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What is better for mitigating carbon emissions – Renewable energy or nuclear energy? A panel data analysis

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ABSTRACT

This paper investigates the determinants of carbon emissions based on energy consumption, analyzing the data of 30 countries using nuclear energy for the period 1990–2014. Renewable energy and nuclear energy consumption are adopted as determinants, and real coal price and real GDP are used as additive variables. The panel cointegration analysis and Granger causality tests are conducted to investigating the relationship among the variables. First, the panel cointegration test results suggest that long-run equilibrium relationship exists among carbon emissions, renewable energy consumption, and nuclear energy consumption. The results of the long-run cointegrating vector and Granger causality tests indicate that nuclear energy does not contribute to carbon reduction unlike renewable energy. Thus, the development and expansion of renewable, not nuclear, energy are essential to prevent global warming. Though there is a concern that rising energy prices caused by the expansion of renewable energy may impact the economy negatively, our empirical results also imply that renewable energy consumption will promote economic growth. In other words, our evidence shows that using and expanding renewable energy is both economically and ecologically beneficial.

1. Introduction

Greenhouse Gas (GHG) emissions have received considerable attention because of global warming. For example, the Intergovernmental Panel on Climate Change (IPCC) publishes a yearly report on these aspects. The United Nations Framework Convention on Climate Change (UNFCCC) also holds an annual meeting called the Conference of the Parties (COP) to discuss these topics. However, attempts to control carbon emissions have not been entirely successful. The first period of the Kyoto Protocol concluded in 2012, and thereafter, the Copenhagen Climate Change Conference (COP15) was unsuccessful because the decisions made therein had no binding force among the parties. The most recent and successful conference, COP21, was held in 2015 and drew up the Paris Agreement which has binding force. The Intended Nationally Determined Contributions (INDCs) were set by the participating nations, and the Paris Agreement was ratified on November 4, 2016.

GHGs include not only carbon dioxide (CO_2) but also gases such as methane, Nitrous oxide, CFC-12, and HCFC-22. In addition, GHGs also include numerous variation of gases above this. According to [1], CO_2 is not the main contributor to global warming in per unit terms. For example, CO_2 and methane (CH_4) are assigned the Global Warming Potential (GWP)[1] of 1 and 21, respectively. Despite this fact, CO_2 is acknowledged to be the biggest contributor to global warming because of its overwhelming quantity. CO_2 accounted for 76% of total GHG emissions as of 2010, as per [2]. In addition, according to [3], energy will play an important role in achieving INDCs, because two-thirds of all GHG emissions result from energy production and consumption. Therefore, we attempt to analyze the determinants of carbon emissions using two kinds of energy consumption variables.

Although renewable and nuclear energy are recognized as contributors of carbon emissions reduction, there has been a lot of controversy as to which is better. According to [4], renewable energy may adversely affect carbon emissions, an effect that is beneficial to the

Abbreviation: ADF, Augmented Dickey–Fuller; AMG, Augmented Mean Group; AIC, Akaike Information Criterion; ARDL, Autoregressive-Distributed Lag; COP, Conference of the parties; DOLS, Dynamic Ordinary Least Squares; FLM, ECM, Error Correction Model; ECT, Error Correction Term; EKC, Environmental Kuznets Curve, Fourier Lagrange Multiplier; FMOLS, Fully Modified Ordinary Least Squares; GDP, Gross Domestic Product; GHG, Greenhouse Gas; GMM, Generalized Method of Moment; GNI, Gross National Income; GWP, Global warming potential; IEA, International Energy Agency; IPCC, Intergovernmental Panel on Climate Change; IPS, Im-Pesaran-Shin; INDC, Intended nationally determined contribution; LLC, Levin-Lin-Chu; LLL, Larsson–Lyhagen–Löthgren; LM, Lagrange Multiplier; KPSS, Kwiatkowski–Phillips–Schmidt–Shin; SVAR, Structural Vector Auto Regression; VECM, Vector Error Correction Model; ZA, Zivot–Andrews; REG, Renewable Electricity Generation

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[1] GWP indicates the GHG emissions impact in the CO_2 equivalent form. For example, methane has 21 times higher impact on global warming than carbon dioxide in the same quantity.

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Table 1
Selected studies on the link between Renewable Energy Consumption (REC) and carbon emissions (CE).

