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Analyzing the Impact of Nuclear Power on CO_2 Emissions

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Received: 1 July 2017; Accepted: 10 August 2017; Published: 12 August 2017

Abstract: This study investigates the relationship between the nuclear power proportion and CO_2 emissions per capita using the panel dynamic ordinary least square method. The panel datasets consist of 18 countries covering 95% of the global nuclear reactors. The results indicate that a long-term 1% increase in nuclear power led to a 0.26–0.32% decrease in CO_2 emissions per capita. Additionally, in France, Germany, and Switzerland they demonstrate the existence of the environmental Kuznets curve—an inverted U-shaped relationship between environmental pollution and income per capita.

Keywords: CO_2 emissions; nuclear power; environmental Kuznets curve; panel dynamic ordinary least squares

1. Introduction

Nuclear power is an important means of reducing greenhouse gas emissions. The International Energy Agency (IEA) [1] proposes reduction measures such as demand management, energy efficiency improvement, carbon capture and storage, new and renewable energy, and nuclear power to hold the increase in global temperature below 2 °C above the pre-industrial level. It predicts that nuclear power use will increase to account for 15% of all annual greenhouse gas reductions by 2050. The Intergovernmental Panel on Climate Change [2] also highlights the benefit of nuclear power over other energy sources in terms of greenhouse gas emissions. It estimates the CO_2 emissions coefficient for nuclear power over its life cycle as 12 tCO_2/GWh, which represents a 40-fold reduction from the emissions coefficient of liquefied natural gas at 490 tCO_2/GWh and a 68-fold reduction over that of coal at 820 tCO_2/GWh. The International Atomic Energy Agency (IAEA) [3] emphasizes the role of nuclear power in achieving sustainable development and mitigating CO_2 emissions in developing countries. IAEA [4] further presents the contribution of nuclear power to CO_2 mitigation by showing that over the period 1970–2013, hydropower avoided 87 Gt CO_2, nuclear power avoided 66 Gt CO_2, and other renewables avoided 10 Gt CO_2, respectively.

Recently, several studies attempted to investigate the relationship between nuclear power and CO_2 emissions in the context of the environmental Kuznets curve (EKC) framework [5–7]. The original EKC hypothesis presumes an inverse U-shaped relationship between environmental pollution and income per capita (we refer readers to Kaika and Zervas [8] for an extensive overview of this topic). According to this hypothesis, the deterioration of the environment increases with income per capita during the initial stages of economic growth, but decreases with income per capita after arriving at a certain turning point. Research shows that the EKC hypothesis is explained through three channels: scale effect, composition effect, and technique effect [9]. Holding other effects constant, the scale effect is that emissions tend to rise proportionally as the scale of economic activity increases; the composition effect is that emissions can fall if an economy transits toward producing a set of goods that are cleaner and less polluting; the technique effect is that emissions can fall as cleaner techniques substitute for dirtier ones in the production of goods. Understandably, the EKC hypothesis can be accounted for with some mixture of scale, composition, and technique effects. The empirical evidence for this hypothesis is mixed at best, according to the estimation method, the data time periods and types, and the characteristics of countries [10].

There are mainly three research groups to examine the relationship between economic growth and environmental quality (we refer the reader to References [8,11–14] for a comprehensive survey). The first group investigates the relationship between economic development and environmental degradation in the framework of the EKC hypothesis. Recent studies include References [11,15–17]. The second group examines the relationship between economic development and energy consumption and tests the causal relationship between these variables. Payne [18] delivers an extensive review on this issue. The third group combines the two research groups by investigating the relationship among environmental degradation, economic growth, and energy consumption. Many recent studies focus on the impact of renewable energy on CO_2 emissions in the EKC framework [12,13,19–23].

Consistent with the third research group focusing on nuclear power, Iwata et al. [5] estimated the EKC with the additional variable of nuclear power, and provided statistical evidence of the important role of nuclear power in reducing CO_2 emissions. Similarly, Iwata et al. [6] investigated the EKC for CO_2 emissions in 11 OECD countries by considering the role of nuclear power. These studies employ the autoregressive distributed lag (ARDL) model by Pesaran et al. [24] to consider the co-integration relation among their set of variables and analyze the role of nuclear power in reducing CO_2 emissions on an individual country basis. The ARDL has econometric advantages, in that it can be used with a mixture of I(0) and I(1) variables, and estimate the short-run and long-run parameters simultaneously (a time-series is said to be I(d) variable if its d'th difference is stationary), as a single co-integration approach. Iwata et al. [7] also analyzed the impacts of nuclear energy on CO_2 emissions using the pooled mean group (PMG) estimation method by Pesaran et al. [25]. Regarding nonstationary heterogeneous panels, the PMG approach allows the short-run coefficients to be heterogeneous but constrains the long-run coefficients to be identical across groups.

