Journal of the Knowledge Economy (2024) 15:2383–2400
https://doi.org/10.1007/s13132-023-01337-2

Solar Energy and CO2 Emissions: CCEMG Estimations for 26 Countries

Taner Güney[1] · **Duygu İnce**[2]

Received: 18 March 2022 / Accepted: 25 February 2023 / Published online: 18 March 2023

Abstract

This study examines the long-term relationships between solar energy, globalization, coal energy consumption, economic growth, and CO2 emissions. We included data from 26 countries for which data are available for 2000-2019. To consider the cross-sectional dependence and slope homogeneity, which are prominent in the panel data analysis, we preferred the mean group of co-related effects (CCEMG) method. According to OLS, FMOLS, and CCEMG estimations, solar energy consumption negatively affects CO2 emissions. A 1 % increase in solar energy consumption causes a 0.0106671% reduction in CO2 emissions. There is bidirectional causality between solar energy consumption and CO2 emissions in the long run. Globalization does not have a significant effect on CO2 emissions. However, coal energy consumption and economic growth appear to cause an increase in CO2 emissions. Because of the diversity and consistency of the methods we used to measure the relationships between variables in our article, the dominant power of solar energy in reducing carbon emissions has been proven once again. Encouraging the use of solar energy by countries and supporting investments in this field has emerged as benefiting from solar energy based only on the geographical advantage they have, regardless of globalization. For this reason, it is essential for environmental sustainability that governments give tax advantages and energy investment incentives to companies that prefer solar energy in their production processes. As a result, reduced carbon emissions will also bring about a greener environment.

Keywords Solar energy · Globalization · CO_2 emissions · CCEMG · Panel causality

✉ Taner Güney
tanerguney@kmu.edu.tr

Duygu İnce
inceduygu@gmail.com

[1] Department of Economics, The Faculty of Economics and Administrative Sciences, Karamanoglu Mehmetbey University, P.O. Box 70100, Karaman, Turkey

[2] Department of Economics, Social Sciences Institute, Karamanoglu Mehmetbey University, P.O. Box 70100, Karaman, Turkey

Introduction

The use of renewable energy sources reduces carbon emissions that are harmful to nature is a phenomenon that everyone can predict. In our study, we have reduced renewable energy sources to solar energy, which seems infinite compared to human life. While going from general to specific, we used the data of the age of globalization and the data of coal, the most frequently consumed fossil fuel. We analyzed the variables used in our study together for the first time in the literature. In contrast to the studies limited to only one country's data, we preferred countries with data diversity. With these differences, our article can give new ideas for pioneering future studies. The current energy system is scattered around the world, and this energy system is based on the burning of non-renewable fossil fuels and is unsustainable. In addition, the world population, estimated to reach approximately 9.3 billion by 2050, is increasing rapidly. This increase is expected to increase global energy demand by 1.5 to 3 times (Shahsavari & Akbari, 2018). Moreover, this increase could lead to the depletion of fossil fuels after about 70 years. Carbon emissions from burning fossil fuels are causing global warming that threatens the future of the world (Gyamfi et al., 2021; Joshua et al., 2020). Emissions from burning fuels were 32.5 Gtoe in 2018 (IEA, 2020). The Paris Agreement aims to limit global warming to well below 2 °C, preferably 1.5 °C, compared to pre-industrial levels (UNFCCC, 2015). The Paris Agreement goals are achieved by using renewable energy sources at an international level. Globalization, which affects human life socially, politically, and economically, plays a significant role in the widespread use of fossil energies (Faisal et al., 2021). With globalization, industrialization has accelerated, and this situation has increased the energy demand of growing economies. As a result, world energy consumption has doubled in the last 40 years (Koçak et al., 2020; Khan et al., 2021; Wei et al., 2022). Industry consumed 57% of the total energy of 11.5 Gtoe in 2018 (IEA, 2020). Total energy consumption is expected to increase by about 40% of daily energy consumption by 2040 (Weldekidan et al., 2018). Coal, which is more usable and cost-effective than other energy types, is mainly used in developed and developing economies to meet high energy demands (Adebayo et al., 2021). Globally, coal, the second-largest energy source, accounts for almost 30% of energy consumption, and more than 40% is used for electricity generation (Adedoyin et al. 2020). As a result, the economy's demand for non-renewable energy sources is expected to increase global energy-related CO_2 emissions by 4.8% in 2021 (IEA, 2021).

Moreover, this situation encourages the international community to shift to renewable energy sources such as solar energy (Anvari et al., 2019). The Eco-Environmental Assessment predicts that the proposed renewable energy-based energy system can prevent 485 tons of CO_2 emissions annually (Cao et al., 2020). The sun is an abundant energy source and has an essential role in forming other types of energy. The solar energy falling on the earth's surface is more than the total global energy supply of 13.800 Mtoe (Koçak et al., 2020). Solar energy is a clean resource that provides efficient solutions to reduce carbon emissions and is also a potential substitute for fossil fuels (Anvari et al., 2019; Banacloche et al., 2020). According to the report United Nations Environment Program (UNEP) 2015, each of the 1.4 MWth (2000 m2) solar energy systems can save about 175 metric tons of CO_2 emissions depending on the location (UNEP, 2015). It has been found that preferring renewable energy sources instead of non-renewable energy reduces CO_2 emissions by about 3% per 10 TWh/year (Noorollahi et al., 2021; Dagar et al., 2022; Alvarado et al., 2022). Countries should prefer solar energy to reduce dependence on fossil fuels such as oil and increase environmental sustainability (Salam and Khan, 2018). In about 10 years, CO_2 emissions can be reduced by 57%. For this, a solar-powered system capable of insulating 1387 tons of greenhouse gases per year will be sufficient (Ishaq, 2021). According to the forecasts for the future, solar energy, which is the renewable energy source with the highest potential, may cause the CO_2 level to decrease significantly (Anvari et al., 2019). So, with the preference for solar energy, the CO_2 level in 2050 will be 75% less than in 1985 (Kabir et al., 2018). A carbon-neutral status can be completed over a long time (about 30 years) (Marrchi et al., 2018). In addition, carbon emissions will decrease by 30% and 60% by 2050 compared to 2015 levels (Zhou et al., 2018). Solar energy markets have shown extraordinary growth, accelerating since the early 2000s (Timilsina et al., 2012). With the development of science and technology, solar energy research and applications are gaining attention worldwide. It is predicted to play a more significant role in the energy mix in the coming years (Du et al., 2014). Solar energy installation reduces diesel consumption by 12% and yields $6844/kW (Robertson et al., 2020). It determined that the return on solar energy use is $177.41 (USD), which is 45.15% of the total operating revenue (Darwesh & Ghoname, 2021). The installation of solar systems is shown to reduce fuel consumption by 17–38% in suitable regions (Son et al., 2019), and these systems play an essential role in sustainable development (Adenle, 2020). It has been shown that there is a social interest in the use of solar energy and a strong preference for solar power (Cousse, 2021). Investment in solar energy stimulates the growth and development of other industries and attracts new investment (Marolin et al., 2020). Because solar energy is cheaper than other energy generation sources (Rabaia et al., 2021) and abundant, it can expand its place in the life cycle with a range of policies and measures (Liu, 2020).

