sustainability

MDPI

Article

The Effects of Foreign Direct Investment, Economic Growth, Industrial Structure, Renewable and Nuclear Energy, and Urbanization on Korean Greenhouse Gas Emissions

Suyi Kim

School of Business Management, College of Business Management, Hongik University, Sejong, 30016, Korea; suyikim@hongik.ac.kr; Tel.: +82-10-9495-9096

Received: 31 December 2019; Accepted: 18 February 2020; Published: 21 February 2020

Abstract: This study analyzes the effects of foreign direct investment (FDI), economic growth, industrial structure, renewable and nuclear energy, and urbanization on Korean greenhouse gas (GHG) emissions from 1981 to 2014. The cointegration relationship of the variables is examined using autoregressive distributed lag (ARDL) bounds test. The test confirmed the long-run equilibrium among the variables. After that, the short-run and long-run coefficients are estimated by an ARDL error-correction model. The result shows that in the long run, economic growth and urbanization are the main contributors to the increase of GHG emissions, while manufacturing industry share, renewable energy and nuclear energy contributed to the reduction of GHG emissions. The inflow of FDI has led to the increase of greenhouse gases, but the coefficients is negligible. In the short run, economic growth has caused an increase in GHG emissions, while renewable and nuclear energy have contributed to the reduction in GHG emissions. FDI and urbanization did not play a role in increasing of GHG emissions in the short term.

Keywords: GDP; FDI; industrial structure; renewable and nuclear energy; ARDL bounds; causality

1. Introduction

Today, greenhouse gas (GHG) emissions are continuously increasing worldwide, although there are different trends across countries. The damage caused by abnormal climate change due to global warming is also increasing with the increase in GHG emissions. According to World Bank data, CO_2 emissions amounted to 36,138 million tons in 2014, the highest level in history. The Intergovernmental Panel on Climate Change (IPCC) [1] forecasts that the global average temperature will rise 3.5 °C by the year 2100 compared to the pre-industrial period if there are no further mitigation efforts. In the Kyoto Protocol, the burden of greenhouse gas reduction was only on Annex 1 countries (developed countries including transition economies). However, in the Paris Agreement, a consensus was reached asserting that developing countries as well as developed countries should participate in the reduction of GHG emissions. Therefore, developing countries, including China, have set voluntary GHG reduction targets.

According to the Intended Nationally Determined Contributions (INDCs) submitted to United Nations, Korea has also set a goal of reducing GHG emissions by 37% compared to Business as Usual by 2030. In addition, since 2015, Korea has been trying to reduce GHG emissions in various sectors, including the emission trading scheme for GHG or energy-intensive industries or buildings. If each country's GHG reduction policy is actively implemented, the regulations on the country's GHG intensive industries will be further strengthened, and these industries will be relocated among other countries. Therefore, there is a possibility that foreign direct investment (FDI) is a conduit for pollution havens. This is likely to be linked to economic growth in each country and affect the country's GHG emissions. Comprehensive research studies on FDI, GHG emissions, and economic growth have begun in recent years. The relationship between FDI and GHG emissions is based on two hypotheses—one is the pollution haven hypothesis, and the other is the halo effect hypothesis. According to the halo effect, FDI can reduce GHG emissions through the host country's advanced technology. The pollution haven hypothesis proposes that the investing country relocates GHG intensive industries to foreign countries, thereby increasing the GHG emissions of the host countries.

Table 1 shows for the studies on the relationship between FDI and GHG emissions. The results vary depending on the countries and time periods studied. Recent studies supporting the pollution haven hypothesis include Pao and Tsai [2], Seker et al. [3], Zhu et al. [4], and Behera and Dash [5], and the studies supporting the halo effect hypothesis include Tang and Tan [6], Mert and Bölök [7], and Abdouli and Hammami [8]. Mixed results for both the pollutant haven hypothesis and the halo effect hypothesis are found in Merican et al. [9], Peng et al. [10], and Zhang and Zhou [11].

Table 1. The studies on foreign direct investment (FDI) and greenhouse gas (GHG) emissions.

	Countries	Periods	Methods
Pao and Tsai [2]	BRICs (Brazil, Russia, India, China)	1992–2007	Panel Vector Error Correction Model
Seker et al. [3]	Turkey	1974–2010	Autoregressive Distributive Lag (ARDL)
Zhu et al. [4]	ASEAN (South East Asian Nations) Countries	1981–2011	Fixed effect panel quantile regression
Behera and Dash [5]	SSEA (South and Southeast Asian), 17 countries	1980–2012	Panel Vector Error Correction Model)
Tang and Tan [6]	Vietnam	1976–2009	VECM (Vector Error Correction Model)
Mert and Bölök [7]	21 Kyoto Annex I Countries	1970–2010	Panel Autoregressive Distributive Lag (ARDL)
Abdouli and Hammami [8]	MENA (Middle Eastern and North African), 17 countries	1990–2012	Panel VAR (Vector Auto regression)
Merican et al. [9]	Malaysia, Thailand, Indonesia, Singapore, Philippines	1970–2001	Autoregressive Distributive Lag (ARDL)
Peng et al. [10]	China, 16 provinces	1985–2012	Generalized Method of Moments (GMM) Panel granger Causality
Zhang and Zhou [11]	China, 11 eastern provinces, eight middle provinces, and 10 western provinces	1995–2010	Panel Vector Error Correction Model