Although these studies convincingly argue the relationship between nuclear power and CO_2 emissions, there are some limitations, in that the ARDL approach is based on individual countries and the PMG approach imposes that the long-run coefficient be homogenous across groups with nonstationary heterogeneous panels. To overcome such limitations, this study uses the panel dynamic ordinary least squares (PDOLS) method by Pedroni [26], which has the advantage of combining cross-sectional and time-series data to secure sufficient data points, and allows for the heterogeneity of coefficients across groups with nonstationary heterogeneous panels. This study aims to examine the relationship between the nuclear power proportion (the ratio of electricity produced from nuclear power to total electricity) and CO_2 emissions per capita using the PDOLS method with nonstationary heterogeneous panels. The panel datasets in this study consist of 18 countries with more than four nuclear power plants each as of 2016, which operate 420 reactors, or approximately 95% of the 444 reactors worldwide. The results indicate that a long-term 1% increase in the nuclear power proportion leads to decreases of 0.26–0.32% in CO_2 emissions per capita.

The main contribution of this study is, with the PDOLS approach, it provides statistical results as to how much nuclear power reduces CO_2 emissions per capita for both the group mean and individual countries currently operating most of the nuclear reactors in the world. Additionally, this study compares nuclear power with renewable energy in terms of mitigating CO_2 emissions.

The remainder of this paper is structured as follows. Section 2 briefly reviews the econometric methodology used to analyze the relationship between nuclear power and CO_2 emissions. Section 3 features the data utilized. The results are presented in Section 4. Section 5 concludes the study.

2. Estimation Methodology

A three-stage procedure with nonstationary heterogeneous panels to analyze the relationship between the nuclear power proportion and CO_2 emissions per capita is employed in this study. First, a panel unit root test suggested by Im, Pesaran, and Shin (IPS) [27] is conducted to check whether time-series variables in the datasets are stationary. Second, if the variables are not stationary, a panel co-integration test suggested by Pedroni [28] is used to assess whether the variables are characterized by a co-integration relation. Finally, if there is a co-integration relation among the variables, the econometric model in this study is estimated by using the PDOLS method.

2.1. Panel Unit Root Test

Prior to the PDOLS analysis, as a first step, the IPS test as a panel unit root test is conducted to check for the stationarity of time-series variables. Though the panel datasets in this study are unbalanced, the IPS test is known to be applicable for unbalanced panels. The following augmented Dickey–Fuller (ADF) regression model is estimated for the IPS test:

$$\Delta y_{i,t} = \alpha_i + \beta_i y_{i,t-1} + \sum_{j=1}^{p} \rho_{i,j} \Delta y_{i,t-1} + \epsilon_{i,t}, \quad (1)$$

where i (=1, 2, ..., N) is the number of cross-sectional data, t (=1, 2, ..., T) is the number of time-series data, Δ represents the first difference of each variable, $y_{i,\,t}$ is each variable under consideration in the econometric model, α_i is the individual fixed effect, p is the number of lags to remove serially correlated errors, and $\epsilon_{i,t}$ is the error term. The null hypothesis of the IPS test is that all panels contain a unit root ($H_0 : \beta_i = 0$ for all i). The alternative hypothesis is that the fraction of panels is stationary ($H_a : \beta_i < 0$ for at least one i). The IPS test relaxes the assumption that all panels have a common autoregressive parameter β. Instead, it allows for the heterogeneity of β indexed by i. The IPS test conducts individual panel unit root tests for N number of cross-section units, and then the IPS t-bar statistic $\bar{t}$ is based on the average value of individual ADF statistics as follows:

$$\bar{t} = \frac{1}{N} \sum_{i=1}^{N} t_{iT}, \quad (2)$$

where t_{iT} is the value of the individual ADF statistic. IPS [27] shows that if the $\bar{t}$ statistic is properly standardized, it is asymptotically standard normally distributed as follows:

$$t_{IPS} = \frac{\sqrt{N}\left(\bar{t} - \frac{1}{N}\sum_{i=1}^{N} E[t_{iT}|\beta_i = 0]\right)}{\sqrt{\frac{1}{N}\sum_{i=1}^{N} Var[t_{iT}|\beta_i = 0]}} \Rightarrow N(0,\ 1) \text{ as } T\ \rightarrow\ \infty \text{ and } N\ \rightarrow\ \infty, \quad (3)$$

2.2. Panel Co-Integration Test

Once each of the variables contains a panel unit root and is thus integrated of order one, I(1), as a second step, there needs to be a check for the relationship of co-integration among variables. Pedroni [28] proposes a method to check for a co-integration relationship among variables when multiple independent variables exist. The following regression model is estimated for Pedroni's [28] panel co-integration test:

$$y_{i,t} = \alpha_i + \beta_{1i} x_{1i,t} + \beta_{2i} x_{2i,t} + \cdots + \beta_{mi} x_{mi,t} + e_{i,t}, \quad (4)$$

where i (=1, 2, ..., N) is the number of cross-sectional data, t (=1, 2, ..., T) is the number of time-series data, m (=1, 2, ..., M) is the number of independent variables, $y_{i,t}$ is the dependent variable, $x_{mi,t}$ is the independent variable, and $e_{i,t}$ is the error term. The individual fixed effect α_i and the slope coefficient β_{mi} are permitted to vary across cross-sections. The estimated residuals from the above equation are structured as follows:

$$\hat{e}_{i,t} = \hat{\gamma}_i \hat{e}_{i,t-1} + \hat{\mu}_{i,t}, \quad (5)$$

Regarding the estimated residuals as above, Pedroni [28] proposes seven test statistics to check for co-integration relationships in nonstationary panels. These seven statistics can be divided into two types. The first type is the "panel" statistics, including Panel v statistic, Panel rho statistic, Panel t statistic, Panel ADF statistic, based on pooling along the within-dimension. The second type is the "group-mean" statistics, including Group rho statistic, Group t statistic, Group ADF statistic, based on pooling the between-dimension. The seven test statistics are described in detail in Appendix A. The null hypothesis of no co-integration for both types is $H_0 : \gamma_i = 1$ for all i; however, their alternative hypotheses are different. The alternative hypothesis for the "panel" statistics is $H_a : \gamma_i = \gamma < 1$ for all i, whereas the alternative hypothesis for the "group-mean" statistics is $H_a : \gamma_i < 1$ for all i. Pedroni [28] derives asymptotic distribution and critical values for the seven test statistics via Monte Carlo simulation. The asymptotic distributions for each of the seven test statistics can be expressed as follows:

$$\frac{\chi_{N,T} - \mu\sqrt{N}}{\sqrt{\upsilon}} \Rightarrow N(0,\ 1) \text{ as } T \rightarrow \infty \text{ and } N \rightarrow \infty, \tag{6}$$

where $\chi_{N,T}$ is the properly standardized form for each of the seven test statistics, and μ and υ are the mean and variance adjustment terms, respectively. While Panel v statistic for a one-sided test diverges to positive infinity as the other test statistics diverge to negative infinity, the null hypothesis of no co-integration is rejected. Baltagi [29] states the intuition of rejection of the null hypothesis as follows: "Rejection of the null hypothesis means that enough of individual cross-sections have statistics 'far away' from the means predicted by theory were they to be generated under the null".

2.3. Panel Dynamic Ordinary Least Squares

After determining the relationship of co-integration among variables, the econometric model can be estimated by using the PDOLS method developed by Pedroni [26]. The PDOLS estimator accounts for endogeneity in the regressors and serial correlation in the errors by including leads and lags of differenced endogenous variables as instruments. The PDOLS model in this study is as follows:

$$\begin{aligned} \ln CO_{2i,t} = \beta_{0,i} + \beta_{1,i}\ln GDP_{i,t} + \beta_{2,i}(\ln GDP)^2_{i,t} + \beta_{3,i}\ln Nuc_{i,t} + \textstyle\sum_{k=-k_i}^{k_i} \alpha_{i,k}\Delta \ln GDP_{i,t-k} + \\ \textstyle\sum_{k=-k_i}^{k_i} \lambda_{i,k}\Delta(\ln GDP)^2_{i,t-k} + \sum_{k=-k_i}^{k_i} \theta_{i,k}\Delta \ln Nuc_{i,t-k} + \epsilon_{i,t}, \end{aligned} \tag{7}$$

where CO_2 is the CO_2 emissions per capita, GDP is the gross domestic product per capita, Nuc is the electricity production from nuclear power (the ratio of electricity produced from nuclear power to total electricity), $-K_i$ and K_i refer to leads and lags of differenced endogenous variables, and $\epsilon_{i,t}$ is the error term. Pedroni's [26] PDOLS model allows for the heterogeneity of the β coefficient between dimensions. This flexibility is an important advantage in the presence of heterogeneity of the co-integrating vectors. The group-mean PDOLS value indicates the average value of the individual β coefficient between dimensions, and can be described as follows:

$$\hat{\beta}_{GD} = \frac{1}{N}\sum_{i=1}^{N}\hat{\beta}_{D,i}, \tag{8}$$

where $\hat{\beta}_{D,i}$ indicates the DOLS of the individual i.

2.4. The EKC Hypothesis for the Model

One representative variable that influences CO_2 emissions is the GDP variable. The EKC hypothesis assumes increasing CO_2 emissions during the early period of economic growth, followed by decreasing CO_2 emissions when the economy is at a certain level of development. In other words, the EKC hypothesis assumes an inverted U-shaped relationship between the CO_2 emissions and GDP. Validating the EKC hypothesis is a widely-studied topic, and represents a leading research area for the relationship between CO_2 emissions and GDP. This study avoids the construction of an ad-hoc model in analyzing changes in CO_2 emissions regarding changes in nuclear power proportion in this respect, but adds nuclear power proportion as an additional variable to the well-known EKC model. A similar attempt is utilized by Iwata et al. [5–7]. It is expected that β_1 has a positive value while β_2 has a negative one if the EKC hypothesis is valid for (7). Moreover, if there is an inverse relationship between nuclear power proportion and CO_2 emissions per capita, it is expected that β_3 has a negative value.

3. Data

Countries with more than four operating nuclear reactors as of October 2016 were selected as the targets of this study. The total number of operable nuclear reactors worldwide is 444, with 100 reactors operated by the United States—the country most active in nuclear energy at the time of writing. The U.S. is followed by France, with 58 reactors, Japan, with 43 reactors, China, with 36 reactors, Russia, with 36 reactors, and Korea, with 25 reactors. Including these countries, the countries with more than four nuclear reactors in operation total 19. Slovakia currently operates four nuclear reactors, but is excluded from the analysis due to difficulties in accessing data. Table 1 provides an overview.

Table 1. Nuclear power by country.