For the above reasons, the study aims to investigate the effect of solar energy on CO_2 emissions. For this purpose, we created an equation based on CO_2 emissions, solar energy consumption, coal energy consumption, financial globalization, and growth. The panel includes data for the period 2000–2019 for 26 countries whose data are available. In addition to the ordinary least square (OLS) and fully modified ordinary least square (FMOLS) methods, we also used the CCEMG method, which takes into account cross-section dependence and slope homogeneity to predict long-term relationships between the variables. According to estimates, the reduction in CO_2 emissions is caused by solar energy. Furthermore, according to the causality estimates, there is a bilateral causality relationship between the two variables. In conclusion, this study emphasizes the importance of the role of solar energy in reducing CO_2 emissions and makes essential contributions to the literature. It is the first study to analyze the relationship between CO_2 emissions, solar energy consumption, coal energy consumption, financial globalization, and growth. It contributes to this significant gap created by the literature's lack of existing studies on solar energy. Second, the countries used in this study are analyzed in the same panel data for the first time, as the current studies are constantly based on the data of the same country. Third, the coefficient estimator, and causality method used in the study account for cross-sectional dependence and slope homogeneity.

The order of the parts of the study is as follows: "Literature Survey" includes the relevant literature, and "Data and Empirical Model" section consists of the data and imperial model followed by "Empirical Methodology" section, "Estimation Results" section includes the analysis estimates. "Conclusion and Policy Implications" section contains conclusions and policy recommendations.

Literature Survey

Solar Energy and CO_2 Emissions

This section includes studies examining the relationship between solar energy and CO_2 emissions. Few studies in the literature take into account and examine the effect of solar energy on carbon emissions. Sharif et al. (2021) analyzed the dynamic relationship between ecological footprints and solar energy consumption using the quantile-on-quantile (QQ) approach for the top 10 countries with the highest solar energy consumption (excluding England and India) during 1990–2017. Ecological footprints are used in place of carbon emissions to measure environmental degradation. The results of the study show that solar energy consumption facilitates the reduction of environmental footprint. Magazzino et al. (2021) investigated the causal relationship between solar and wind energy production, coal consumption, economic growth, and CO_2 emissions in China (1990–2017), India (1986–2017), and the USA (1983–2017). They used the causal direction from the dependency (D2C) model in a machine learning technique. Their conclusions are as follows: there is hope for China and the USA to reduce their overall carbon emissions, it is suggested that India should switch from fossil to renewable sources to reduce its rising carbon emissions, and for this, India needs to limit its reliance on coal. Ortega et al. (2020) estimated the gross employment generated by deploying three renewable electricity technologies for all member countries of the European Union by 2050. The results show that the work developed by these three technologies can be significant, but significant differences are observed between technologies, activities, and countries. Dong (2017), in his study of BRICS countries between the years 1985 and 2016, discovered that renewable energy reduced carbon dioxide emissions by 0.2601%, and there was a bidirectional panel causal relationship between renewable energy and CO_2 in both the short and long run. Dogan and Seker (2016) investigated the effects of renewable and non-renewable energy, real income, and trade openness on carbon emissions in the environmental Kuznets curve (EKC) model for the European Union during 1980–2012. Panel estimation methods based on cross-section dependency are used in the study. The presence of EKC is confirmed for the EU based on the positive and negative effects of GDP and GDP^2 on carbon emissions. Lin and Moubarak (2014) investigated the relationship between renewable energy consumption and economic growth in the Chinese economy from 1977 to 2011. As a result of cointegration analysis applied to determine the long-run relationship between variables, a long-run relationship between renewable energy and economic growth was found. Destek and Aslan (2020) investigated the relationship between disaggregated renewable energy (hydropower, biomass, wind, and solar power), economic performance, and carbon emissions for G-7 countries during 1991–2014. The panel bootstrap Granger causality method considered cross-sectional dependence and country-specific heterogeneity and augmented used mean group estimators to investigate this relationship. In France and Italy, solar energy reduces emissions. In the case of panels, carbon emissions decreased with increased hydropower, biomass, and wind energy consumption.

In contrast, the effect of solar energy consumption was statistically insignificant in G-7 countries. Finally, Koengkan et al. (2020a) examined the relationship between carbon emissions, renewable and non-renewable energy sources, economic growth, and urbanization. The analysis used data from Argentina, Brazil, Paraguay, Uruguay, and Venezuela between 1980 and 2014. According to panel vector autoregression (PVAR) estimates, renewable energy reduces carbon emissions. There is also a bidirectional causality relationship between fossil fuel consumption, economic growth, renewable energy consumption, and carbon emissions.

Financial Globalization and CO_2 Emissions

In this section, studies analyzing the relationship between financial globalization and CO_2 emissions are included. For example, Ulucak et al. (2020) investigated the impact of financial globalization on environmental degradation in 15 emerging economies. Researchers used data from 1974 to 2016. According to the study, financial globalization contributes to the improvement of environmental quality levels in developing economies. Farouquk et al. (2021) investigated the asymmetric relationship between financial globalization uncertainty and environmental quality. Data from nine Saharan African countries for the period 1980–2019 are used. It is estimated that the uncertainty of financial globalization has a negative and significant effect on environmental quality. Yashodha et al. (2018) examined the environmental impact of economic globalization based on the environmental Kuznets curve (EKC) hypothesis. They used data from 76 middle-income countries for the 1994–2014 period in their generalized method of moment (GMM) estimates. As regards estimates, there is no consistent relationship between economic globalization and carbon emissions. Asongu (2018) analyzed the impact of globalization on CO_2 emissions in 44 sub-Saharan African countries. Under the results of the study, the effect of globalization on CO_2 emissions is negative. Koengkan et al. (2020b) analyzed the effect of economic, social, and political globalization on carbon emissions in 18 Latin American and Caribbean countries. Koengkan et al. (2020b) analyzed the data for the period 1990–2014. According to the study, globalization can reduce carbon emissions. Le and Ozturk (2020) investigate the relationship between globalization and CO_2 emissions in 47 emerging markets and emerging economies (EMDEs). This study used data from 1990 to 2014. It is estimated that globalization increases CO_2 emissions.