Recently, studies on the role of urbanization in GHG emissions have been actively conducted. According to Table A1, the studies on the effect of urbanization on CO_2 emissions include Martinez-Zarzoso and Maruotti [12], Zhu et al. [13], Sadorsky [14], Dogan and Turkekul [15], Ali et al. [16], He et al. [17], Bekhet and Othman [18] and Pata [19,20]. Martinez-Zarzoso and Maruotti [12] investigated the effects of urbanization on GHG emissions for 88 developing countries over the period 1975–2003 using stochastic impacts by regression on population, affluence and technology (STIRPAT) model. Zhu et al. [13] analyzed these effects for 20 emerging countries over the period 1992–2008 using a semi-parametric panel data model. Sadorsky [14] investigated these effects for emerging economies including South Korea for the period 1971–2009 using a STIRPAT model. Dogan and Turkekul [15], and Ali et al. [16] analyzed these effects for the US and Singapore, respectively, using autoregressive distributed lags (ARDL) model. In addition, He et al. [17] analyzed these effects for China, Bekhet and Othman [18] for Malaysia and Pata [19,20] for Turkey. He et al. [17], Bekhet and Othman [18], and Pata [19,20] used SPIRPAT, VECM, and ARDL models, respectively. Among them, Ali et al. [16] and Bekhet and Othman [18] have shown that urbanization reduces CO_2 emissions, while other studies show that urbanization increases CO_2 emissions.

Higher production of renewables and nuclear energy will replace fossil fuels, resulting in lower GHG emissions. Recently, there has been active studies on the role of renewable and nuclear energy in reducing CO_2 emissions. According to Table A2, Representative studies include Menyah and Wolde_Rufael [21], Apergis et al. [22], Iwata et al. [23], Shafiel and Salim [24], Jaforullah and King [25], Bilgili et al, [26], Dogan and Seker [27], Ito [28], and Zoundi [29]. Ito [28] and Zoundi [29] investigated the effects of clean energy on GHG emissions for 42 developing countries and 25 selected African countries, respectively. The studies on these effects for developed countries include Menyah and Wolde_Rufael [21], Iwata et al. [23], Shafiel and Salim [24], Jaforullah and King [25], Bilgili et al. [26], and Dogan and Seker [27]. Apergis et al. [22] investigated these effects for both developing and developed countries. The methodologies on this topic vary, including ARDL, STIRPAT, VAR, GMM, and PMG. For the analysis on one country, VAR, ARDL, and VECM were used, and for the panel analysis on multiple countries, panel VECM, STIRPAT, panel FMOLS, and panel FMOLS were used. Most of above studies on the effects of clean energy on GHG emissions have shown that an increasing share of renewable and nuclear energy contributes to the reduction of CO_2 emissions.

Additionally, GHG emissions are affected by various factors. As the economy grows, GHG emissions are expected to increase due to increased energy consumption. However, recently, the decoupling between economic growth and GHG emissions has been increasing. Meanwhile, GHG emissions are expected to increase as the proportion of the manufacturing industry increases. This is because the manufacturing industry is regarded as being more dependent on energy than the service industry.

Hence, this study analyzes the effects of FDI on GHG emissions in Korea, considering various factors such as economic growth, the share of the manufacturing industry, the share of renewable energy and nuclear energy, and urbanization. Korea has achieved high economic growth rates over the past 30 years and has a relatively high share of the manufacturing industry compared to other countries. In addition, the share of nuclear power generation is higher than that of other countries and Korea possesses world-class nuclear technology. These factors are also expected to have an effect on GHG emissions. And people's life styles have also changed as urbanization. As foreign direct investment has been introduced for a long time, it is important to analyze how these various factors influenced Korea's GHG emissions.

In this study, the autoregressive distributed lag (ARDL) method is used as in Tang and Tan [6], Mert and Bölök [7], Ali [16], Iwata et al [23], and Fernández and Fernández [30]. This method has been widely used in recent studies as it can produce significant results even when sample size is small in case of one country. To date, this is the first study to analyze the effect of FDI on GHG emissions incorporating economic growth, the share of the manufacturing industry, the share of renewable and nuclear power generation, and urbanization using the ARDL method. Chapter 2 presents the data and methods, and Chapter 3 presents the empirical findings. Chapter 4 concludes and discusses policy implications.