	Country	Number of Reactors	Total Net Electrical Capacity (MW)
1	United States of America	100	100,350
2	France	58	63,130
3	Japan	43	40,290
4	China	36	31,402
5	Russia	36	26,557
6	Korea, Republic of	25	23,133
7	India	22	6225
8	Canada	19	13,524
9	Ukraine	15	13,107
10	United Kingdom	15	8918
11	Sweden	10	9651
12	Germany	8	10,799
13	Belgium	7	5913
14	Spain	7	7121
15	Czech Republic	6	3930
16	Switzerland	5	3333
17	Finland	4	2752
18	Hungary	4	1889
19	Slovakia	4	1814
20	Argentina	3	1632
21	Pakistan	3	690
22	Brazil	2	1884
23	Bulgaria	2	1926
24	Mexico	2	1440
25	Romania	2	1300
26	South Africa	2	1860
27	Armenia	1	375
28	Iran, Islamic Republic of	1	915
29	The Netherlands	1	482
30	Slovenia	1	688
	Total	444	387,030

Source: IAEA PRIS database [30].

CO_2 emissions per capita, GDP per capita, nuclear power proportion, and renewable energy proportion during 1970–2015 were collected from Enerdata [31] for each country. CO_2 emissions are measured as metric ton per capita, GDP is measured in current U.S. dollars, nuclear power proportion is the ratio of electricity produced from nuclear power to total electricity, and renewable energy proportion is the ratio of electricity produced from renewable energy to total electricity. Renewable energies include hydro, wind, and solar energy.

Figure 1 shows the trends of CO_2 emissions per capita for the 18 analyzed countries during the years from 1970 to 2015. The U.S. has the highest CO_2 emissions per capita, followed by Canada, Korea, China, the Czech Republic, and Germany, in 2015. The trends in CO_2 emissions per capita can be divided by countries experiencing an increase or decrease. The U.S. shows a decreasing trend, while Korea exhibits an increasing trend, for example.

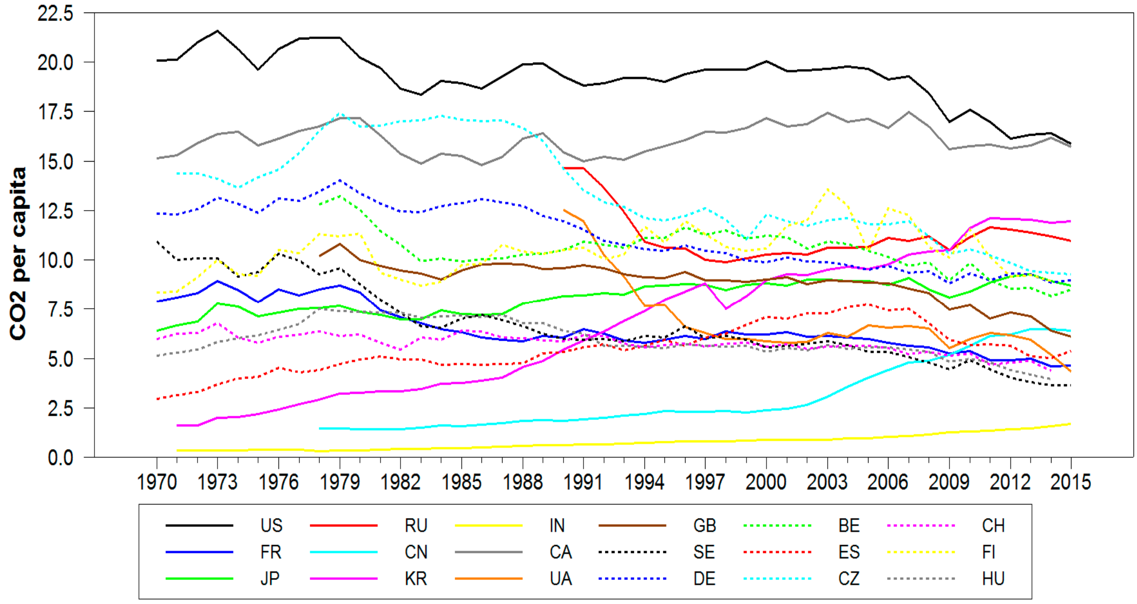

Figure 1. Trends in CO_2 emissions per capita. Top to bottom, left to right: U.S., France, Japan, Russia, China, Korea, India, Canada, Ukraine, United Kingdom, Sweden, Germany, Belgium, Spain, Czech Republic, Switzerland, Finland, and Hungary.

Figure 2 shows the nuclear power proportion of the 18 countries throughout 1970–2015. France has the highest nuclear power proportion, with more than 75% of its electricity generated by nuclear plants as of 2015, followed by Slovakia, Ukraine, Hungary, Switzerland, and Belgium. Regarding Japan, almost 25% of total electricity was produced from nuclear power in 2011 prior to the Fukushima nuclear power plant incident; however, the reactors have since ceased operating, with almost 0% of electricity from nuclear as of 2015.