Data and Empirical Model

Data

This study consists of annual time series data covering the period from 2000 to 2019 for 26 countries: Austria, Argentina, Australia, China, Canada, Denmark, Egypt, Finland, France, Germany, India, Italy, Japan, Luxembourg, Mexico, Netherlands, Norway, Portugal, South Africa, South Korea, Spain, Sri Lanka, Sweden, Switzerland, United States of America (USA), and the UK. In the study, countries with available data were preferred. We could not include other countries in this study because the data were insufficient for analysis. We determined the variables in this study according to the relevant literature. The first variable, solar energy consumption per capita, is taken from British Petroleum (BP). BP calculates solar energy consumption in a million tons of oil equivalent per capita. Financial globalization data is obtained from KOF Swiss Economic Institute (KOF). KOF financial globalization data takes values between 0 and 100. Coal energy consumption data, calculated as million tons of oil equivalent per capita, were obtained from BP. GDP per capita (current USD) data is from World Development Indicators. Figure 1 shows the course of solar energy consumption of 26 countries in the 2000–2019 period. Twenty-six countries were divided into two groups high-income and middle-income countries. According to the figure, solar energy consumption in all countries is on an upward trend. Moreover, it is seen that the solar energy consumption of middle-income countries such as China, Egypt, Mexico, Sri Lanka, India, and South Africa, which seemed stagnant until 2010, increased rapidly in 2010.

Figure 2 shows the course of countries' CO_2 emissions in the 2000–2019 period. According to the figure, the CO_2 emissions of countries tend to stay at the same level.

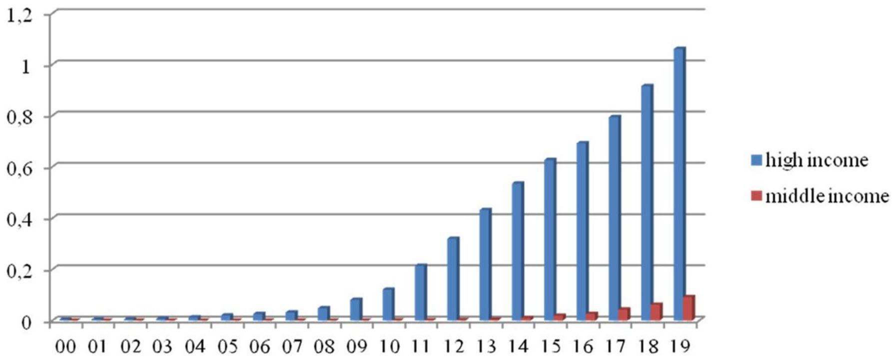

Fig. 1 Solar energy consumption of countries

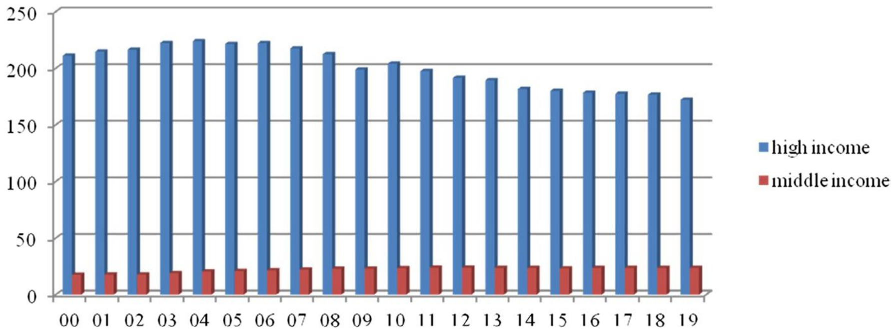

Fig 2 CO_2 emission of countries

Table 1 Variables' name, symbol, and source

Variables	Symbol	Unit	Source
Carbon emissions per capita	CO_2	Million tonnes	British Petroleum statistic
Solar energy consumption per capita	SE	million tonnes of oil equivalent	British Petroleum statistic
Financial globalization index	FiGI	KOF index from 0 to 100	KOF Index of Globalization
Coal energy consumption per capita	CE	million tonnes of oil equivalent	British Petroleum statistic
Gross domestic product per capita	GDP	Current US dollar	World Data Bank

Table 2 Descriptive statistics of the variables

Variables	Mean	Maximum	Minimum	Std. dev.	Observations
CO_2	1.905894	3.329646	−0.595082	0.784944	520
SE	−7.138216	−1.883197	−15.27135	3.012951	520
CE	−1.314472	1.021039	−12.27569	1.697516	520
FiGI	4.262150	4.584396	3.363479	0.255378	494
GDP	9.964663	11.68540	6.094279	1.245654	520

std. dev. indicates standard deviation

Although the consumption of carbon emissions in high-income countries decreased after 2007, there was no significant decrease. And the course of carbon consumption in middle-income countries is stable. It increases after 2013. Tables 1 and 2 show the definitions and statistical values for the variables used in this study.

Empirical Model

This study investigates the relationship between solar energy consumption, CO_2 emissions, coal energy consumption, and GDP per capita for 26 countries during 2000−2019. The functional relationship of the variables is developed as follows:

$$\mathrm{CO}_2 = f(\mathrm{SE}, CE, \mathrm{FiGI}, \mathrm{GDP}) \tag{1}$$

The natural logarithms of all variables are taken. The econometric model set up in the analysis is shown in Eq. (2),

$$\mathrm{lnCO}_{2\mathrm{it}} = \beta_0 + \beta_1 \mathrm{lnSE}_{\mathrm{it}} + \beta_2 \mathrm{lnCE}_{\mathrm{it}} + \beta_3 \mathrm{lnFiGI}_{\mathrm{it}} + \beta_4 \mathrm{lnGDP}_{\mathrm{it}} + \varepsilon_{\mathrm{it}} \tag{2}$$

where i indicates the number of cross-sections (i.e., 1, 2, 3, 4...N) and T represents the period (2000–2019). $\mathrm{lnCO}_{2\mathrm{it}}$ is the natural logarithms of carbon dioxide emissions per capita; β_0 is the slope-intercept. $\mathrm{lnSE}_{\mathrm{it}}$ is the natural logarithms of solar energy consumption per capita. $\mathrm{lnCE}_{\mathrm{it}}$ is the natural logarithms of coal energy consumption per capita. $\mathrm{lnFiGI}_{\mathrm{it}}$ is the natural logarithms of financial globalization. $\mathrm{lnGDP}_{\mathrm{it}}$ is the natural logarithms of GDP per capita.