2. Data and Methods

As shown in previous studies, CO_2 emissions are affected by the various factors such as economic growth, expansion of clean energy such as renewable energy, the share of manufacturing industry, the progress of urbanization, and inflows and outflows of foreign direct investment. This study analyzes the extent to which these variables affect CO_2 emissions in Korea. The six variables for analysis are CO_2 emissions per capita as a proxy for GHG emissions; the net inflows of FDI as a proxy for foreign direct investment; the share of renewable and nuclear energy in primary energy supply as a proxy for renewable and nuclear energy; the urban population in the total population as a proxy for urbanization; and the share of manufacturing in GDP as a proxy for industrial structure. The long-run empirical model reflecting the effect of these exogenous variables on CO_2 emissions can be specified as the following equation as modified from the structural formula of Merican et al [9] and Talukdar and Meisner [31].

$$\ln(CO_2)_t = \beta_0 + \beta_1 \ln GDP_t + \beta_2 \ln MV_t + \beta_3 \ln RNE_t + \beta_4 \ln URBAN_t + \beta_5 \ln FDIS_t + \varepsilon_t \quad (1)$$

where, *ln* represents the natural logarithm. CO_2 denotes CO_2 emissions per capita (metric tons per capita); *GDP* denotes gross domestic product per capita (constant 2010 US $); *MV* denotes the share of manufacturing value added in GDP (%); RNE denotes the share of renewable and nuclear energy in primary energy supply (%); *URBAN* denotes the urbanization ratio, which is measured by the share of the urban population in the total population (%); *FDIS* denotes the net inflows of FDI (% of GDP); ε_t denotes error terms.

ARDL model is appropriate for analyzing the long-run effects of each explanatory variables on CO_2 emissions because the analysis target is just one country and the analysis period is relatively short. ARDL model is also applied to the previous studies as Tang and Tan [6], Mert and Bölök [7], Ali [16], Iwata et al [23], and Fernández and Fernández [30].

ARDL cointegration methods were developed by Pesaran and Pesaran [32], Pesaran and Shin [33] and Pesaran et al. [34]. It have been used for decades in various studies. In recent years, they were used as test methods for the existence of long-run relationships between economic variables in the time series analysis. Compared to other cointegration methods proposed by Engle and Granger [35] and Johansen and Juselius [36], ARDL cointegration methods have several advantages as the follows. First, as mentioned earlier in Shrestha and Bhatta [37], the ARDL cointegration methods can be applied when the variables are a mixture of mixed order of integration, while Johansen cointegration methods require that all variables have the same order of integration. Without affecting the asymptotic distribution of the test statistic, the ARDL cointegration methods can be applied to the model with different orders of lag length as well as the equal number of lag length for the corresponding variables (Pesaran et al. [34]). Second, the ARDL methods yield estimates and valid t-statistics, even if autocorrelation and endogeneity exist in the model (Harris and Sollis [38]). Third, the ARDL cointegration methods is efficient even for small and finite sample data sizes while the Johansen cointegration methods require large data for statistical validity. Fourth, after the long-run cointegration relationship is confirmed by ARDL cointegration test, the short-run coefficients can be estimated by ARDL error correction model (ECM) without losing valid long-run coefficients. Fifth, the ARDL cointegration test provide effective results in various cases which the variables are integrated at I(0), at I(1) or mutually cointegrated, while Johansen cointegration test requires all the variables to be I(1). (Pesaran et al. [34]).

There are two step procedures in estimating long-run relationship. The first step in estimating long-run relationship, as in Equation (1), is the ARDL bounds test. If long-run equilibrium relationship is identified in the first step, the second step is estimating the long-run parameters.

In the first step, the specific ARDL model is formulated as shown by Equation (2) and is called the unrestricted ECM or "conditional ECM" (Pesaran et al. [34]).

$$\begin{gathered}\Delta \ln(CO_2)_t = \alpha_0 + \sum_{k=1}^{p} \alpha_{1k} \Delta \ln(CO_2)_{t-k} + \sum_{k=0}^{q_1} \alpha_{2k} \Delta \ln GDP_{t-k} + \sum_{k=0}^{q_2 \alpha_{3k} \Delta \ln MV_{t-k} +} \\ \sum_{k=0}^{q_3} \alpha_{4k} \Delta \ln RNE_{t-k} + \sum_{k=0}^{q_4} \alpha_{5k} \Delta \ln URBAN_{t-k} + \sum_{k=0}^{q_5} \alpha_{6k} \Delta \ln FDIS_{t-k} + \alpha_7 \ln(CO_2)_{t-1} + \\ \alpha_8 \ln GDP_{t-1} + \alpha_9 \ln MV_{t-1} + \alpha_{10} \ln RNE_{t-1} + \alpha_{11} \ln URBAN_{t-1} + \alpha_{12} \ln FDIS_{t-1} + u_t,\end{gathered} \tag{2}$$