References	Countries (Period)	Methodology	Variables	Additive variables	Results
[23]	G7 countries (1980–2005)	Pedroni cointegration FMOLS DOLS	REC CE	Real oil price	Unidirectional CE to REC (positive)
[24]	19 developed, developing countries (1984–2007)	LLL cointegration LLL long-run estimator Granger causality	REC CE	Real GDP Nuclear energy consumption	Bidirectional REC to CE (positive) CE to REC (negative)
[5]	U.S (1960–2007)	Toda–Yamamoto Granger causality	REC CE	Nuclear energy consumption Real GDP Energy Price index	Unidirectional CE to REC (positive)
[25]	India (1960–2009)	SVAR model	REC CE	Real GDP	Unidirectional REC to CE (negative)
[9]	U.S. (1949–2009)	Toda–Yamamoto Granger causality	REC CE	Real GDP Real oil price	No relationship
[26]	7 Central American countries (1980–2010)	Bai–Perron cointegration FMOLS Regime-wise Granger causality	REC CE	Real GDP Real oil price Real coal price	Bidirectional REC to CE CE to REC (the sign is unreported)
[27]	16 EU countries (1990–2008)	Panel fixed effect model	REC CE	Real GDP EKC Fossil fuel consumption	Positive relationship
[28]	10 MENA countries (1980–2009)	Pedroni, Kao cointegration FMOLS DOLS VECM	REG CE	Real GDP EKC Nonrenewable electricity generation	Unidirectional REC to CE (the sign is unreported)
[29]	BRICS countries (1971–2010)	ZA unit root ARDL FMOLS DOLS VECM	REC CE	Real GDP Trade openness	Unidirectional India, South Africa CE to REC (positive)
[30]	29 OECD countries (1980–2011)	Johansen–Fisher, Westerlund cointegration AMG Granger causality	REC CE	Nonrenewable energy consumption Population Urbanization Population density Real GDP EKC Energy intensity Share of industry (% of GDP) Share of services (% of GDP)	Unidirectional CE to REC (positive)
[31]	SAARC countries (1975–2010)	Johansen cointegration Granger causality	REC CE	Real GDP Resource depletion (% of GNI) Poverty	Unidirectional: Bangladesh, India REC to CE Bidirectional: Nepal REC to CE CE to REC (the sign is unreported)
[32]	11 South American countries (1980–2010)	Pedroni cointegration FMOLS Granger causality	REC CE	Real GDP Real oil price	Bidirectional REC to CE (negative) CE to REC (positive)
[33]	Tunisia (1980–2009)	ZA unit root ARDL VECM	REC CE	Real GDP Nonrenewable energy consumption Trade EKC	Unidirectional CE to REC (positive)
[34]	Turkey (1961–2010)	ADF KPSS unit root ARDL Granger causality	REG CE	Real GDP EKC	Unidirectional REC to CE (positive)
[10]	U.S. (1960-2007)	FLM unit root test Johansen cointegration Granger causality	REC CE	Nuclear energy consumption Real GDP Energy price index	Unidirectional REC to CE (negative)
[8]	China (1952–2012)	Johansen cointegration Granger causality	REG CE	Fossil fuel energy consumption Labor force Real GDP	No relationship
[4]	27 advanced economies (1990–2012)	Kao and Fisher cointegration FMOLS Granger causality	REC CE	Nonrenewable energy consumption Real GDP EKC Trade openness Urbanization Energy price	Unidirectional REC to CE (negative)
[35]	17 OECD countries (1977–2010)	Pedroni cointegration FMOLS DOLS	REC CE	Real GDP EKC	Negative relationship

(continued on next page)

Table 1 (*continued*)

References	Countries (Period)	Methodology	Variables	Additive variables	Results
[7]	Italy (1960-2011)	ZA unit root	REG	Nonrenewable electricity generation	No relationship
		ARDL			
		Gregory–Hansen cointegration	CE	Real GDP	
		Toda–Yamamoto causality		International trade	
[36]	23 top-ranked countries in terms of	Pedroni	REG	Real GDP	Negative relationship
	REC (1985–2011)	LM bootstrap panel cointegration		EKC	
		DOLS	CE	Nonrenewable electricity generation	
				Trade openness	
[37]	25 African countries (1980–2012)	Pedroni, Kao, Westerlund	REC	Real GDP	Negative relationship
		cointegration		EKC	
		Long-run estimator	CE	Population	
				Primary energy consumption	
[6]	25 OECD countries (1980–2010)	Pedroni cointegration	REC	Real GDP	No relationship
		FMOLS		Nonrenewable energy consumption	
		DOLS			
		Dynamic VECM	CE	International trade	
				EKC	
[38]	34 Upper middle income countries	Pedroni cointegration	REC	Energy consumption	Unidirectional
	(2001–2014)			Financial Development Index	Asia
		FMOLS	GHG		GHG to REC
		GMM		Trade openness	
		Dynamic VECM		Urbanization	(the sign is unreported)
[39]	Pakistan (1981–2015)	Johansen cointegration	REC	Agriculture value added	Bidirectional
				Electricity production from coal	REC to GHG
				source	GHG to REC
		Engle and Granger causality	GHG	Electricity production from	
		Toda-Yamamoto Granger causality		hydroelectric source	(the sign is unreported)
				Forest area	
				Vegetable area	

