Applied Economics*, *47*(52), 5614–5633.

Aslan, A., Ocal, O., Ozsolak, B., and Ozturk, I. (2022). "Renewable energy and economic growth relationship under the oil reserve ownership: Evidence from panel VAR approach," *Renewable Energy*, 188, 402-410, https://doi.org/10.1016/j.renene.2022.02.039

Aydin, M. and Bozatli, O. (2022). "Do transport taxes reduce air pollution in the top 10 countries with the highest transport tax revenues? A country-specific panel data analysis," *Environmental Science and Pollution Research*, https://doi.org/10.1007/s11356-022-19651-8.

Awan, A. M., Azamn, M., Saeed, U. I., and Bakhtyar, B. (2020). "Does globalization and financial sector development affect environmental quality? A panel data investigation for the Middle East and North African countries", *Environmental Science and Pollution Research*, 7:45405-45418, https://doi.org/10.1007/s11356-020-10445-4.

Barros, J. J. C., Coira, M. L., de la Cruz López, M. P., and del Caño Gochi, A. (2017). "Comparative analysis of direct employment generated by renewable and non-renewable power plants," *Energy*, *139*, 542–554. https://doi.org/https://doi.org/10.1016/j.energy.2017.08.02

Blanco, M. I. and Rodrigues, G. (2009). "Direct employment in the wind energy sector: An EU study," *Energy Policy*, 37(8), 2847-2857. https://doi.org/DOI: 10.1016/j.enpol.2009.02.049

Blomquist, J. and Westerlund J. (2013). "Testing slope homogeneity in large panels with serial correlation", *Economics Letters*, 121(3), 374-378.

Blyth, W., Gross, R., Speirs, J., Sorrell, S., Nicholls, J., Dorgan, A., and Hughes, N. (2014). "Low Carbon Jobs: The evidence for net job creation from policy support for energy efficiency and renewable energy," *London: UK Energy Research Centre*.

BLS. Bureau of Labour Statistics (2017). *Measuring Green Jobs*. https://www.bls.gov/green/

Born, B. and Breitung J. (2016). "Testing for Serial Correlation in Fixed-Effects Panel Data Models," *Econometric Reviews*, 35,1290-1316.

Borzuei, D., Moosavian, S. F. and Ahmadi, A. (2022). "Investigating the dependence of energy prices and economic growth rates with emphasis on the development of renewable energy for sustainable development in Iran," *Sustainable Development*, 30, 848-854, DOI: 10.1002/sd.2284.

Bowen, A. (2012). *Green'growth,'green'jobs and labour markets, Centre for Climate Change Economics and Policy*. Working Paper.

Breusch, T. S. and Pagan, A. R. (1980). "The Lagrange multiplier test and its applications to model specification in econometrics," *The Review of Economic Studies*, 47(1), 239–253.

Buonocore, J. J., Hughes, E. J., Michanowicz, D. R., Heo, J., Allen, J. G., and Williams, A. (2019). "Climate and health benefits of increasing renewable energy deployment in the United States", *Environmental Research Letters*, 14 (11), 114010, https://doi.org/10.1088/1748-9326/ab49bc

Burke, M. J. and Stephens, J. C. (2018). "Political power and renewable energy futures: A critical review," *Energy Research and Social Science*, *35*, 78-93.

Chang, T., Fang, W. and Wen, L.-F. (2001). "Energy consumption, employment, output, and temporal causality: evidence from Taiwan based on cointegration and error-correction modelling techniques," *Applied Economics*, *33*(8), 1045–1056.

Chen, H., Tackie, E. A., Ahakwa, I., Musah, M., Salakpi, A., Alfred, M., and Atingabili, S. (2022). "Does energy consumption, economic growth, urbanization, and population growth influence carbon emissions in the BRICS? Evidence from panel models robust to cross-sectional dependence and slope heterogeneity," *Environmental Science and Pollution Research*, 29 (25), 37598-37616, https://doi.org/10.1007/s11356-021-17671-4

Çelik, O. (2021). "Assessment of the relationship between renewable energy and employment of the United States of America: Empirical evidence from spectral Granger causality," *Environmental Science and Pollution Research*, 28(11), 13047-13054.