Empirical Methodology

Cross-section dependence is an essential issue for studies using panel data. Ignoring cross-section dependence will lead to incompatible estimates and deceptive information (Grossman & Krueger, 1995). For this reason, Pesaran (2004) suggested that the tests were used in this study. The Pesaran-scaled LM and Pesaran CD test presented by Pesaran (2004) is quite suitable for detecting cross-section dependence in the model. The Pesaran-scaled LM test was obtained from Breusch and Pagan (1980). Pesaran (2004) proposes an alternative statistic, the Pesaran CD test given in Eq. (3), which exploits the residuals of the model used. This test produces more consistent results in detecting panel cross-sectional dependence. In Eq. (3), $\hat{\rho}_{ij}^2$ represents the correlation coefficients obtained from the residuals of the model.

$$CD = \sqrt{\frac{2}{N(N-1)}} \sum_{i=0}^{N-1} \sum_{j=i+1}^{N} \mathrm{T}_{ij} \hat{\rho}_{ij}^2 \rightarrow N(0,1) \tag{3}$$

When the panel is heterogeneous, the assumption that the slope is homogeneous leads to misleading estimates (Breitung, 2005). Therefore, the presence of cross-sectional heterogeneity should be tested when examining empirical results. To test for homogeneity of the slope parameters, one can use the estimator proposed by Pesaran and Yamagata (2008) for panels of $N > T$. In Eqs. (4) and (5), slope homogeneity is determined using pooled ordinary least squares (OLS), pooled weighted fixed effect (WFE) estimator, and deviations from the mean.

$$S = \sum_{i=1}^{N} \left(\beta_{\mathrm{i}} - \beta_{WFE}\right), \frac{\left(x_{\mathrm{i}}' M_{\tau} x_i\right)}{\sigma_i^2} \left(\beta_i - \beta_{WFE}\right) \tag{4}$$

$$\Delta = \sqrt{N}\left(\frac{N^{-1}S - k}{\sqrt{2k}}\right) \tag{5}$$

where β_i indicates the coefficient obtained from the OLS, β_{WFE} also shows coefficients from the WFE estimation. x_i is the matrix including descriptive variables in deviations from the mean, M_τ is the identity matrix, σ_i^2 is the estimate of σ_i, and k is the number of regressors.

Testing the presence of unit roots in panel data depends on whether there is a cross-section dependency in the panel. If there is no cross-sectional dependence in the panel, traditional first-generation panel unit root tests are valid. Since the panel has cross-sectional dependence, the second-generation panel unit root test allows for cross-section dependence in the panels. The second-generation unit root test proposed by Pesaran (2007) is called the Pesaran CIPS panel unit root test. Unlike other panel unit root tests, the test aims to remove the cross-sectional dependence asymptotically in the panel. Cross-sectional augmented Dickey-Fuller's (CADF) regression, which considers cross-sectional averages to eliminate cross-section dependence, can be calculated as in Eq. (6):

$$\Delta y_{it} = \alpha_i + b_i y_{i,t-1} + c_i \overline{y}_{t-1} + \sum_{j=0}^{p} d_{ij} \Delta \overline{y}_{t-j} + \sum_{j=1}^{p} \delta_{ij} \Delta \overline{y}_{t-j} + e_{it} \tag{6}$$

where $\overline{y}_{t-j}$ represents the cross-sectional averages of lagged levels and $\Delta\overline{y}_{t-j}$ indicates the first differences of individual series, respectively. After the CADF regression is estimated, to obtain the CIPS statistic, the means of t statistics ($CADF_i$) of lagged variables in Eq. (7) are calculated as follows:

$$CIPS = N^{-1} + \sum_{i=1}^{N} CADF_i \tag{7}$$

Standard cointegration tests ignore cross-sectional dependence, like Pedroni (2001) and Kao (1999). However, the data used in this study are cross-sectionally dependent. Error correction-based panel cointegration tests developed by Westerlund (2005) take into account cross-section dependence. Therefore, in this study, we preferred the Westerlund (2005) method to test the cointegration relationship between the variables. The Westerlund (2005) method can be estimated as follows:

$$\Delta z_{it} = \delta_i' d_i + \theta_i \left(z_{i(\mathrm{t}-1)} + \pi_i' y_{i(t-1)}\right) + \sum_{j=1}^{\mathrm{m}} \theta_{ij} \Delta z_{i(t-j)} + \sum_{j=0}^{m} \varphi_{ij} \Delta y_{i(t-j)} + \omega_{it} \tag{8}$$

Equation (8) makes estimates that consider the cross-sectional dependency and are error correction-based. θ_i is the adjustment term that determines the speed for the system to back to the equilibrium relationship. Westerlund (2005) suggests four error correction-based panel cointegration statistics, 2 of which are mean group statistics and 2 of which are panel statistics, based on OLS estimates. These error correction-based panel cointegration tests can be estimated as follows:

$$G_\tau = N^{-1}\sum\nolimits_{i=1}^{N}\frac{\theta_i}{SE(\hat{\theta}_i)} \tag{9}$$

$$G_\alpha = N^{-1}\sum\nolimits_{i=1}^{N}\frac{T\theta_i}{\theta_i'(1)} \tag{10}$$

$$P_\tau = \frac{\hat{\theta}_i}{SE(\hat{\theta}_i)} \tag{11}$$

$$\mathrm{P}_\alpha = T\hat{\theta}_i \tag{12}$$

In Eqs. (9) and (10), G_τ and G_α are mean group statistics, and in Eqs. (11 and (12), P_τ and P_α are panel statistics. After confirming the existence of the cointegration relationship, this study first uses the OLS and the panel FMOLS models to calculate the long-run coefficients of the panel data. Pedroni (2001) improves the panel FMOLS model. However, the OLS and FMOLS methods do not account for cross-sectional dependence and slope homogeneity between panel sections in the estimation. Estimates by ignoring inter-section dependence can induce erroneous and conflicting results, as noted by Pesaran and Smith (1995). In this study, the CCEMG (common correlated effect mean group) method is used, which estimates by taking into account cross-sectional dependence and slope homogeneity. Pesaran (2006) proposes the CCEMG estimator. The CCEMG estimator can be evaluated as follows:

$$y_{it} = \alpha_{li} + b_i x_{it} + c_i f_t + \alpha_i \overline{y}_{ti} + \beta_i \overline{x}_{ti} + e_{it} \tag{13}$$

In Eq. (13), y_{it} and x_{it} are observables; b_i is the country-specific estimates of coefficients; f_t is the unobserved common factor with heterogeneous factor; α_i is the intercept term, and e_{it} is the error term.

The causality relationship between the variables whose long-term coefficients are estimated can be determined. Therefore, the last step in our study involves determining the direction of causality of variables. By testing the direction of causality, we can draw meaningful conclusions about the relationships of variables. The Dumitrescu and Hurlin (2012) panel causality test allows for cross-section dependence and is used to examine the direction of causality in this empirical study. The Dumitrescu and Hurlin (2012) (D-H) introduced the panel causality test based on Granger's (1969) individual Wald's statistic. The D-H panel causality test can be examined as follows:

$$y_{it} = a_i + \sum\nolimits_{j=1}^{J}\lambda_i^j y_{i(t-j)} + \sum\nolimits_{j=1}^{J}\beta_i^j x_{i(t-j)} + e_{it} \tag{14}$$

In Eq. (14), y and x are the observables, λ_i^j is the autoregressive parameters, and β_i^j is the regression coefficient estimates. λ_i^j and β_i^j are assumed to vary between