environment. On the other hand, [5] showed that nuclear energy can mitigate carbon emissions. However, some studies have pointed out that either one or both forms of energy do not contribute to carbon emissions reduction [6–10].

Nuclear energy is well-recognized as a low carbon emissions energy source. However, if it is proved that nuclear energy does not contribute to carbon emissions mitigation in reality, it is likely to lose its favored position because of the environmental impacts of radioactive wastes and the danger of nuclear accidents as exemplified by the Chernobyl and Fukushima incidents [11]. Fossil fuel prices have been the lowest on record of late; however, they have not impeded the expansion of renewable energy, the use of which has increased at an unprecedented rate according to [12]. Considering these facts, our study adopts both renewable and nuclear energy consumption as determinants. The detailed research questions are as follows: first, considering entire usage process, have renewable and nuclear energy consumption contributed to carbon emissions reduction? Second, in case they have, which energy source provides a higher contribution? In short, the purpose of this study is to investigate the determinants of carbon emissions, focusing on renewable and nuclear energy consumption.

In econometric analysis, more data translates into better informative power. A bigger data set, however, is preferable only if there is no outlier. For this reason, we adopt a panel framework to utilize the time series and cross-section data simultaneously. In general, panel analysis is better than using a single time series [13]. Furthermore, [14] discuss the omitted variable problem in the econometrics field. Thus, real GDP per capita and real coal price are employed as additive variables to prevent this problem.

Coal price is an important additive variable for the selected countries using nuclear energy as they are highly dependent on coal imports. Furthermore, the energy policy of countries with low coal import dependency is also influenced by the coal price since coal can be a good substitute for nuclear fuel; both types of energy satisfy the base load requirement in the power sector.

This empirical paper makes several contributions. We adopt panel data analysis to extend the scope of policy implication and utilize the extensive dataset. In addition, our empirical model provides more concise results by including coal price as an additive variable, considering substitutability and import dependency. Finally, this is the first approach to aim on discover the contributor of carbon mitigation between renewable and nuclear energy, not to aim on energy-economy nexus by targeting on nuclear generating countries.

The rest of this paper is organized as follows. Section 2 introduces the existing literature on renewable energy, nuclear energy, and carbon emissions. Section 3 explains the methodology and analysis framework. Section 4 presents the empirical results. Finally, Section 5 concludes.

2. Literature survey

As discussed above, the considerable interest in renewable energy results from the need to reduce GHG emissions. It is clear that renewable energy is cleaner than traditional energy sources (coal and petroleum) in terms of carbon emissions. Thus, renewable energy has received much attention from researchers in energy and ecological economics. Accordingly, this section reviews the various papers analyzing the environmental impacts of renewable energy consumption. These papers can be categorized into the following three types. The first comprises nexus studies [15–20], which analyze the relationship between energy sources and economic growth. The second category refers to studies on the factors affecting renewable energy [21,22]. Aspects related to policy and economic structure are considered in such analyses. The last category touches upon environmental degradation, wherein the studies analyze whether renewable energy use can mitigate carbon emissions. In addition, renewable energy consumption or electricity generation from renewable energy sources is proposed as a determinant factor of carbon emissions. Most papers fall under one or more combined categories.

Our paper on empirical analysis can be classified as belonging to the third category. Two representative theories dominate in this regard: first, renewable energy sources can mitigate carbon emissions, and second, renewable energy use can affect carbon emissions reduction adversely. Although the prior theory is more intuitive because renewable energy is cleaner than that from other energy sources (as mentioned above), it is possible that renewable energy may not contribute

Table 2
Variable units.