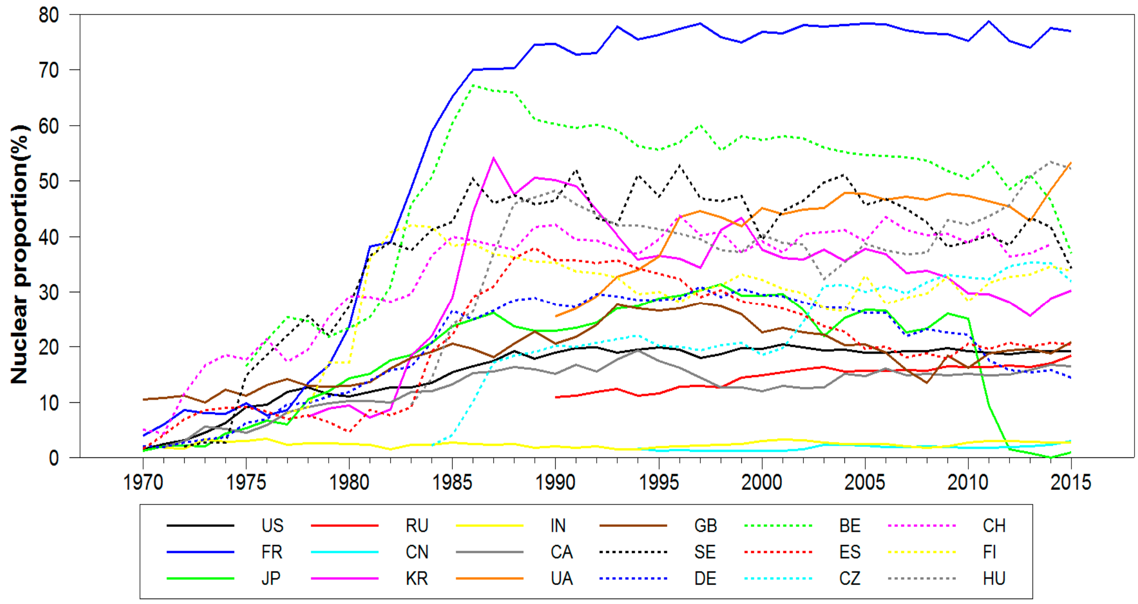

Figure 2. Trends in nuclear power proportion. Top to bottom, left to right: U.S., France, Japan, Russia, China, Korea, India, Canada, Ukraine, United Kingdom, Sweden, Germany, Belgium, Spain, Czech Republic, Switzerland, Finland, and Hungary.

4. Results

4.1. Estimation Results

Table 2 indicates the results of the IPS test, which is divided into two cases, where the time-series variable is level or the first difference. When the time-series variable is level, all variables were non-stationary, except for the nuclear power proportion variable in the case of the first difference; however, all variables were found to be stationary. Therefore, the panel unit root test indicates that each variable is integrated of order one, I(1), except for the nuclear power proportion variable.

Table 2. Im, Pesaran, and Shin (IPS) panel unit root test.

Variables	CO_2	GDP	GDP^2	Nuclear	Renewable
Level	−0.54	1.26	−0.92	−8.58 ***	−0.83
First difference	−22.02 ***	−10.65 ***	−10.71 ***	-	−24.46 ***

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3 shows the results of the panel co-integration test proposed by Pedroni [28]. While the panel statistic ν nears positive infinity, or as the other statistics approach negative infinity, the null hypothesis of no co-integration relationship is rejected [29]. Table 3 shows there is a statistically significant co-integration relationship among CO_2 emissions, GDP, and renewable energy proportion.

Table 3. Pedroni panel co-integration test.

Within-Dimension	Statistic Value	Between-Dimension	Statistic Value
Panel v	5.202 ***	Group rho	–1.824 **
Panel rho	–2.862 ***	Group t	–1.432 *
Panel t	–2.338 ***	Group ADF	–1.047
Panel ADF	–1.443 *		

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. ADF: augmented Dickey–Fuller statistic.

Given the presence of a co-integration relationship among the variables, the PDOLS model for nonstationary heterogeneous panels was estimated to analyze changes in CO_2 emissions regarding changes in nuclear power proportions. Table 4 shows the results of the PDOLS estimates. The group-mean PDOLS estimates indicate that all coefficients are statistically significant. The results for the validation of the EKC hypothesis indicate that the hypothesis is valid within the analysis period, with values of $\beta_1 = 0.3133$, and $\beta_2 = -0.02769$. Considering that most countries operating nuclear reactors are advanced countries, these results are to be expected. β_3 was found to be -0.3233, indicating an inverse relationship between the nuclear power proportion and CO_2 emissions per capita. This indicates that a long-term increase of 1% in the nuclear power proportion leads to a 0.32% decrease in CO_2 emissions per capita during the analysis period.

PDOLS analysis also shows the DOLS values for individual countries. First, the countries with conditions that validated the EKC hypothesis were France, Russia, India, Sweden, Germany, and Switzerland. Second, countries with inverse relationships between nuclear power proportion and CO_2 emissions per capita were the U.S., France, Japan, China, Korea, Canada, Ukraine, the United Kingdom, Germany, and Switzerland. Finally, the only three countries of the 18 analyzed meeting both conditions of valid EKC hypothesis and inverse relationships between nuclear power proportion and CO_2 emissions per capita were France, Germany, and Switzerland.

Table 4. Panel dynamic ordinary least square results (case 1).