Table 3 Cross-section dependence tests

Variables	Breusch-Pagan LM		Pesaran-scaled LM		Pesaran CD	
	CD statistics	Prob.	CD statistics	Prob.	CD statistics	Prob.
lnCO_2	3874.120***	0.0000	139.2079***	0.0000	16.04361***	0.0000
lnSE	-5347.983***	0.0000	197.0176***	0.0000	72.79268***	0.0000
lnCE	2444.304***	0.0000	83.12583***	0.0000	10.78369***	0.0000
lnFiGI	2139.489***	0.0000	71.13088***	0.0000	26.86863***	0.0000
lnGDP	4739.480***	0.0000	172.7579***	0.0000	67.83070***	0.0000

*** indicates the level of significance at 1%, respectively.

Table 4 Slope homogeneity tests

	Test statistic	P-value
Δ	14.862	0.000***
Δ_{adj}	17.959	0.000***

*** indicates the level of significance at 1%, respectively.

cross-sections. In addition, can examine the D-H panel causality test based on an average Wald statistic. Thus, the mean of the individual Wald statistics produced by the D-H panel causality test can be measured as follows. In Eq. (15), $W_{i,T}$ is the individual Wald statistic for each cross-section unit.

$$W_{N,T}^{HNC} = N^{-1}\sum_{i=1}^{N} W_{i,T} \tag{15}$$

Estimation Results

First, we test for cross-sectional dependence to examine the long-term relationship between carbon emission, solar energy consumption, coal energy consumption, and growth variables. Table 3 shows the results of the cross-sectional dependence tests. According to the Breush-Pagan LM test results, Pesaran-scaled LM test, and Pesaran CD test, the null hypothesis of no cross-sectional independence is rejected at the 1% significance level for all variables. This result indicates a strong cross-sectional dependence. These results imply that methods that allow for cross-section dependence are more appropriate for this study. Table 4 shows the results of the slope homogeneity tests. The null hypothesis of the slope homogeneity hypothesis is rejected for both tests. This result confirms the existence of slope heterogeneity.

Consequently, if cross-sectional dependence exists, should also use robust methods to slope homogeneity in this study. The Pesaran CIPS panel unit root test is used in this study to examine stationarity and determine the level of integration of all selected variables. Table 5 shows the test results, where not all variables

Table 5 Pesaran CIPS panel unit root tests

CIPS Variables	Levels		First differences	
	Constant	Constant and trend	Constant	Constant and trend
$lnCO_2$	−1.148	-2.458	-3.962***	-4.086***
lnSE	−1.644	−1.723	−2.504***	−3.021***
lnCE	−1.104	−2.473	−4.399***	−4.434***
lnFiGI	−2.519***	−2.920***	−4.934***	−5.132***
lnGDP	−2.675***	−2.357	−3.352***	−3.125***

the maximum lag length is taken as 2. Optimal lag length is determined according to Akaiki information criteria (AIC)

***indicates level of significance at 1%, respectively

Table 6 Westerlund's cointegration tests

Variables	Gτ		Gα		Pτ		Pα	
	Sta.	Prob.	Sta.	Prob.	Sta.	Prob.	Sta.	Prob.
lnSE	−3.761***	0.000	−9.941	0.933	−16.741***	0.000	−16.197***	0.000
lnCE	−4.337***	0.000	−14.792***	0.013	−13.170***	0.003	−12.064***	0.004
lnFiGI	−4.269***	0.000	−15.060***	0.008	−12.984***	0.005	−13.754***	0.000
lnGDP	−4.458***	0.000	−12.094	0.440	−16.059***	0.000	−17.979***	0.000

maximum lag and lead length is selected to be 2. Constant and trend are included in the analysis

***indicates level of significance at 1%, respectively

Table 7 Pedroni and Kao's cointegration tests

Pedroni's residual cointegration tests					
	Weighted statistic	Prob.		Test statistic	Prob.
Within-dimension			*Between-dimension*		
Panel v-statistic	−0.870132	0.8079			
Panel rho-statistic	9.45E-05	0.5000	Group rho-Statistic	2.534948	0.9944
Panel PP-statistic	−4.185821***	0.0000	Group PP-Statistic	−2.413121***	0.0079
Panel ADF-statistic	−5.914919***	0.0000	Group ADF-Statistic	−4.504396***	0.0000
Kao residual cointegration tests					
ADF	t-statistic		Prob.		
	−1.522490*		0.0639		

* and *** indicate the levels of significance at 10% and 1%, respectively.

are stationary at levels, except for FiGI. When the first difference of the variables is taken, the null hypothesis is rejected. This result means that all variables are cointegrated.

These estimates allow us to investigate whether there is a long-run equilibrium relationship between the selected variables. For this purpose, we used the error correction-based panel cointegration approach developed by Westerlund (2005). Westerlund's (2005) test is very suitable for this analysis since slope homogeneity and cross-section dependence are considered. The results of Westerlund's panel cointegration test for the variables are presented in Table 6. Again, the null hypothesis of no cointegration is rejected. Therefore, the long-run cointegration relationship is supported by all of Westerlund's test statistics.

In this study, Pedroni (2001) and Kao (1999) cointegration tests, which are frequently used in the literature, are also included to support Westerlund's cointegration tests. Table 7 shows the results of Pedroni (2001) and Kao (1999) cointegration tests. According to the Pedroni cointegration test results, most of the statistics are statistically significant. Therefore, it was concluded that there is cointegration between the variables. The Kao test results rejected the null hypothesis of no cointegration and obtained the same effect as the other tests.

After applying the cross-section dependence, slope homogeneity, unit root, and cointegration tests, the next step is to calculate the long-term estimates for the variables. Table 8 shows the OLS, panel FMOLS, and CCEMG estimations. The estimates obtained in this study are like the findings of studies such as Dong (2017), Sharif et al. (2021), Destek and Aslan (2020), and Koengkan et al. (2020a). It can see from this table that these three estimation methods give similar results. According to the results of the OLS and FMOLS estimators, the coefficients of all variables except lnFiGI are significant. According to the OLS and FMOLS estimations, the increase in solar energy consumption leads to a decrease in CO_2 emissions. Although the results are significant and consistent, these two methods ignore cross-sectional dependence and slope homogeneity.

Therefore, the CCEMG method, which considers cross-sectional dependence and slope homogeneity, was preferred in this study. Consistent with the OLS and FMOLS estimates for the panel, the coefficients of lnCE and lnGDP are positive and significant, while the coefficient of lnSE is negative and significant. While a 1% increase in lnSE causes a 0.0106671% decrease in $lnCO_2$. Therefore, the increase in solar energy consumption causes decreases in carbon emissions. Thus, both OLS, FMOLS, and CCEMG estimates display the importance of solar energy in reducing

Table 8 OLS, FMOLS, and CCEMG estimates

Dependent variable: $lnCO_2$						
	OLS		FMOLS		CCEMG	
Variables	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.
lnSE	−0.032144***	0.0000	−0.029937***	0.0000	−0.0106671*	0.055
lnCE	0.227625***	0.0000	0.104081***	0.0000	0.2403829***	0.000
lnFiGI	−0.032084	0.7383	0.066317	0.3881	−0.0538893	0.336
lnGDP	0.420279***	0.0000	0.225284***	0.0000	0.0652308*	0.050

* and *** indicate the levels of significance at 10% and 1%, respectively.