Variables	Units	Reference
Carbon emissions (CE)	kt per capita (metric)	[41]
Renewable energy consumption (RE)	ktoe per capita	[42]
Nuclear energy consumption (NE)	ktoe per capita	[42]
Real GDP (Y)	2005 constant US$ per capita	[42]
Coal price (CP)	US$ per metric tonne	[43]

to carbon emissions reduction. According to [10], as renewable energy use is quantitatively quite low compared to that of other energy sources, renewable energy consumption is yet to cross the threshold required to begin carbon emissions mitigation.

As carbon emissions reduction is also influenced by other environmental factors, the Environmental Kuznets Curve (EKC) hypothesis is frequently analyzed during the assessment of carbon emissions determinants. In this case, we use the renewable energy consumption variable as a control variable. Table 1 summarizes the existing literature on the relationship between carbon emissions and renewable energy consumption. Some studies also use an EKC additive variable.

Given the urgency about addressing global warming, various countries have begun conducting research on renewable energy. As the EKC hypothesis notes, various indicators of environmental degradation tend to worsen as economic growth occurs, which is particularly true of developed countries. Thus, most of the existing literature on this topic relates to the relationship between renewable energy and carbon emissions targets in developed countries [4,6,27,30,35,36].

As shown in Table 1, the existing literature uses the Gross Domestic Product (GDP) as a proxy of economic activity in each country. In addition, some papers employ population components as control variables [4,30,37]. the idea probably originating from the IPAT model, which measures the environmental impacts (I) of population (P), affluence-cum-economic activities (A), and industry structure or technology (T). Some studies have also employed the Stochastic Impacts by Regression on Population, Affluence and Technology (STIRPAT) model, which is basically the stochastic estimation of the IPAT model [40]. Other studies have considered price factors. [4,5,10] adopted the energy price index. [9,23,26,32] used real oil price. Notably, [26] considered the real coal price, which is also applied in this study.

Although [5] and [10] analyzed the same data set, their results are rather different. While the former showed that renewable energy consumption has no impact on carbon emissions, according to [10], renewable energy consumption can mitigate carbon emissions. Thus, we use energy prices in an effort to add new information to the model. Most remarkably, [24,34] showed that renewable energy consumption accelerates, rather than mitigates, carbon emissions. This finding may be attributed to the inclusion of carbon emissions resulting from the construction and production stages of renewable energy facilities, in addition to the fact that the countries analyzed in these studies have yet to cross the threshold required to begin carbon emissions mitigation.

In effect, our paper extends the studies of [5,10]. We adopt a panel framework and study the relationship between renewable energy consumption and carbon emissions, and nuclear energy consumption and carbon emissions, controlling the economic output and coal price for each country. Although this study focuses on the above-mentioned energy sources and carbon emissions, it would be very difficult to draw policy implications for specific countries unless their respective local characteristics are reflected suitably. As this is difficult to accomplish given the lack of specific data, we do not consider local (country-level) properties by using widespread data. Notably, we adopt the coal price to discern more realistic behavior between variables. Our empirical study proceeds as follows. First, we recognize the trend components of each variable to prevent spurious regression. Thereafter, we conduct the cointegration, long-run estimator, and Granger causality analyses.

3. Data, model specification, and method

3.1. Data

The literature review shows that country selection is an important issue in panel analysis. This may not only affect the results of the analysis, but also lead to the possibility of country selection bias. Thus, we need to be careful while selecting the countries for the analysis. As mentioned in Section 1, the purpose of our analysis is to determine which energy source is better at mitigating carbon emissions. Thus, we collected annual data of 30 countries using renewable and nuclear energy from 1990 to 2014. Each included country must be the one having been used both of renewable and nuclear energy under our analysis framework which insists the role of renewable and nuclear energy on carbon emission mitigation. 30 countries are most of countries that uses renewable and nuclear energy. We consider the following countries in our analysis: Argentina, Armenia, Belgium, Brazil, Bulgaria, Canada, China, the Czech Republic, Finland, France, Germany, Hungary, India, Japan, South Korea, Mexico, the Netherlands, Pakistan, Romania, the Russian Federation, the Slovak Republic, Slovenia, South Africa, Spain, Sweden, Switzerland, Chinese Taipei, Ukraine, the United Kingdom, and the United States.