	Country	GDP	GDP^2	Nuclear
1	United States	0.0074 (0.0379)	−0.0384 (−0.8028)	–0.7021 *** (–3.4290)
2	France	0.3320 *** (5.5760)	−0.2786 *** (−7.8350)	–0.2297 *** (–6.4320)
3	Japan	0.0668 (0.6562)	−0.0090 (−0.4563)	–0.1601 *** (–3.8270)
4	China	0.4017 * (1.8630)	0.1438 (1.3400)	–1.249 *** (–8.4430)
5	Russia	0.8055 *** (10.7500)	−0.0865 *** (−7.5530)	0.0972 *** (3.9850)
6	South Korea	0.8770 *** (2.8760)	0.3509 *** (3.7230)	–0.2305 ** (–1.9780)
7	India	0.3943 ** (2.2160)	−0.0910 *** (−8.4410)	0.4977 *** (4.2170)
8	Canada	0.0277 (0.1598)	0.0311 (0.9807)	–0.8216 *** (–4.8630)
9	Ukraine	0.4940 (1.2040)	−0.0371 (−0.5274)	–1.6580 *** (–2.8900)
10	United Kingdom	2.6510 *** (2.9400)	0.2664 *** (2.9160)	–1.1380 ** (–2.1810)
11	Sweden	0.7005 *** (4.9790)	−0.3292 *** (−6.3760)	–0.2848 (–1.6020)
12	Germany	0.8374 *** (10.8800)	−0.2647 *** (−13.0500)	–0.1167 *** (–2.5930)
13	Belgium	0.0913 (0.6179)	−0.4068 *** (−13.4800)	0.4972 *** (7.1700)
14	Spain	−0.6068 ** (−2.2920)	0.0227 (0.7229)	–0.0792 (–1.6170)
15	Czech Rep.	−0.9325 *** (−6.3890)	0.1904 *** (2.7760)	0.0842 * (1.8070)
16	Switzerland	0.1916 *** (2.7430)	−0.0876 *** (−3.0610)	–0.5492 *** (–2.6440)
17	Finland	0.1498 (1.4820)	−0.0945 *** (−6.1760)	0.0985 * (1.8680)
18	Hungary	−0.849 *** (−9.6590)	0.2195 *** (5.2350)	0.1261 ** (2.0610)
Panel group Number of observations: 738		0.3133 *** (7.220)	−0.0277 *** (−11.8000)	−0.3233 *** (−5.0420)

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The numbers in parentheses are t-statistics for the corresponding coefficient.

Besides the nuclear power proportion variable, the PDOLS analysis was carried out, including a renewable energy proportion variable. Table 5 summarizes the analysis results. There were no meaningful differences between the analysis results shown in Table 4 in terms of the group-mean PDOLS estimates. All coefficients were found to be statistically significant, with $\beta_1 = 0.3289$ and $\beta_2 = -0.05561$, thus satisfying the EKC hypothesis. The nuclear power proportion, β_3, is -0.2754, which is slightly lower than the previous results. The renewable energy proportion, β_4, is -0.1092, which is lower than the coefficient for nuclear power proportion; however, as expected, an inverse relationship was found between the renewable energy proportion and CO_2 emissions per capita.

Table 5. Panel dynamic ordinary least square results (case 2).

	Country	GDP	GDP^2	Nuclear	Renewable
1	United States	0.1374 (0.7001)	−0.0439 (−1.2800)	−0.5633 ** (−2.4970)	−0.2159 (−0.7575)
2	France	0.1344 (1.3010)	−0.2961 *** (−8.2850)	−0.1552 *** (−3.2080)	0.2985 ** (2.4720)
3	Japan	−0.1695 (−1.3640)	−0.0355 ** (1.9730)	−0.0164 (−0.3140)	1.232 *** (4.5000)
4	China	0.2935 (1.1630)	0.1016 (1.4460)	−1.0350 *** (−3.5640)	−0.4016 (−1.1420)
5	Russia	0.9246 *** (12.5300)	−0.0881 *** (−11.5700)	0.1964 *** (8.4440)	1.095 *** (3.8720)
6	South Korea	0.3833 *** (3.7700)	0.1336 *** (2.7170)	0.0325 (0.6884)	−0.3395 *** (−5.4760)
7	India	0.2612 * (1.7600)	−0.03074 (−0.9795)	0.2106 (1.4520)	−0.8379 * (−1.8750)
8	Canada	−0.1077 (−0.7220)	−0.0143 (−0.5613)	−0.8615 *** (−7.1650)	−0.2166 (−1.0660)
9	Ukraine	0.3214 *** (7.3180)	0.1346 *** (15.9200)	−0.7200 *** (−9.3120)	−0.7918 *** (−41.6900)
10	United Kingdom	3.6000 *** (2.6380)	−0.0663 (−0.2826)	−1.6570 *** (−3.6330)	1.2550 ** (2.0920)
11	Sweden	0.8628 *** (4.9340)	−0.2550 *** (−5.8330)	−0.4103 ** (−2.5380)	−0.0457 (−0.2195)
12	Germany	0.4603 ** (2.2050)	−0.1633 *** (−4.1320)	−0.1239 *** (−2.8390)	−0.1716 ** (−2.0880)
13	Belgium	−0.6908 *** (−3.2320)	−0.3821 *** (−14.0700)	0.8756 *** (12.8400)	−0.4876 *** (−4.7660)
14	Spain	−0.7699 *** (−3.1680)	−0.0065 (−0.2353)	−0.0929 ** (−2.4180)	−0.1371 (−0.5018)
15	Czech Rep.	0.0857 (0.9190)	0.0163 (0.6271)	0.0606 *** (4.0640)	−1.393 *** (−12.5400)
16	Switzerland	0.1523 *** (4.6470)	−0.0537 *** (−2.8960)	−0.9340 *** (−4.3080)	−0.1201 (−1.5850)
17	Finland	0.442 *** (3.6720)	−0.1076 *** (−8.0210)	0.195 *** (3.4850)	−0.4011 *** (−2.7870)
18	Hungary	−0.4002 *** (−4.5150)	0.1563 *** (7.1780)	0.0414 (1.1580)	−0.2862 *** (−8.0880)
Panel group Number of observations: 738		0.3289 *** (8.1440)	−0.0556 *** (−7.5970)	−0.2754 ** (−2.2770)	−0.1092 *** (−16.8900)