Table 9 D-H panel causality tests

Null hypothesis	W-bar stat.	Z-bar stat.	Prob.
lnSE does not cause lnCO_2	6.3860***	19.4196	0.0000
lnCO_2 does not cause lnSE	3.5443***	9.1737	0.0000
lnCE does not cause lnCO_2	2.7050***	6.1473	0.0000
lnCO_2 does not cause lnCE	4.7327***	13.4586	0.0000
lnFiGI does not cause lnCO_2	2.2062***	4.3491	0.0000
lnCO_2 does not cause lnFiGI	1.2574	0.9281	0.3534
lnGDP does not cause lnCO_2	5.9850***	17.9737	0.0000
lnCO_2 does not cause lnGDP	4.2150***	11.5919	0.0000

*** indicates the level of significance at 1%, respectively.

CO_2 emissions. In the long run, a 1% increase in lnCE and lnGDP is associated with a 0.2403829 and 0.0652308% increase in lnCO_2, respectively. And the rise in GDP has a positive effect on carbon emissions. After estimating the long-run coefficients of the cointegrated variables, we can test possible causality among the variables. For this purpose, the D-H causality test was used in this study.

Table 9 presents results showing the direction of causality relationships between variables in the panel data. For the panel, bidirectional causality is found between CO_2 emissions and solar energy consumption. These results are similar to Koengkan et al. (2020a) and Dogan and Seker (2016). The existence of a bilateral causal relationship once again highlights the importance of the relationship between solar energy and CO_2 emissions. The causality between coal energy consumption and economic growth with carbon emissions is also found to be bidirectional. On the contrary, the unidirectional causality is found to run from financial globalization to CO_2 emission.

Conclusion and Policy Implications

The most significant factor that encouraged us in our work was the existence of a source, such as the sun, which has infinite energy compared to our human lifespan. To use different methods to measure the benefit of solar energy to nature, the CCEMG method was used as a result of hard work in the literature. As a result of the data scans, the countries containing all the values related to our subject were selected so there would be no gaps in the study. The challenge here was not being able to reach enough data or being limited to the data of developed countries. But we chose to use data from countries with different income levels. In the literature, some studies are generally based on a single country. This study analyzes solar energy consumption, coal energy consumption, financial globalization, growth, and carbon dioxide emissions. In the analysis, we used the data from the 2000-2019 period of 26 countries whose data are available. First, the unit roots of the variables were examined using the CIPS test proposed by Pesaran (2007). The results obtained from the CIPS panel unit root tests showed that the variables became stationary at their first difference. Then, we used Westerlund's (2005) cointegration method to determine the cointegration relationship between the variables. Finally, we used Pedroni (2001) and Kao's (1999) cointegration tests to support the predictions of Westerlund (2005). Westerlund's cointegration test confirmed the existence of a long-run relationship between the variables. These results are also compatible with Pedroni's (2001) and Kao's (1999) cointegration tests. Used OLS and FMOLS methods to estimate the long-term coefficients of the cointegrated variables. However, these methods do not consider possible cross-sectional dependence and slope homogeneity. Therefore, the CCEMG method, which considers cross-sectional dependence and slope homogeneity, was used. According to CCEMG's estimations, there is a negative relationship between solar energy consumption and CO_2 emissions. In other words, as solar energy consumption increases, CO_2 emissions decrease. OLS and FMOLS estimations also support this result. In addition, there may be casualty relationships among the variables that are related in the long run. Dumitrescu and Hurlin's (2012) test determined possible casualties among the variables. As seen from the empirical results of the causality test, there is bidirectional causality between solar energy consumption and CO_2 emissions. In addition, identified two other bidirectional causes between CO_2 emissions with coal energy consumption and GDP. Furthermore, there is unidirectional causality from financial globalization to CO_2.

Based on these findings, we can make several policy recommendations. First, we found solar energy is a valuable energy source to reduce carbon emissions. Therefore, can create a rational policy to increase investment in the solar energy sector. Second, field studies should be conducted to determine the areas that can use solar energy more intensively before investing. Thus, as a result of these studies, investment recovery could be more effective. Third, for the development of technology related to the use of solar energy, institutes working on solar energy should be established. And competent personnel to work in this field should be trained in higher education institutions. Fourth, motivational rebates should be applied to make people aware of the impact of solar energy on environmental sustainability. For example, it should reflect the discount rate on the bills of those who use a solar system to heat their home. Fifth, governments should give tax advantages and energy investment incentives to companies that prefer solar energy in their production processes. Thus, countries will benefit from solar energy sufficiently to reduce CO_2 emissions. As a result of all these practices and incentives, countries sswill benefit from solar energy sufficiently to reduce CO_2 emissions.

References

Adebayo, T. S., Kirikkaleli, D., Adeshola, I., Oluwajana, D., Akinsola, G. D., & Osemeahon, O. S. (2021). Coal consumption and environmental sustainability in South Africa: The role of financial development and globalization. *International Journal of Renewable Energy Development, 10*(3), 527–536.

Adedoyin, F. F., Gumede, M. I., Bekun, F. V., Etokakpan, M. U., & Balsalobre-Lorente, D. (2020). Modelling coal rent, economic growth and CO2 emissions: does regulatory quality matter in BRICS economies? *Science of the Total Environment, 710*, 136284. https://doi.org/10.1016/j.scitotenv.2019.136284

Adenle, A. A. (2020). Assessment of solar energy technologies in Africa-opportunities and challenges in meeting the 2030 agenda and sustainable development goals. *Energy Policy, 137*, 111180. https://doi.org/10.1016/j.enpol.2019.111180

Alvarado, R., Tillaguango, B., Cuesta, L., Pinzon, S., Alvarado-Lopez, M. R., Işık, C., & Dagar, V. (2022). Biocapacity convergence clubs in Latin America: An analysis of their determining factors using quantile regressions. *Environmental Science and Pollution Research, 29*, 66605–66621.