where Δ denotes the difference operator; α_7~α_{12} are the long terms; and p and q_1~q_5 are the optimal leg length of this model which is defined by the Akaike information criterion (AIC) or Schwarz Bayesian criterion (SBC). The F-statistic of the lagged terms in Equation (2) is used to test the long-term equilibrium relationship whether there is a cointegration among the variables or not. The null hypothesis is $H_0 : \alpha_7 = \alpha_8 = \alpha_9 = \alpha_{10} = \alpha_{11} = \alpha_{12} = 0$, while the alternative hypothesis is $H_1 : \alpha_7 \neq 0 \; or \; \alpha_8 \neq 0 \; or \; \alpha_9 \neq 0 \; or \; \alpha_{10} \neq 0 \; or \; \alpha_{11} \neq 0 \; or \; \alpha_{12} \neq 0$. This F-test depends on several conditions: (1) whether the corresponding variables are I(0) or I(1). (2) How many the number of regressors are in the model, and (3) whether the model contains an intercept, or a trend. The test involves asymptotic critical value bounds, depending on whether the variables are I(0) or I(1). Two bounds are given, the first is the lower bound that assumes all of the variables are I(0), and the second is the upper bound that assumes all of the variables are I(1). If the computed F-statistic calculated from the model is below the lower bound, the null hypothesis can't be rejected and we can conclude that there is no cointegration among the variables. If the F-statistic exceeds the upper bound, the null hypothesis can be rejected and we can conclude that there is a cointegration relationship among the variables. If the computed F-statistic exists between the lower bound and the upper bound, the cointegration among the variables is inconclusive. If the long-run equilibrium cointegration relationship among the variables is identified through ARDL bounds test, this long-run cointegration relationships can be estimated using the ARDL models (Fernández and Fernández [31]).

In addition, a bound t-test is performed to ensure reliability. The null hypothesis for this test is H_0: $\alpha_7 = 0$, while the alternative hypothesis is H_1: $\alpha_7 < 0$. If the t-statistic is greater than I(1) bound, we can reject the null hypothesis and conclude that there is a long-run cointegration relationship among the variables. If the t-statistic is less than the I(0) bound, we can accept the null hypothesis and conclude that there is no long-run cointegration relationship and the time variables are all stationary (Pesaran et al. [34]).

If a stable long-run relationship is identified by the first step, then in the second step, the augmented ARDL model is estimated using the following Equation (3):

$$\begin{gathered}\ln(CO_2)_t = \gamma_0 + \sum_{k=1}^{p} \gamma_{1k} \ln(CO_2)_{t-k} + \sum_{k=0}^{q_1} \gamma_{2k} \ln GDP_{t-k} + \sum_{k=0}^{q_2} \\ \gamma_{3k} \ln MV_{t-k} + \sum_{k=0}^{q_3} \gamma_{4k} \ln RNE_{t-k} + \sum_{k=0}^{q_4} \gamma_{5k} \ln URBAN_{t-k} + \sum_{k=0}^{q_5} \gamma\alpha_{6k} \ln FDIS_{t-k} + v_t,\end{gathered} \tag{3}$$

Equation (3) can be reduced to the following Equation (4), which represents the long-run equilibrium relationship. The long-run coefficients of the dependent variables are estimated from Equation (4):

$$\begin{gathered}\ln(CO_2)_t = \lambda\gamma_0 + \lambda \sum_{k=0}^{q_1} \gamma_{2k} \ln GDP_t + \lambda \sum_{k=0}^{q_2} \gamma_{3k} \ln MV_t + \lambda \sum_{k=0}^{q_3} \gamma_{4k} \ln RNE_t + \lambda \sum_{k=0}^{q_4} \gamma_{5k} \ln URBAN_t \\ + \lambda \sum_{k=0}^{q_5} \gamma\alpha_{6k} \ln FDIS_t + \lambda v_t \text{where, } \lambda = \frac{1}{1 - \sum_{k=1}^{p} \gamma_{1k}},\end{gathered} \tag{4}$$

The short-run coefficients of the explanatory variables can be estimated using the associated ARDL-ECM. The ARDL-ECM model considering long-run equilibrium is described as follows:

$$\begin{gathered}\Delta \ln(CO_2)_t = \delta_0 + \sum_{k=1}^{p} \delta_{1k} \Delta \ln(CO_2)_{t-k} + \sum_{k=0}^{q_1} \delta_{2k} \Delta \ln GDP_{t-k} + \sum_{k=0}^{q_2} \delta_{3k} \Delta \ln MV_{t-k} + \\ \sum_{k=0}^{q_3} \delta_{4k} \Delta \ln RNE_{t-k} + \sum_{k=0}^{q_4} \delta_{5k} \Delta \ln URBAN_{t-k} + \sum_{k=0}^{q_5} \delta_{6k} \Delta \ln FDIS_{t-k} + \delta_7 ECT_{t-1} + \rho_t\end{gathered} \tag{5}$$

If the ECT_{t-1} coefficients (δ_7) is statistically significant and negative sign, we can conclude that any long-run disequilibrium among dependent variable and several independent variables converges into the long-run equilibrium.