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The numbers in parentheses are t-statistics for the corresponding coefficient.

When the analysis included the renewable energy proportion variable, there were no meaningful differences in the DOLS values for each country. Compared with the results in Table 4, countries with inverse relationships between nuclear power proportion and CO_2 emissions per capita were the U.S., France, China, Canada, Ukraine, the United Kingdom, Germany, and Switzerland. These countries demonstrated robust results, but Japan and Korea are excluded from the results. When the analysis included the renewable energy proportion variable, the countries with both valid EKC hypothesis and inverse relationships between nuclear power proportion and CO_2 emissions per capita were still the three previous countries of France, Germany, and Switzerland.

4.2. One Possible Implication

James Hansen is one of the first scientists to raise concerns about global climate change, and argues that 115 new reactors per year should be built by 2050 to avoid the worst effects of climate change [32]. His argument—which sounds rather extreme—is based on the claim that the 100% renewable scenarios are not realistic at all, and large amounts of nuclear power should close the energy gap. Here, we attempt to evaluate his argument based on the main findings of this study.

As of 2015, the average CO_2 emissions per capita and nuclear power proportion for the 18 countries in this study are 5.93 metric tons and 14%, respectively [31]. Suppose that the reduction target for those countries is set to be a 20% cut in CO_2 emissions per capita from 1990 levels and the target could be reached only by nuclear power. Then, the nuclear power proportion would need to extend from 14% to roughly 48–64% to achieve the target, based on the result that the estimated long-run elasticity of CO_2 emissions per capita on nuclear power proportion is about 0.26–0.32%. Although the proportion to be raised is not an exact figure and cannot be directly comparable to Hansen's suggestion, the main message is the same: nuclear power is the most urgent component of decarbonization—at least, in the near future.

5. Conclusions

This article investigates the impact of nuclear power generation on CO_2 emissions by estimating the EKC with nuclear energy as an additional variable. The datasets encompass 18 countries with more than four nuclear reactors in operation during 1970–2015, thus covering approximately 95% of the number of nuclear reactors worldwide. PDOLS was employed as an estimation methodology to fully capture information from panel datasets.

The estimation results indicated that a long-term increase of 1% in the nuclear power proportion led to a 0.26–0.32% decrease in CO_2 emissions per capita. Regarding individual countries, countries with robust inverse relationships between nuclear power proportion and CO_2 emissions per capita were the U.S., France, China, Canada, Ukraine, the United Kingdom, Germany, and Switzerland. Additionally, countries with both valid EKC hypothesis and inverse relationships between nuclear power proportion and CO_2 emissions per capita were France, Germany, and Switzerland. One possible implication of the estimation results is that the average nuclear power proportion for the 18 countries would need to extend from the 2015 level of 14% to approximately 48–64% to reduce CO_2 emissions per capita by 20% below 1990 levels.

To conclude, the findings in this paper provide empirical evidence for the claim that nuclear power can contribute to reducing greenhouse gas emissions, while meeting the ever-increasing demand for energy. It is true that several OECD countries (e.g., France, Germany, recently South Korea, and Taiwan) have decided to lower the weight of nuclear power generation in their energy mix due to its potential catastrophic risks. However, nuclear power is still of importance to other countries—particularly developing ones—because it has a large, well-developed, and plentiful resource base as well as potentially favorable economics over other energy sources. The situation in each country is different; hence, the nuclear power option should be kept open under the Paris Agreement for parties that wish to include it and thereby enhance the cost effectiveness of their climate change mitigation actions.

Acknowledgments: This paper is partly based on the results from the Korean Economics Energy Institute Research Paper No. 2016-11.

Author Contributions: Sanglim Lee designed the research and wrote the paper; Minkyung Kim obtained the data and analyzed the results; and Jiwoong Lee improved and revised the manuscript. All authors provided comments on the manuscript and approved the final version.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