Table 2 presents the variables used in this paper and their characteristics. Panel data for carbon emissions per capita (CE) in kilo tonne per capita (metric) are collected from the European Commission (EC) [41]. Data on renewable (RE) and nuclear (NE) energy consumption in ktoe per capita and GDP (Y) per capita in billion (2010 US$, using Purchase Power Parities (PPPs)) are derived from the IEA [42]. The time series data for coal price (CP) are sourced from YCharts [43].

3.2. Model specification

Most papers studying the determinants of carbon emissions adopted the linear model given in the following equation [5,9,10,23,26,32].

$$CE = f\,(RE,\ NE,\ Y,\ CP) \tag{1}$$

where CE, RE, NE, Y, and CP indicate carbon emissions, renewable energy consumption, nuclear energy consumption, economic growth, and coal price, respectively. The estimation model is presented below

$$CE_{it} = \beta_0 + \beta_1 RE_{it} + \beta_2 NE_{it} + \beta_3 Y_{it} + \beta_4 CP_{it} + \varepsilon_{it} \tag{2}$$

where i and t represent each cross section (30 nuclear energy-consuming countries) and the time series (1990–2014), respectively. Each β indicates the slope coefficient of the corresponding variable. This means that assuming that the other variables remain fixed, a one-unit increase in one explanatory variable increases (or decreases) carbon emissions by β units. ε_{it} denotes the estimation residual.

3.3. Panel unit root test

We adopt the three unit root tests proposed by [44–46] to recognize the stochastic trend component in each variable. The Levin, Lin, and Chu (LLC) unit root test uses the following regression form:

$$\varDelta y_{it} = \delta y_{it-1} + \sum_{L=1}^{P_i} \theta_{iL} \varDelta y_{it-L} + \varepsilon_{it} \tag{3}$$

where $\varDelta$ and P_i denote the first-difference operator and max-lag, respectively. [44] recommended the computation of pooled t-statistics derived from estimating the above equation for each cross-section. The Im, Pesaran, and Shin (IPS) unit root test follows a procedure similar to that of the LLC test. After estimating the above equation, they derived the average t-statistics for the Auto-Regressive (AR) coefficient. According to [45], the IPS test generally outperforms the LLC test. We use these two unit root tests to confirm the robustness of the test results. The third unit root test used in this study was derived by [46]. This model adjusts the short-run serial correlation and considers cross-sectional dependence while adopting a pre-whitening procedure and Generalized Least Squares (GLS) t-statistics. All tests use the presence of the unit root as the null hypothesis (H_0). If the result of the unit root test for the level variable does not reject the null hypothesis, which indicates non-stationarity and rejection of the first difference, we consider that this variable follows the I(1) process.

3.4. Panel cointegration

After confirming the trend component of each variable, we proceed with cointegration analysis for the variables following the I(1) process. The cointegration analysis is essential to investigate the relationship between non-stationary variables. We adopt two cointegration methodologies, that of [47,48] and [49], to recognize long-run relationship between variables.

The Pedroni cointegration test is a kind of residual-based cointegration technique based on following equation:

$$y_{it} = \alpha_i + \delta_i t + \sum_{m=1}^{M} \beta_{mi}, X_{mit} + e_{it} \tag{4}$$

where α_i, $\delta_i t$, and m denote the country-specific intercept, deterministic trend component, and number of regressors, respectively. This test utilizes seven test statistics, which are derived from the estimation residual. Four out of seven statistics are based on within-dimension statistics, and the remaining are called between-dimension statistics. However, just one cointegration test may not fully explain the real relationship between the variables. To overcome this problem, we conduct one more cointegration test, that proposed by [49]. The Kao cointegration test is also a residual-based cointegration test. It adapts the panel version of the Augmented Dickey–Fuller (ADF) test to the estimation residual. Two cointegration test adopted in this paper use null hypothesis of no cointegration.

3.5. Long-run estimator

We adopt the FMOLS (Fully Modified Ordinary Least Squares) and DOLS (Dynamic Ordinary Least Squares) estimators suggested by [50] and [51] to analyze the cointegrating vector between the cointegrated variables proved by the cointegration analysis. As these variables follow the I(1) process, the Ordinary Least Squares (OLS) estimators of the cointegrating equation must be biased by endogeneity and suffer the serial correlation problem. According to [52], the FMOLS and DOLS estimators can correct these biases.