The data used in this study covers the period 1981-2014. The data for CO_2 emissions per capita (CO_2), GDP per capita (*GDP*), the share of manufacturing industry in GDP (*MV*), the urbanization ratio (*URBAN*), and the net inflows of FDI in GDP (*FDIS*) are from the World Bank's DataBank [39]. The share of renewable and nuclear energy in primary energy supply (*RNE*) is from the Korea Energy Statistical Information System [40] of the Korea Energy Economics Institute. The data of *RNE* includes nuclear energy and renewable energy including hydropower electricity which is generated by hydropower.

Time series plots of each data in Figure 1. CO_2 emissions per capita increased rapidly until 1997, but dropped sharply in 1998 due to the Asian financial crisis. Since then, CO_2 emissions per capita have increased, but at a slower rate than before the Asian financial crisis. Since 2010, CO_2 emissions per capita have tended to decrease slightly. GDP per capita continued to increase during the period, except both the Asian and global financial crisis period. GDP per capita decreased during those economic crisis period. GDP per capita decreased more during the Asian financial crisis than during the global financial crisis.

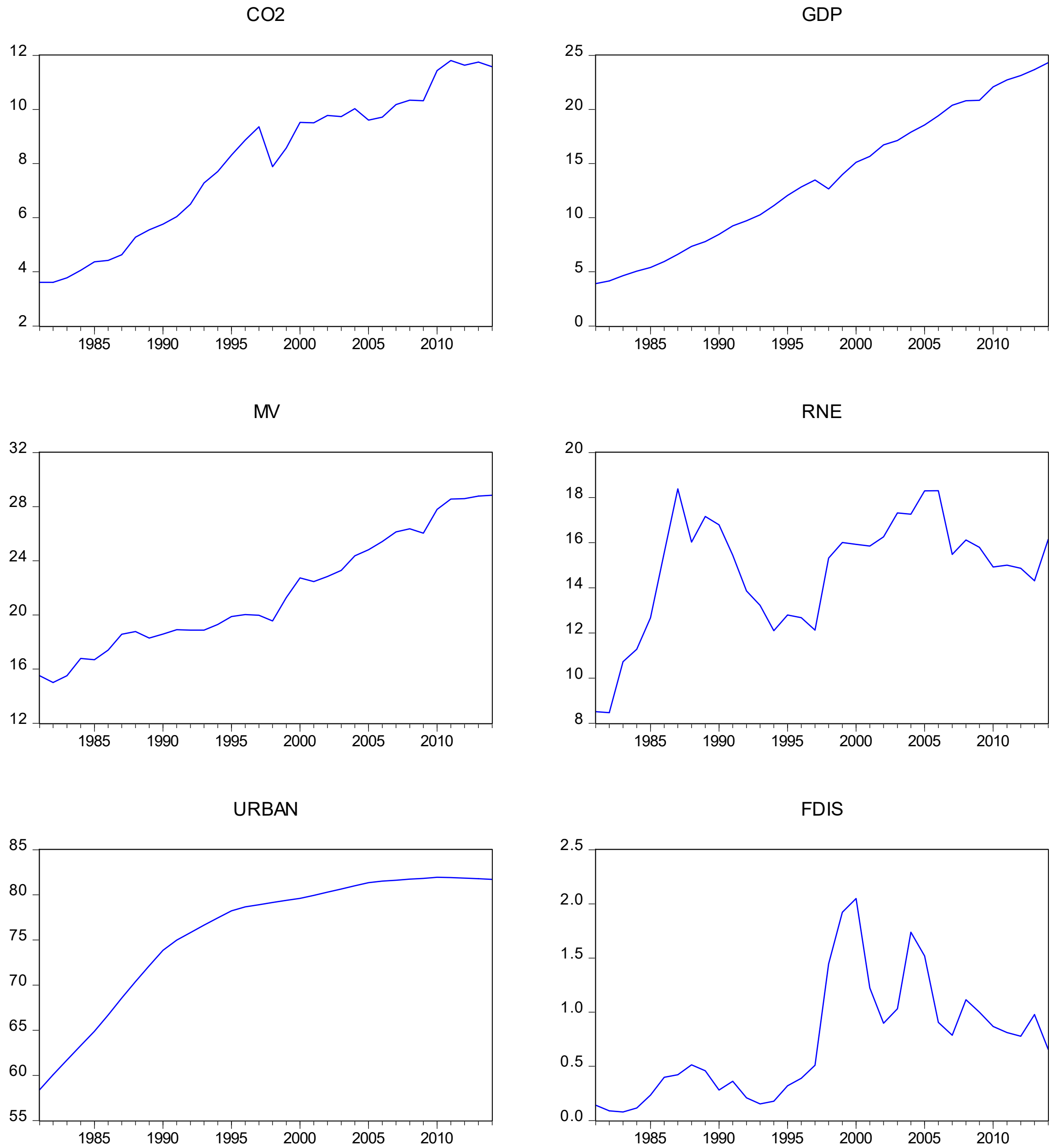


Figure 1. Time series plots for each data. CO_2 denotes CO_2 emissions per capita (metric tons per capita); *GDP* denotes gross domestic product per capita ($1000, constant 2010 USD); *MV* denotes the share of manufacturing value added in GDP (%); RNE denotes the share of renewable and nuclear energy in primary energy supply (%); *URBAN* denotes the urbanization ratio, which is measured by the share of the urban population in the total population (%); *FDIS* denotes the net inflows of FDI (% of GDP).

The share of manufacturing value added in GDP accounted for 15.5% of GDP in 1981, but increased steadily to 28.8% in 2014. However, this share of the manufacturing sector also declined slightly during the Asian and global financial crisis.