Çıtak, F., Şişman, Y. M. and Bağcı, B. (2022). "Nexus between disaggregated electricity consumption and CO2 emissions in Turkey: new evidence from quantile-on-quantile approach, *Environmental and Ecological Statistics*, 28, 843–860, https://doi.org/10.1007/s10651-021-00504-5

Denmark's Integrated National Energy and Climate Plan (2019). https://energy.ec.europa.eu/system/files/2020-01/dk_final_necp_main_en_0.pdf

Dumitrescu, E. I. and Hurlin, C. (2012). "Testing for Granger non-causality in heterogeneous panels," *Economic Modelling*", 29(4), 1450-1460.

Eberhardt, M. (2012). "Estimating panel time-series models with heterogeneous slopes," *Stata Journal*, *12*(1), 61.

Eberhardt, M. and Bond, S. (2009). *Cross-section dependence in nonstationary panel models: a novel estimator*

Fragkos, P. and Leonidas P. (2018), "Employment creation in EU related to renewables expansion," *Applied Energy*, 230, 935-945.

Frees, E. W. (1995). "Assessing cross-sectional correlation in panel data," *Journal of Econometrics*, 69, 393-414.

Fremstad, A. and Paul, M. (2022). "Neoliberalism and climate change: How the free-market myth has prevented climate action", *Ecological Economics,* 197, 107353. https://doi.org/10.1016/j.ecolecon.2022.107353

Frumkin, H. (2022). "Hope, Health, and the Climate Crisis," *The Journal of Climate Change and Health*, *5,* 100115. https://doi.org/10.1016/j.joclim.2022.100115

George, E. O., and Oseni, J. E. (2012). "The relationship between electricity power and unemployment rates in Nigeria," *Australian Journal of Business and Management Research*, 2(2),10.

Hienuki, S., Kudoh, Y., and Hondo, H. (2015). "Life cycle employment effect of geothermal power generation using an extended input–output model: the case of Japan," *Journal of Cleaner Production*, *93*, 203–212.

Hillebrand, B., Buttermann, H. G., Behringer, J. M., and Bleuel, M. (2006). "The expansion of renewable energies and employment effects in Germany," *Energy Policy*, 34(18), 3484–3494.

Hondo, H. and Moriizumi, Y. (2017). "Employment creation potential of renewable power generation technologies: A life cycle approach," *Renewable and Sustainable Energy Reviews*, *79*, 128–136.

Hussain, I., Rehman, A. and Işık, C. (2022). "Using an asymmetrical technique to assess the impacts of CO2 emissions on agricultural fruits in Pakistan," *Environmental Science and Pollution Research*, 29, 19378-19389. https://doi.org/10.1007/s11356-021-16835-6.

Ibrahiem, D. M., and Sameh, R. (2020). "How do clean energy sources and financial development affect unemployment? Empirical evidence from Egypt," *Environmental Science and Pollution Research* 27(18), 22770-22779.

IEA. International Energy Agency (2022). World Energy Investment 2022.

ILO. International Labour Organization (2017). *The Green Jobs Programme of the ILO*.

IRENA. International Renewable Energy Agency (2011). Renewable Energy Jobs: Status, Prospects and Policies. In *Biofuels and grid-connectedelectricity generation*.

IRENA. International Renewable Energy Agency (2016). Renewables 2016 Global Status Report.

IRENA. International Renewable Energy Agency (2016). International Renewable Energy Agency. Renewable Energy Benefits: Measuring TheEconomics.

IRENA. International Renewable Energy Agency (2017). Renewables 2016 Global Status Report. *Renewable Energy and Jobs Annual Review*.

IRENA. International Renewable Energy Agency (2019). Global Energy Transformation a Road Map to 2050.

IRENA. International Renewable Energy Agency (2019). *Renewable Energy and Jobs Annual Review*.

IRENA. International Renewable Energy Agency (2020). *Renewable Energy and Jobs Annual Review*.

IRENA. International Renewable Energy Agency (2021). *Renewable Energy and Jobs Annual Review*.

IRENA. International Renewable Energy Agency (2022). *Renewable Energy and Jobs Annual Review*.