With regard to the FMOLS and DOLS estimators, we consider the following equation:

$$y_{it} = \alpha_i + \delta_i t + \sum_{k=-K_i}^{K_i} \beta_{ik}, \Delta X_{it-k} + e_{it} \tag{5}$$

They are classified depending on how the endogeneity is treated. While the FMOLS approach adopts the demeaning process, the DOLS estimator considers the lagged and leaded values of ΔX_{it-k} together with demeaning. As suggested by [53], the FMOLS method can be less robust than the DOLS approach. Thus, we attempt to improve the significance of the results by comparing the FMOLS and DOLS estimators.

3.6. Panel Granger causality

Two methods are used to investigate Granger causality, depending on the cointegration results. While the Error Correction Model (ECM) is utilized for Granger causality estimation in the case of existing cointegration relationships, the Auto Regressive (AR) model is adopted if there is no long-run relationship. The former, which is represented by the two-step procedure proposed by [54], can assess short-run, long-run, and joint (strong) causalities. On the other hand, the latter estimates only short-run causality [55,56].

In this analysis, we adopt the former Granger causality method as the cointegration results indicate a long-run relationship between selected variables. We apply the following two-step procedure. First, we derive the residual from the cointegrating equation. Second, we use Eq. (6), called the Dynamic ECM, suggested by [57].

$$\Delta CE_{it} = \alpha_{1i} + \textstyle\sum_{k=1}^{h} \varphi_{11ik} \Delta RE_{it-k} + \sum_{k=1}^{h} \varphi_{12ik} \Delta NE_{it-k} + \sum_{k=1}^{h} \varphi_{13ik} \Delta Y_{it-k} + \sum_{k=1}^{h} \varphi_{14ik} \Delta CP_{it-k} + \lambda_{1i} ECT_{1it-1} + \varepsilon_{1it} \tag{6}$$

where α_{1i} and ECT_{it-1} indicate heterogeneity and the Error Correction Term (ECT), respectively. k represents lag length. As mentioned above, the ECT is derived from the cointegrating equation. For short-run causality, the Wald statistics of φ_{1ik}, φ_{2ik}, and φ_{3ik} denote the short-run causality from renewable energy consumption, nuclear energy consumption, and economic growth to carbon emissions, respectively. In case of long-run causality, the t-statistic of λ_{1i} (adjustment speed) is utilized. We estimate the above equation using the Generalized Method of Moments (GMM) estimator proposed by [58], as it can handle serial correlation and endogeneity. Statistical significance as well as the signs of the coefficients are important in our analysis because the latter play a direct role in policy implications concerning the energy mix.

Table 3
Unit root test results.

Variables	Method	Intercept only		Intercept and trend	
		Level statistic (P-value)	1st difference statistic (P-value)	Level statistic (P-value)	1st difference statistic (P-value)
Carbon emissions (CE)	LLC	1.5125 (0.9348)	− 14.1620 (0.0000)^c	− 2.7268 (0.0032)^c	− 11.4133 (0.0000)^c
	IPS	1.6063 (0.9459)	− 16.1963 (0.0000)^c	− 2.0401 (0.0207)^b	− 14.5037 (0.0000)^c
	Breitung	–	–	4.4778 (1.0000)	− 8.5096 (0.0000)^c
Renewable energy consumption (RE)	LLC	6.9068 (1.0000)	− 12.5620 (0.0000)^c	1.2877 (0.9011)	− 13.7747 (0.0000)^c
	IPS	7.0819 (1.0000)	− 13.7588 (0.0000)^c	3.7800 (0.9999)	− 14.4363 (0.0000)^c
	Breitung	–	–	8.3214 (1.0000)	1.1517 (0.8753)
Nuclear energy consumption (NE)	LLC	− 0.2627 (0.3964)	− 17.1232 (0.0000)^c	− 0.8207 (0.2059)	− 14.4898 (0.0000)^c
	IPS	0.4432 (0.6712)	− 16.3916 (0.0000)^c	− 0.4701 (0.3192)	− 16.1485 (0.0000)^c
	Breitung	–	–	1.4517 (0.9267)	− 6.3683 (0.0000)^c
Real GDP per capita (Y)	LLC	3.3849 (0.9996)	− 10.1807 (0.0000)^c	− 1.6754 (0.0469)^b	− 10.5531 (0.0000)^c
	IPS	6.8476 (1.0000)	− 11.6480 (0.0000)^c	− 0.3605 (0.3592)	− 9.1897 (0.0000)^c
	Breitung	–	–	1.9339 (0.9734)	− 6.2535 (0.0000)^c
Coal price (CP)	ADF	− 1.5009 (0.5114)	− 6.8886 (0.0000)^c	− 2.4665 (0.3384)	− 0.8647 (0.9396)

Note: b and c denote rejection of the null hypothesis at the 5% and 1% significance level, respectively.