The share of renewable and nuclear energy in primary energy supply reached 18.4%, the highest level in 1987, but declined until the mid-1990s and then increased again. Since the mid-1980s, this share has declined because of the rapid increase in oil demand by the increase of automobiles, and increased demand for natural gas on apartment heating. Since the mid-1990s, this share has increased again as the expansion of additional nuclear power plants and the supply of automobiles have reached their limits. Since the mid-2000s, coal and gas power have increased, and this share has decreased again. The primary energy supply by energy source is shown in Figure 2. The share of coal declined slightly from 33.3 % in 1981 to 29.9 % in 2014, but the share of oil declined sharply from 51.8% in 1981 to 37.1 % in 2014. The share of natural gas has slowly increased since 1987, recording 16.9% in 2014. The share of nuclear energy increased from 1.6% in 1981 to 16% in 2005 and again declined to 11.7 % in 2014. The share of renewable energy was less than 1% before 2000, but increased up to 3.9% in 2014. According to the main features in recent years, the share of oil is decreasing and the share of natural gas and renewable energy is increasing.

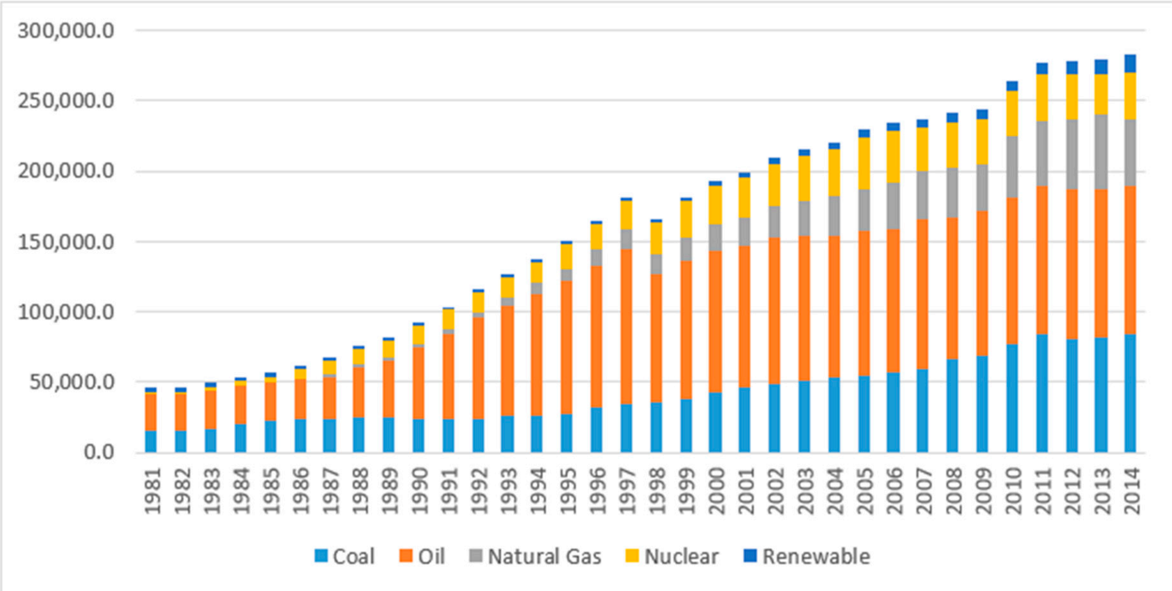


Figure 2. The share of each energy source in primary energy supply. Unit: ton of oil equivalent (TOE).

The urbanization rate was only 58.4% in 1981, but continued to increase to 81.7% in 2010. Since 2010, the urbanization rate has remained almost stagnant. Before 2000, the urbanization rate increased steeply, but since then the rate of growth has slowed significantly. The net FDI inflows in GDP showed the increasing trends. However, these trends are highly volatile because massive FDI occurred intermittently.