The seven test statistics for a panel co-integration test are based on residual-based tests. Residuals $\hat{\mu}_{i,t}$, $\hat{\mu}^*_{i,t}$, and $\hat{\eta}_{i,t}$ are collected from (4), (5), and the following regressions:

$$\Delta y_{i,t} = \Delta\beta_{1i}x_{1i,t} + \Delta\beta_{2i}x_{2i,t} + \cdots + \Delta\beta_{mi}x_{mi,t} + \eta_{i,t}, \tag{A1}$$

$$\hat{e}_{i,t} = \hat{\gamma}_i\hat{e}_{i,\,t-1} + \sum_{k=1}^{K_i} \hat{\gamma}_{i,k}\Delta\hat{e}_{i,\,t-1} + \hat{\mu}^*_{i,t}, \tag{A2}$$

where i (= 1, 2, ..., N) is the number of cross-sectional data, t (= 1, 2, ..., T) is the number of time-series data, m (= 1, 2, ..., M) is the number of independent variables, k (= 1, 2, . . . , K) is the number of lags. Next, with residuals $\hat{\mu}_{i,t}$, $\hat{\mu}^*_{i,t}$, and $\hat{\eta}_{i,t}$, the following terms are calculated:

$$\hat{s}_i^{*2} = \frac{1}{T}\sum_{t=1}^{T} \hat{\mu}_{i,t}^{*2}, \tag{A3}$$

$$\tilde{s}_{N,T}^{*2} = \frac{1}{N}\sum_{n=1}^{N} \hat{s}_i^{*2}, \tag{A4}$$

$$\hat{L}_{11i}^{-2} = \frac{1}{T}\sum_{t=1}^{T} \hat{\eta}_{i,t}^2 + \frac{2}{T}\sum_{s=1}^{k_i}\left(1 - \frac{s}{k_i+1}\right)\sum_{t=s+1}^{T} \hat{\eta}_{i,t}\hat{\eta}_{i,t-s}, \tag{A5}$$

$$\hat{\lambda}_i = \frac{1}{T}\sum_{s=1}^{k_i}\left(1 - \frac{s}{k_i+1}\right)\sum_{t=s+1}^{T} \hat{\mu}_{i,t}\hat{\mu}_{i,t-s}, \tag{A6}$$

$$\hat{s}_i^2 = \frac{1}{T}\sum_{t=1}^{T} \hat{\mu}_{i,t}^2, \tag{A7}$$

$$\hat{\sigma}_i^2 = \hat{s}_i^2 + 2\hat{\lambda}_i, \tag{A8}$$

$$\tilde{\sigma}_{N,T}^2 = \frac{1}{N}\sum_{n=1}^{N} \hat{L}_{11i}^{-2}\hat{\sigma}_i^2, \tag{A9}$$

Then, the seven test statistics are constructed with the appropriate terms described above. Details on how these statistics are constructed are discussed in Pedroni [28].

$$\text{Panel v statistic}: \quad T^2N^{\frac{3}{2}}\left(\sum_{i=1}^{N}\sum_{t=1}^{T} \hat{L}_{11i}^{-2}\hat{e}_{i,t-1}^2\right)^{-1}, \tag{A10}$$

$$\text{Panel rho statistic}: \quad T\sqrt{N}\left(\sum_{i=1}^{N}\sum_{t=1}^{T} \hat{L}_{11i}^{-2}\hat{e}_{i,t-1}^2\right)^{-1}\sum_{i=1}^{N}\sum_{t=1}^{T} \hat{L}_{11i}^{-2}\left(\hat{e}_{i,t-1}\Delta\hat{e}_{i,t} - \hat{\lambda}_i\right), \tag{A11}$$

$$\text{Panel t statistic}: \quad \left(\tilde{\sigma}_{N,T}^2\sum_{i=1}^{N}\sum_{t=1}^{T} \hat{L}_{11i}^{-2}\hat{e}_{i,t-1}^2\right)^{-\frac{1}{2}}\sum_{i=1}^{N}\sum_{t=1}^{T} \hat{L}_{11i}^{-2}\left(\hat{e}_{i,t-1}\Delta\hat{e}_{i,t} - \hat{\lambda}_i\right), \tag{A12}$$

$$\text{Panel ADF statistic}: \quad \left(\tilde{s}_{N,T}^{*2}\sum_{i=1}^{N}\sum_{t=1}^{T} \hat{L}_{11i}^{-2}\hat{e}_{i,t-1}^{*2}\right)^{-\frac{1}{2}}\sum_{i=1}^{N}\sum_{t=1}^{T} \hat{L}_{11i}^{-2}\hat{e}_{i,t-1}^{*}\Delta\hat{e}_{i,t}^{*}, \tag{A13}$$

$$\text{Group rho statistic}: \quad T\frac{1}{\sqrt{N}}\sum_{i=1}^{N}\left(\sum_{t=1}^{T} \hat{L}_{11i}^{-2}\hat{e}_{i,t-1}^2\right)^{-1}\sum_{t=1}^{T}\left(\hat{e}_{i,t-1}\Delta\hat{e}_{i,t} - \hat{\lambda}_i\right), \tag{A14}$$

$$\text{Group t statistic}: \quad \frac{1}{\sqrt{N}}\sum_{i=1}^{N}\left(\hat{\sigma}_i^2\sum_{t=1}^{T} \hat{e}_{i,t-1}^2\right)^{-\frac{1}{2}}\sum_{t=1}^{T}\left(\hat{e}_{i,t-1}\Delta\hat{e}_{i,t} - \hat{\lambda}_i\right), \tag{A15}$$

$$\text{Group ADF statistic}: \quad \frac{1}{\sqrt{N}}\sum_{i=1}^{N}\left(\sum_{t=1}^{T} \hat{s}_i^{*2}\hat{e}_{i,t-1}^{*2}\right)^{-\frac{1}{2}}\sum_{t=1}^{T} \hat{e}_{i,t-1}\Delta\hat{e}_{i,t}. \tag{A16}$$

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