Table 4
Pedroni cointegration test results.

Test statistics	Statistic (P-value)	Weighted Statistic (P-value)
H_1: common AR coefficients (within-dimension)		
Panel υ-statistic	− 0.0081 (0.5032)	0.1222 (0.4514)
Panel rho-statistic	− 0.3038 (0.3806)	0.7586 (0.7760)
Panel PP-statistic	− 6.3099 (0.0000)^c	− 3.3153 (0.0005)^c
Panel ADF-statistic	− 3.4931 (0.0002)^c	− 2.2033 (0.0138)^b
H_1: individual AR coefficients (between-dimension)		
Group rho-statistic	2.5537 (0.9947)	
Group PP-statistic	− 3.6179 (0.0001)^c	
Group ADF-statistic	− 3.2258 (0.0006)^c	

Note: b and c denote rejection of the null hypothesis at the 5% and 1% significance level, respectively.

4. Empirical results

4.1. Unit root test results

We utilize the following three panel unit root tests to recognize the stochastic trend components: LLC, IPS, and Breitung. Table 3 summarizes the unit root test results. The lag selection considers the Akaike Information Criterion (AIC). As shown in Table 3, most level series cannot reject the null hypothesis of no unit root. On the other hand, the first difference series does not have a unit root. Accordingly, we can say that all the variables follow the I(1) process. Now, considering these results, we proceed with the cointegration analysis

4.2. Long-run specification

As mentioned above, we adopted the cointegration analysis proposed by [47,48] and [49]. The results are presented in Tables 4 and 5. We select the lag length based on the AIC and assume deterministic intercepts for all tests.

Four out of seven test statistics of the Pedroni cointegration test reject the null hypothesis of no cointegration. The Kao cointegration test statistic also rejects the same null hypothesis. Briefly said, the results of these two cointegration tests indicate that the variables are cointegrated. That is, the variables selected for our analysis have long-run equilibrium relationships. We estimate the long-run vector in the next step. Table 6 shows the long-run vector estimators.

All the estimated coefficients are statistically significant at the 1% significance level, except for nuclear energy consumption and coal price in the DOLS estimation. The signs of the coefficients are consistent. Thus, while economic growth has a positive relationship with carbon emissions, renewable energy consumption and coal price adversely affect carbon emissions in the long run. Therefore, renewable energy usage can mitigate carbon emissions in the long run. However, it is uncertain whether nuclear energy contributes to carbon emissions reduction. The results of the FMOLS and DOLS methods indicate that a one-unit increase in renewable energy consumption can mitigate about six units and four units of carbon emissions, respectively. Regarding the economic output, carbon emissions rise by about 116 or 144 units when economic growth increases by one unit. According to the [59], carbon emissions have been associated with global economic growth for 40 years. That is, economic activity essentially involves carbon emissions

Table 5
Kao cointegration test results.

Test statistics	Statistic (P-value)
ADF	2.0570 (0.0198)^b

Note: b denotes rejection of the null hypothesis at the 5% significance level.

Table 6
Long-run estimators.

Variables	FMOLS Coefficient (P-value)	DOLS Coefficient (P-value)
Renewable energy consumption (RE)	− 5.9199 (0.0000)^c	− 3.9929 (0.0000)^c
Nuclear energy consumption (NE)	− 0.1919 (0.3311)	0.4283 (0.5437)
Real GDP per capita (Y)	143.8743 (0.0000)^c	116.0050 (0.0000)^c
Coal price (CP)	− 10.9846 (0.0000)^c	− 8.3244 (0.0503)^a
R-squared	0.9590	0.9890

Note: b and c denote rejection of the null hypothesis at the 5% and 1% significance level, respectively.

production. Thus, the sign of the coefficients is intuitive enough to be understood easily. The coal price coefficient is estimated to have a negative relationship with carbon emissions. Thus, coal price may adversely affect coal consumption, which is in line with the market rule. As coal consumption is a major source of carbon emissions, the increase in coal price can cause coal consumption to fall, leading to carbon emissions mitigation.