3. Results

3.1. Unit root analysis

The ARDL cointegration method can be valid if the variables are stationary in the case of I(0) or I(1) or a mixed integrating order. The most important assumption of the ARDL method is that the variables must be integrated at I(0) or I(1) or I(0)/I(1). The two unit root tests—the augmented Dickey–Fuller test (ADF) and the Phillips–Perron test (PP)—are usually applied to verify whether each variable is stationary or not. Table 2 shows the results of the ADF and PP unit root tests which reveal that the variables of the study are stationary at different order. According to the ADF test, each variable except *lnURBAN* has unit root at level and doesn't have unit root at first difference. This means that each variable except *lnURBAN* are I(1). The variable *lnURBAN* does not have a unit root at level. The PP unit root test also shows the same results as ADF test. Therefore, the variables $lnCO_2$, *lnGDP*, *lnMV*, *lnRNE* and *lnFDIS* are integrated at level I(1), *lnURBAN* is integrated I(0). All variables fit I(0) or I(1) as the requirement for ARDL cointegration method, so the ARDL model can be applied in this research.

Table 2. Result of unit root tests.

Variables	ADF Test (at Level)	ADF Test (at First Difference)	PP Test (at Level)	PP Test (at First Difference)
lnCO_2	−1.040	−6.063 ***	−0.777	−6.825 ***
lnGDP	−0.994	−5.683 ***	−0.976	−13.968 ***
lnMV	−2.776	−6.333 ***	−2.776	−6.098 ***
lnRNE	−2.750	−4.496 ***	−2.766	−4.620 ***
lnURBAN	−3.248 *	−0.931	−3.254 *	−1.189
lnFDIS	−2.585	−4.165 **	−1.876	−4.029 **

Notes: *, **, *** mean the rejection of the null hypothesis at the 10%, 5% and 1% level of significance, respectively. The null hypothesis is that each variable has a unit root. Each test has an intercept. ADF test indicates Augmented Dickey Fuller test, and PP test indicates Phillips–Perron Test.

3.2. Lag Length Criteria

The selection of the appropriate lag length is important before applying the ARDL bounds test because inappropriate lag lengths reduce the reliability of the model and lead to incorrect estimation results. Here, Akaike information criteria (AIC) were used to choose the appropriate lag length. Figure 3 shows top twenty models by AIC. The model with the lowest AIC value is ARDL (2, 1, 0, 1, 0, 0). Therefore, the appropriate lag lengths for p, q_1, q_2, q_3, q_4 and q_5, corresponding to each variable such as *ln*CO_2, *lnGDP, lnMV, lnRNE, lnURBAN*, and *lnFDIS* in Equation (2) are 2, 1, 0, 1, 0, and 0 respectively.

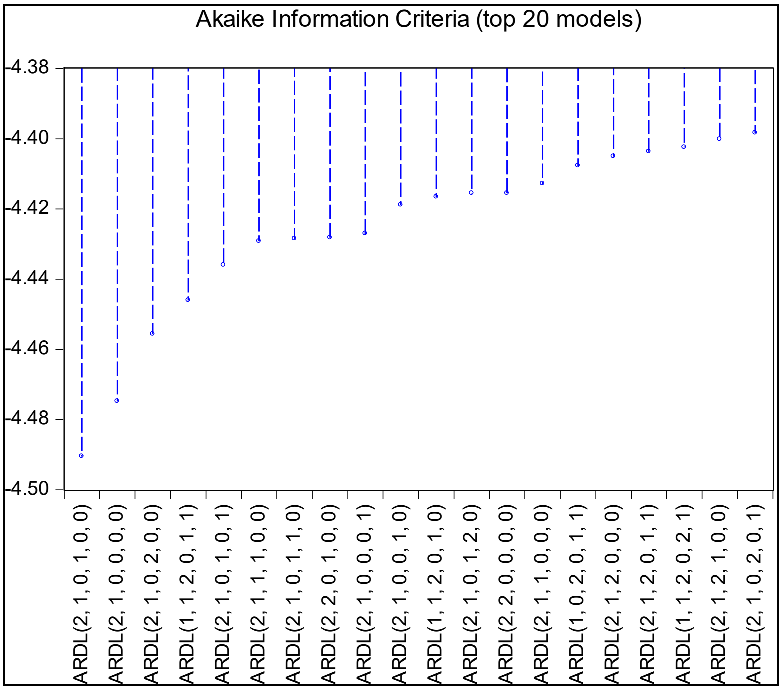


Figure 3. Lag length criteria.