Anvari, S., Khalilarya, S., & Zare, V. (2019). Power generation enhancement in a biomass-based combined cycle using solar energy: Thermodynamic and environmental analysis. *Applied Thermal Engineering, 153*, 128–141. https://doi.org/10.1016/j.applthermaleng.2019.02.112

Asongu, S. A. (2018). ICT, openness and CO 2 emissions in Africa. *Environmental Science and Pollution Research, 25*(10), 9351–9359. https://doi.org/10.1007/s11356-018-1239-4

Banacloche, S., Herrera, I., & Lechón, Y. (2020). Towards energy transition in Tunisia: Sustainability assessment of a hybrid concentrated solar power and biomass plant. *Science of The Total Environment, 744*, 140729. https://doi.org/10.1016/j.scitotenv.2020.140729

Breitung, J. (2005). A parametric approach to the estimation of cointegration vectors in panel data. *Econometric Reviews, 24*(2), 151–173. https://doi.org/10.1081/ETC-200067895

Breusch, T. S., & 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. https://doi.org/10.2307/2297111

Cao, Y., Rad, H. N., Jamali, D. H., Hashemian, N., & Ghasemi, A. (2020). A novel multi-objective spiral optimization algorithm for an innovative solar/biomass-based multi-generation energy system: 3E analyses, and optimization algorithms comparison. *Energy Conversion and Management, 219*, 112961. https://doi.org/10.1016/j.enconman.2020.112961

Cousse, J. (2021). Still in love with solar energy? Installation size, affect, and the social acceptance of renewable energy technologies. *Renewable and Sustainable Energy Reviews, 145*, 111107. https://doi.org/10.1016/j.rser.2021.111107

Dagar, V., Khan, M. K., Alvarado, R., Rehman, A., Irfan, M., Adekoya, O. B., & Fahad, S. (2022). Impact of renewable energy consumption, financial development and natural resources on environmental degradation in OECD countries with dynamic panel data. *Environmental Science and Pollution Research, 29*(12), 18202–18212.

Darwesh, M. R., & Ghoname, M. S. (2021). Experimental studies on the contribution of solar energy as a source for heating biogas digestion units. *Energy Reports, 7*, 1657–1671. https://doi.org/10.1016/j.egyr.2021.03.014

Destek, M. A., & Aslan, A. (2020). Disaggregated renewable energy consumption and environmental pollution nexus in G-7 countries. *Renewable Energy, 151*, 1298–1306. https://doi.org/10.1016/j.renene.2019.11.138

Dogan, E., & Seker, F. (2016). Determinants of CO2 emissions in the European Union: The role of renewable and non-renewable energy. *Renewable Energy, 94*, 429–439. https://doi.org/10.1016/j.renene.2016.03.078

Dong, K., Sun, R., & Hochman, G. (2017). Do natural gas and renewable energy consumption lead to less CO2 emission? Empirical evidence from a panel of BRICS countries. *Energy, 141*, 1466–1478. https://doi.org/10.1016/j.energy.2017.11.092

Du, H., Li, N., Brown, M. A., Peng, Y., & Shuai, Y. (2014). A bibliographic analysis of recent solar energy literatures: The expansion and evolution of a research field. *Renewable Energy, 66*, 696–706. https://doi.org/10.1016/j.renene.2014.01.018

Dumitrescu, E. I., & Hurlin, C. (2012). Testing for Granger non-causality in heterogeneous panels. *Economic Modelling, 29*(4), 1450–1460. https://doi.org/10.1016/j.econmod.2012.02.014

Faisal, F., Khan, M. N., Pervaiz, R., Muhamad, P. M., & Rashdan, M. O. J. (2021). Exploring the role of fossil fuels, hydroelectricity consumption, and financial sector in ensuring sustainable economic development in the emerging economy. *Environmental Science and Pollution Research, 28*(5), 5953–5965. https://doi.org/10.1007/s11356-020-10608-3

Farouq, I. S., Sambo, N. U., Ahmad, A. U., & Jakada, A. H. (2021). Does financial globalization uncertainty affect CO 2 emissions? Empirical evidence from some selected SSA countries. *Quantitative Finance and Economics, 5*(2), 247–263.

Granger, C. W. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica: Journal of the Econometric Society, 37*(3), 424–438. https://www.jstor.org/stable/1912791. Accessed 18 Jan 2022.

Grossman, G. M., & Krueger, A. B. (1995). Economic growth and the environment. *The Quarterly Journal of Economics, 110*(2), 353–377 https://www.jstor.org/stable/2118443. Accessed 18 Jan 2022.

Gyamfi, B. A., Adedoyin, F. F., Bein, M. A., Bekun, F. V., & Agozie, D. Q. (2021). The anthropogenic consequences of energy consumption in E7 economies: Juxtaposing roles of renewable, coal, nuclear, oil and gas energy: evidence from panel quantile method. *Journal of Cleaner Production, 295*, 126373. https://doi.org/10.1016/j.jclepro.2021.126373

IEA. (2020). *Key world energy statistics*. Retrieved June 7, 2021 from https://www.iea.org/reports/key-world-energy-statistics-2020.

IEA. (2021). *Global energy review 2021*. Retrieved June 7, 2021 from https://www.iea.org/reports/global-energy-review-2021.

Ishaq, H., Siddiqui, O., Chehade, G., & Dincer, I. (2021). A solar and wind driven energy system for hydrogen and urea production with CO2 capturing. *International Journal of Hydrogen Energy, 46*(6), 4749–4760. https://doi.org/10.1016/j.ijhydene.2020.01.208

Joshua, U., Uzuner, G., & Bekun, F. V. (2020). Revisiting the causal nexus between coal energy consumption, economic growth, and pollutant emission: sorting out the causality. *Environmental Science and Pollution Research, 27*, 30265–30274. https://doi.org/10.1007/s11356-020-09265-3

Kabir, E., Kumar, P., Kumar, S., Adelodun, A. A., & Kim, K. H. (2018). Solar energy: Potential and future prospects. *Renewable and Sustainable Energy Reviews, 82*, 894–900. https://doi.org/10.1016/j.rser.2017.09.094

Kao, C. (1999). Spurious regression and residual-based tests for cointegration in panel data. *Journal of Econometrics, 90*(1), 1–44. https://doi.org/10.1016/S0304-4076(98)00023-2

Khan, M. I., Kamran Khan, M., Dagar, V., Oryani, B., Akbar, S. S., Salem, S., & Dildar, S. M. (2021). Testing environmental Kuznets curve in the USA: What role institutional quality, globalization, energy consumption, financial development, and remittances can play? New evidence from dynamic ARDL simulations approach. *Frontiers in Environmental Science, 576*.