IRENA. International Renewable Energy Agency (2022b). Global Renewables Outlook, Energy Transformation 2050.

Khan, S. A. R., Zhang, Y., Kumar, A., Zavadskas, E., and Streimikiene, D. (2020). "Measuring the impact of renewable energy, public health expenditure, logistics, and environmental performance on sustainable economic growth", *Sustainable development*, 28 (4), 833-843, DOI: 10.1002/sd.2034

Krawchenko, T. (2022). "Managing a just transition in Denmark." https://climateinstitute.ca/publications/managing-a-just-transition-in-denmark/

Krupnik, S., Wagner, A., Koretskaya, O., Rudek, T. J., Wade, R., Mišík, M., ... and von Wirth, T. (2022). "Beyond technology: A research agenda for social sciences and humanities research on renewable energy in Europe," *Energy Research & Social Science*, 89, 102536. https://doi.org/10.1016/j.erss.2022.102536

Lambert, R. J., and Silva, P. P. (2012). "The challenges of determining the employment effects of renewable energy," *Renewable and Sustainable Energy Reviews*, *16*(7), 4667–4674.

Lavidas, G. (2019). "Energy and socio-economic benefits from the development of wave energy in Greece," *Renewable Energy*, *132*, 1290-1300. https://doi.org/https://doi.org/10.1016/j.renene.2018.09.007

Lehr, U., Mönnig, A., Missaoui, R., Marrouki, S., and Salem, G. Ben. (2016). "Employment from renewable energy and energy efficiency in Tunisia–new insights, new results," *Energy Procedia*, *93*, 223–228.

Lehr, U., Nitsch, J., Kratzat, M., Lutz, C., and Edler, D. (2008). "Renewable energy and employment in Germany," *Energy Policy*, *36*(1), 108–117.

Lund, Peter D. (2009). "Effects of energy policies on industry expansion in renewable energy," *Renewable Energy*, 34(1), 53-64.

Li, J. and Li, S. (2020). "Energy investment, economic growth and carbon emissions in China-Empirical analysis based on spatial Durbin model", *Energy Policy*, 140, 111425, https://doi.org/10.1016/j.enpol.2020.111425

Menegaki, A. N. (2011). "Growth and renewable energy in Europe: a random effect model with evidence for neutrality hypothesis," *Energy Economics*, *33*(2), 257–263.

Mostafaeipour, A., Bidokhti, A., Fakhrzad, M-B, Sadegheih, A., Mehrjerdi, Y. Z. (2022). "A new model for the use of renewable electricity to reduce carbon dioxide emissions," *Energy*, 238, 121602, https://doi.org/10.1016/j.energy.2021.121602

Moreno, B., and Lopez, A. J. (2008). "The effect of renewable energy on employment. The case of Asturias (Spain)," *Renewable and Sustainable Energy Reviews*, *12*(3), 732–751.

Moyo, C., Dingela, S., Kolisi, N., Khobai, H., and Anyikwa, I. (2017). *Renewable energy consumption and unemployment in South Africa*.

Mumini, S. and Mwimba, T., (2022), "Modeling Green Energy Consumption and Natural Resources

Rents Impacts on Economic Growth in Africa: An Analysis from the Dynamic Panel ARDL Models and the Feasible Generalized Least Squares Estimator," *Preprints,* 2022090249, doi: 10.20944/preprints202209.0249.v1.

Nagatomo, Y., Ozawa, A., Kudoh, Y., and Hondo, H. (2021). "Impacts of employment in power generation on renewable-based energy systems in Japan-Analysis using an energy system model," *Energy,* 226, 120350.

Nasirov, S., Girard, A., Peña, C., Salazar, F., and Simon, F. (2021). "Expansion of renewable energy in Chile: Analysis of the effects on employment," *Energy,* 226, 120410.

Nakıpoğlu Özsoy, F. and Özpolat, A. (2020). "Relationship Between Renewable Energy and Employment: A Boostrap Granger Causality Analysis," *Uluslararası Ekonomi İşletme ve Politika Dergisi*, 4(2), 263-280.