4.3. Granger causality results

We construct the dynamic Vector Error Correction Model (VECM) using the ECT derived from the cointegrating equation. Table 7 displays the estimation results of the GMM estimator. The first four columns, fifth column, and the remaining columns represent short-run causality, long-run causality, and joint (strong) causality, respectively. The figures indicate the Wald statistics of the corresponding variable coefficient. For the ECT, we present the t-statistics to show whether the VECM converges or not.

As the first row of Table 7 shows, the results pertaining to carbon emissions causality indicate that there is mutual short-run, long-run, and strong causality from each explanatory variable to the dependent variable, except for the coal price in the short run. All the coefficients are statistically significant at the 1% level. The sign of the coefficient of each variable is the same as that of the corresponding long-run vector estimator. This means that the impact of each explanatory variable on carbon emissions is the same for the short-run, long-run, and equilibrium states. In the case of the ECT, the coefficient is statistically significant at the 1% level and has a gradual speed of adjustment (about −0.35).

In short, the Granger causality test results provide evidence of short-run bidirectional causality between renewable energy consumption and carbon emissions, and between nuclear energy consumption and carbon emissions. For the long run, there is no causality with regard to renewable energy consumption, but we see evidence of causality between carbon emissions and nuclear energy consumption.

5. Conclusions

The goal of our study is to analyze which of the two energy forms, renewable or nuclear, can mitigate carbon emissions to a greater extent. We used the data of 30 countries using both nuclear and renewable energy. To achieve this, we formulated an equation consisting of carbon emissions as well as renewable energy and nuclear energy consumption, to estimate the impact of each energy source. Our empirical results can be summarized as follows. First, the cointegration test results indicate a long-run equilibrium relationship between the variables. Second, with regard to the long-run cointegrating vector, unlike renewable energy consumption, nuclear energy consumption is not certain to mitigate carbon emissions. Third, there is mutual bidirectional causality between renewable energy and carbon emissions and nuclear energy consumption and carbon emissions in the short run. Lastly, long-run causality is detected between carbon emissions and nuclear energy

Table 7
Granger causality results.

Dependent variable	Source of causation (independent variables)										
	Short run					Long run	Joint (strong) causality				
	ΔCE	ΔRE	ΔNE	ΔY	ΔCP	ECT	ECT, ΔCE	ECT, ΔRE	ECT, ΔNE	ECT, ΔY	ECT, ΔCP
ΔCE	–	34.56^{c}	4.79^{c}	52.70^{c}	2.28	− 9.86^{c}	–	53.63^{c}	33.84^{c}	94.17^{c}	55.86^{c}
ΔRE	191.35^{c}	–	27.53^{c}	0.51	23.63^{c}	− 1.33	129.72^{c}	–	20.31^{c}	0.95	20.60^{c}
ΔNE	75.96^{c}	143.78^{c}	–	59.35^{c}	5.15^{c}	− 20.84^{c}	225.00^{c}	191.01^{c}	–	175.15^{c}	382.48^{c}
ΔY	15.61^{c}	2.36^{a}	5.30^{c}	–	9.24^{c}	4.10	14.72	11.52	8.76	–	13.70
ΔCP	4.84^{c}	6.13^{c}	2.52^{a}	18.34^{c}	–	0.61	4.29	8.40	3.79	13.18	–

Note: *b* and *c* denote rejection of the null hypothesis at the 5% and 1% significance level, respectively.

consumption.

Our consideration of coal price derived results different from those of earlier works. While most of the existing literature adopted either the energy price index or did not use a price variable, we used the coal price as an additive variable, considering the relationship between the two energy sources. As mentioned in Section 1, coal acts as a substitute for nuclear energy in electricity generation since both energy sources fulfill the base load. In short, our empirical results are more consistent than those in the existing literature.

Our long-run cointegrating vector and Granger causality test results for the 30 countries using both forms of energy indicate that policies encouraging renewable energy use have contributed to carbon emissions mitigation. Even though nuclear energy consumption has bidirectional causality with carbon emissions in the short run, the sign of the coefficient is positive. This may be caused by the construction of nuclear power plants in the short term. Given that the result of the cointegrating vector of nuclear energy is also inconsistent, we can say that the contribution of nuclear energy to carbon emissions reduction is unclear.

The accelerated development of renewable energy will increase energy prices. However, as mentioned in Section 2, much of the existing literature, including our results, points to a relationship between renewable energy consumption and economic growth, which means that renewable energy use can promote economic growth. In short, it appears that the increased uptake of renewable energy is essential from both the economic and the ecological aspects.

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