Koçak, B., Fernandez, A. I., & Paksoy, H. (2020). Review on sensible thermal energy storage for industrial solar applications and sustainability aspects. *Solar Energy, 209*, 135–169. https://doi.org/10.1016/j.solener.2020.08.081

Koengkan, M., Fuinhas, J. A., & Santiago, R. (2020a). The relationship between CO2 emissions, renewable and non-renewable energy consumption, economic growth, and urbanisation in the Southern Common Market. *Journal of Environmental Economics and Policy, 9*(4), 383–401. https://doi.org/10.1080/21606544.2019.1702902

Koengkan, M., Fuinhas, J. A., & Santiago, R. (2020b). Asymmetric impacts of globalisation on CO 2 emissions of countries in Latin America and the Caribbean. *Environment Systems and Decisions, 40*(1), 135–147. https://doi.org/10.1007/s10669-019-09752-0

Le, H. P., & Ozturk, I. (2020). The impacts of globalization, financial development, government expenditures, and institutional quality on CO 2 emissions in the presence of environmental Kuznets curve. *Environmental Science and Pollution Research, 27*(18), 22680–22697. https://doi.org/10.1007/s11356-020-08812-2

Lin, B., & Moubarak, M. (2014). Renewable energy consumption–economic growth nexus for China. *Renewable and Sustainable Energy Reviews, 40*, 111–117. https://doi.org/10.1016/j.rser.2014.07.128

Liu, F., & Van den Bergh, J. C. (2020). Differences in CO2 emissions of solar PV production among technologies and regions: Application to China EU and USA. *Energy Policy, 138*, 111234. https://doi.org/10.1016/j.enpol.2019.111234

Magazzino, C., Mele, M., & Schneider, N. (2021). A machine learning approach on the relationship among solar and wind energy production, coal consumption, GDP, and CO2 emissions. *Renewable Energy, 167*, 99–115. https://doi.org/10.1016/j.renene.2020.11.050

Marchi, M., Niccolucci, V., Pulselli, R. M., & Marchettini, N. (2018). Environmental policies for GHG emissions reduction and energy transition in the medieval historic centre of Siena (Italy): the role of solar energy. *Journal of Cleaner Production, 185*, 829–840. https://doi.org/10.1016/j.jclepro.2018.03.068

Marolin, M., Drvenkar, N., & Unukić, I. (2020). The potential of solar energy as a driver of regional development-challenges and opportunities. *International Journal of Energy Economics and Policy, 10*(6), 411. https://doi.org/10.32479/ijeep.10068

Noorollahi, Y., Khatibi, A., & Eslami, S. (2021). Replacing natural gas with solar and wind energy to supply the thermal demand of buildings in Iran: A simulation approach. *Sustainable Energy Technologies and Assessments, 44*, 101047. https://doi.org/10.1016/j.seta.2021.101047

Ortega, M., del Río, P., Ruiz, P., Nijs, W., & Politis, S. (2020). Analysing the influence of trade, technology learning and policy on the employment prospects of wind and solar energy deployment: The EU case. *Renewable and Sustainable Energy Reviews, 122*, 109657. https://doi.org/10.1016/j.rser.2019.109657

Pedroni, P. (2001). Purchasing power parity tests in cointegrated panels. *Review of Economics and statistics, 83*(4), 727–731. https://doi.org/10.1162/003465301753237803

Pesaran, H. M. (2004). *General diagnostic tests for cross section dependence in panels*. Cambridge Working Papers in Economics. Paper No. 0435.

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.

Pesaran, M. H., & Yamagata, T. (2008). Testing slope homogeneity in large panels. *Journal of Econometrics, 142*(1), 50–93. https://doi.org/10.1016/j.jeconom.2007.05.010

Pesaran, M. H., & Smith, R. (1995). Estimating long-run relationships from dynamic heterogeneous panels. *Journal of Econometrics, 68*(1), 79–113. https://doi.org/10.1016/0304-4076(94)01644-F

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

Rabaia, M. K. H., Abdelkareem, M. A., Sayed, E. T., Elsaid, K., Chae, K. J., Wilberforce, T., & Olabi, A. G. (2021). Environmental impacts of solar energy systems: A review. *Science of The Total Environment, 754*, 141989. https://doi.org/10.1016/j.scitotenv.2020.141989

Robertson, B., Bekker, J., & Buckham, B. (2020). Renewable integration for remote communities: Comparative allowable cost analyses for hydro, solar and wave energy. *Applied Energy, 264*, 114677. https://doi.org/10.1016/j.apenergy.2020.114677

Salam, M. A., & Khan, S. A. (2018). Transition towards sustainable energy production–a review of the progress for solar energy in Saudi Arabia. *Energy Exploration & Exploitation, 36*(1), 3–27. https://doi.org/10.1177/0144598717737442

Shahsavari, A., & Akbari, M. (2018). Potential of solar energy in developing countries for reducing energy-related emissions. *Renewable and Sustainable Energy Reviews, 90*, 275–291. https://doi.org/10.1016/j.rser.2018.03.065

Sharif, A., Meo, M. S., Chowdhury, M. A. F., & Sohag, K. (2021). Role of solar energy in reducing ecological footprints: An empirical analysis. *Journal of Cleaner Production, 292*, 126028. https://doi.org/10.1016/j.jclepro.2021.126028

Son, S., Heo, J. Y., Kim, N. I., Jamal, A., & Lee, J. I. (2019). Reduction of CO2 emission for solar power backup by direct integration of oxy-combustion supercritical CO2 power cycle with concentrated solar power. *Energy Conversion and Management, 201*, 112161. https://doi.org/10.1016/j.enconman.2019.112161

Timilsina, G. R., Kurdgelashvili, L., & Narbel, P. A. (2012). Solar energy: Markets, economics and policies. *Renewable and Sustainable Energy Reviews, 16*(1), 449–465. https://doi.org/10.1016/j.rser.2011.08.009

Ulucak, Z. Ş., İlkay, S. Ç., Özcan, B., & Gedikli, A. (2020). Financial globalization and environmental degradation nexus: Evidence from emerging economies. *Resources Policy, 67*, 101698. https://doi.org/10.1016/j.resourpol.2020.101698

UNEP. (2015). Solar heat for industrial processes. Retrieved June 7, 2021 from https://www.solarthermalworld.org/sites/default/files/story/2015-10/14/solar_heat_for_industrital_process_technical_report._state_of_the_art_in_the_mediterranean_region.pdf

UNFCCC. (2015). Adoption of the Paris agreement. Retrieved June 7, 2021 from https://unfccc.int/resource/docs/2015/cop21/eng/l09r01.pdf.

Wei, R., Ayub, B., & Dagar, V. (2022). Environmental benefits from carbon tax in the Chinese carbon market: A roadmap to energy efficiency in the post-COVID-19 era. *Frontiers in Energy Research, 10*, 832578.

Weldekidan, H., Strezov, V., & Town, G. (2018). Review of solar energy for biofuel extraction. *Renewable and Sustainable Energy Reviews, 88*, 184–192. https://doi.org/10.1016/j.rser.2018.02.027

Westerlund, J. (2005). New simple tests for panel cointegration. *Econometric Reviews, 24*(3), 297–316.

Yashodha, Y., Habibullah, M. S., Mohamed, A., & Sidique, S. F. A. (2018). Investigating the environmental Kuznets curves through the economic globalization lens: Evidence from middle income countries. *International Journal of Economics and Management, 12*(S2), 599–617.

Zhou, S., Wang, Y., Zhou, Y., Clarke, L. E., & Edmonds, J. A. (2018). Roles of wind and solar energy in China's power sector: Implications of intermittency constraints. *Applied Energy, 213*, 22–30. https://doi.org/10.1016/j.apenergy.2018.01.025