Narayan, P. K. and Smyth, R. (2005). "Electricity consumption, employment and real income in Australia evidence from multivariate Granger causality tests," *Energy Policy, 33*(9), 1109–1116.

Naqvi, S., Wang, J. and Ali, R. (2022). "Towards a green economy in Europe: does renewable energy production has asymmetric effects on unemployment?," *Environmental Science and Pollution Research*, 29(13), 18832-18839.

Okui, R. and Yanagi, T., (2019). "Panel data analysis with heterogeneous dynamics," *Journal of Econometrics*, 212, 451-475.

Ortega, M., del Río, P., Ruiz, P., and Thiel, C. (2015). "Employment effects of renewable electricity deployment. A novel methodology," *Energy, 91*, 940–951.

Osicka, J. and Cernoch, F. (2022). "European energy politics after Ukraine: The road ahead", *Energy Research & Social Science,* 91, 102757, https://doi.org/10.1016/j.erss.2022.102757

Osei, B., Kunawotor, M. E., and Kulu, E. (2022). "Renewable energy production and employment: comparative analysis on European and Asian countries," *International Journal of Energy Sector Management*, https://doi.org/10.1108/IJESM-04-2022-0015

OWD. Our World in Data (2022a). https://ourworldindata.org/energy-production-consumption

OWD. Our World in Data (2022b). https://ourworldindata.org/grapher/share-electricity-source facet?country=GBR~AUT~DNK~FRA~DEU~ESP

OWD. Our World in Data (2022c). https://ourworldindata.org/grapher/share-electricity-coal?tab=table

OWD. Our World in Data (2022d). https://ourworldindata.org/grapher/share-electricity-renewables

OWD. Our World in Data (2022e). https://ourworldindata.org/grapher/share-electricity-wind?tab=table

Özmen, İ., Özcan, G., Özcan, C. C. and Bekun V. F. (2022). "Does fiscal policy spur environmental issues? New evidence from selected developed countries," *International Journal of Environmental Science and Technology,* 19, 10831-10844, https://doi.org/10.1007/s13762-022-03907-4

Özmen, İ. and Dündar-Öztaşçı, D. (2022). Sürdürülebilir Kalkınma ve Yeşil Ekonomi: Marksist Yaklaşımlar Neler Söylüyor, içinde: Sürdürülebilir Kalkınma ve Büyüme Sürecinde Yeşil Ekonomi, Editör: Mahmut Sami Duran, Ekin Basım Yayın Dağıtım: Bursa, ss, 63-87.

Pao, H.-T. and Fu, H.-C. (2013). "Renewable energy, non-renewable energy and economic growth in Brazil," *Renewable and Sustainable Energy Reviews*, *25*, 381–392.

Pata, U. K. (2021). "Do renewable energy and health expenditures improve load capacity factor in the USA and Japan? A new approach to environmental issues," *The European Journal of Health Economics*, 22(9), 1427-1439, https://doi.org/10.1007/s10198-021-01321-0

Payne, J. E. (2009). "On the dynamics of energy consumption and employment in Illinois," *Journal of Regional Analysis and Policy*, 39(2), 126-130

Pesaran, M. H. (2004). *General diagnostic tests for cross section dependence in panels*.

Pesaran, M. H. (2006). "Estimation and inference in large heterogeneous panels with a multifactor error structure," *Econometrica*, *74*(4), 967–1012. https://doi.org/10.1111/j.1468-0262.2006.00692.x

Pesaran M. H. (2007). "A simple panel unit root test in the presence of cross-section dependence," *Journal of applied econometrics,* 22(2), 265–312. https:// doi. org/ 10. 1002/ jae

Pesaran, M. H., and Yamagata, T. (2008). "Testing slope homogeneity in large panels," *Journal of Econometrics*, *142*(1), 50–93.

Pesaran, M. H. (2015). "Testing weak cross-sectional dependence in large panels," *Econometric Reviews*, 34(6-10), 1089–1117.

Rafiq, S., Salim, R., and Sgro, P. M. (2018). "Energy, unemployment and trade," *Applied Economics* 50 (47), 5122-5134.

Raihan, A. and Tuspekova, A. (2022). "Nexus Between Emission Reduction Factors and Anthropogenic Carbon Emissions in India, *Anthropocene Science*, 1, 295-310, https://doi.org/10.1007/s44177-022-00028-y

Rivers, N. (2013). "Renewable energy and unemployment: A general equilibrium analysis", *Resource and Energy Economics*, *35*(4), 467–485.

Saboori, B., Gholipour, H. F. Rasoulinezhad, E., Ranjbar, O. (2022). "Renewable energy sources and unemployment rate: Evidence from the US states, *Energy Policy*, 168, 113155, https://doi.org/10.1016/j.enpol.2022.113155

Sarkodie, S. A. and Owusu, P. A. (2020). "How to apply dynamic panel bootstrap-corrected fixed-effects (xtbcfe) and heterogeneous dynamics (panelhetero)," MethodsX, *7*, 101045.

Sari, R. and Soytas, U. (2004). "Disaggregate energy consumption, employment and income in Turkey," *Energy Economics*, *26*(3), 335–344.

Swain, B. R., Karimu, A., and Gråd, E. (2022). "Sustainable development, renewable energy transformation and employment impact in the EU," *International Journal of Sustainable Development & World Ecology* (2022), 1-14.

Steffen, B. and Patt, A. (2022). "A historical turning point? Early evidence on how the Russia-Ukraine war changes public support for clean energy policies", *Energy Research & Social Science*, 91, 102758, https://doi.org/10.1016/j.erss.2022.102758

Tiwari, A. (2010). *On the dynamics of energy consumption and employment in public and private sector*.

Tourkolias, C. and Mirasgedis, S. (2011). "Quantification and monetization of employment benefits associated with renewable energy technologies in Greece," *Renewable and Sustainable Energy Reviews*, *15*(6), 2876–2886.

Van der Zwaan, B., Cameron, L., and Kober, T. (2013). "Potential for renewable energy jobs in the Middle East," *Energy Policy*, *60*, 296–304.

Vaughan, A. and Webber, S. (2020). "Transitioning to renewable energy in Sydney: Relational and co-evolving energy geographies," *Geographical Research*, 60, 314-327, DOI: 10.1111/1745-5871.12512

Yang, L., Zhou, X., and Feng, X. (2022). "Renewable energy led Economic Growth Hypothesis: Evidence from novel panel methods for N-11 economies," *Renewable Energy*, 197, 790-797, https://doi.org/10.1016/j.renene.2022.07.025.

Yilanci, V., İslamoğlu, E., Yıldırımalp, S., and Candan, G. (2020). "Relationship between Unemployment Rates and Renewable Energy Consumption: Evidence from Fourier ADL Cointegration Test," *Alphanumeric Journal*, 8(1), 17-28.

Zhao, X. and Luo, D. (2017). "Driving force of rising renewable energy in China: Environment, regulation and employment," *Renewable and Sustainable Energy Reviews*, *68*, 48–56. https://doi.org/10.1016/j.rser.2016.09.126

Wang, G., Sadiq, M., Bashir, T., Jain, V., Ali, S. A., and Shabbir, M. S. (2022). "The dynamic association between different strategies of renewable energy sources and sustainable economic growth under SDGs," *Energy Strategy Reviews*, 42, 100886, https://doi.org/10.1016/j.esr.2022.100886

Wang, Q., Dong, Z., Li, R., and Wang, L. (2022). "Renewable energy and economic growth: new insight from country risks," *Energy*, 238, 122018, https://doi.org/10.1016/j.energy.2021.122018

WDI. World Development Indicator (2022). https://databank.worldbank.org/reports.aspx?source=2&series=SL.UEM.TOTL.NE.ZS&country=#

Wei, M., Patadia, S., and Kammen, D. M. (2010). "Putting renewables and energy efficiency to work: How many jobs can the clean energy industry generate in the US?," *Energy Policy*, *38*(2), 919–931.

Westerlund, J. (2007). "Testing for error correction in panel data," *Oxford Bull Econ Stat*, 69(6), 709-748. https:// doi. org/ 10. 1111/j. 1468- 0084. 2007. 00477.x

Wursten, J. (2018). "Testing for serial correlation in fixed-effects panel models", *Stata Journal*, 18 (1): 77-100.