3.3. ARDL Bounds Tests

ARDL bounds test is applied to identify whether there exist a cointegration relationship among *ln*CO_2, *lnGDP, lnMV, lnRNE, lnURBAN*, and *lnFDIS*, when *ln*CO_2 is the dependent variable and other variables are the explanatory variables. The result of bounds test for ARDL (2, 1, 0, 1, 0, 0) model is shown in Table 3. The upper bound assumes that all the regressors are I(1), and the lower bound assumes that the regressors are I(0). Here, null hypothesis of F-Bounds test is that there is no cointegration among variables. If the calculated F-statistic (or t-statistic) is below the lower bound, the null hypothesis will be accepted. If the F-statistic (or t-statistic) is higher than the upper bound, the null hypothesis will be rejected and the cointegration among variables will be verified. If the F-statistic (or t-statistic) lies between the upper and lower bounds, the result can't be conclusive. The critical bound values are different in large and small data samples. The critical bound values for a small sample are given by Narayan [41], and the values for large sample are given by Pesaran et al. [34]. This study, with its small sample, uses the critical bound values given by Narayan [41].

Table 3. Results of ARDL bound tests.

Selected Model: ARDL(2, 1, 0, 1, 0, 0)				
F-Bounds Test	$H_0: \alpha_7 = \alpha_8 = \alpha_9 = \alpha_{10} = \alpha_{11} = \alpha_{12} = 0$			
Test Statistic	Value	Significance	I(0)	I(1)
F-statistic	4.299	10%	1.81	2.93
K = 5		5%	2.14	3.34
		1%	2.82	4.21
t-Bounds Test	H_0: α_7= 0			
Test Statistic	Value	Significance.	I(0)	I(1)
t-statistic	−5.603	10%	−1.62	−3.49
		5%	−1.95	−3.83
		1%	−2.58	−4.44

Since the calculated value of the F-statistic is 4.299 which is above the upper bound 4.21 at the 1% significance level, the null hypothesis is rejected. According to the t-statistic, the null hypothesis is also rejected. These test results indicate the existence of a long-run cointegration when $lnCO_2$ is dependent variable and other variables are independent variables. Therefore, these results confirm that one long-run equilibrium relationship exists among $lnCO_2$, *lnGDP, lnMV, lnRNE, lnURBAN*, and *lnFDIS* when $lnCO_2$ is the dependent variable in the selected ARDL (2, 1, 0, 1, 0, 0).

3.4. Long Run Equilibrium Relationship

As shown in Table 4, the sign of the long-run coefficients of *lnGDP, lnURBAN* and *lnFDIS* are positive. This means that the CO_2 emissions increase as the economy grows, urbanization progresses, and FDI increases. The long-run elasticities for *GDP*, *URBAN*, and *FDIS* are 0.776, 0.502 and 0.055 respectively, meaning a 1% increase of *GDP, URBAN*, and *FDIS* will lead to increase of 0.776%, 0.502% and 0.055% in CO_2 emissions, separately. The biggest factor driving the increase of CO_2 emissions is economic growth, followed by urbanization. The increase in FDI, although accompanied by an increase in GHG emissions, has little effect.

Table 4. Estimated long-run coefficients using the ARDL model.

Selected Model: ARDL(2, 1, 0, 1, 0, 0); Dependent Variable is $lnCO_2$				
Variable	**Coefficient**	**Standard Error**	**t-Statistic**	***p*-value**
lnGDP	0.776 ***	0.061	12.683	0.000
lnMV	−0.345 **	0.140	−2.460	0.022
lnRNE	−0.405 ***	0.104	−3.902	0.001
lnURBAN	0.502 ***	0.071	7.062	0.000
lnFDIS	0.055 **	0.021	2.666	0.014

Notes: *, **, *** mean the rejection of null hypothesis at the 10%, 5% and 1% level of significance, respectively.

Meanwhile, the sign of the long-run coefficients of *lnMV* and *lnRNE* are negative. This means that the CO_2 emissions decrease as the share of manufacturing in GDP increases, and as the share of renewables and nuclear energy increases. The long-run elasticities for *MV* and *RNE* are −0.345 and −0.405%, respectively, meaning a 1% increase of *MV* and *RNE* will lead to a 0.345% and 0.405% decrease in CO_2 emissions, separately. In general, CO_2 emissions are expected to increase as the share of manufacturing increases, but the results are reversed. This is related to industrial restructuring in manufacturing. In other words, the share of the energy intensive industries within the manufacturing industry has decreased and the share of the low carbon emission industries has increased. It also shows that energy saving and CO_2 reduction technologies are being further developed in the manufacturing industry. In addition, CO_2 reduction will occur as the proportion of nuclear power and renewable energy increases, as expected.

3.5. Short-Run Causality

Table 5 shows results of the short-run dynamic coefficients from the ECM model Equation (5). The error correct term (ECT(−1)) coefficient is significant at 1% significance level with the negative sign which is between 0 and −1, implying that the model can converge back to long-term equilibrium quickly after a short-term shock. The value of −0.564 indicates that the disequilibria from this period's shock can be adjusted in the next period about 56.4%. It means that any disequilibrium of CO_2 emissions would converge back in about two years.

Table 5. Error correction representation for the selected ARDL model.

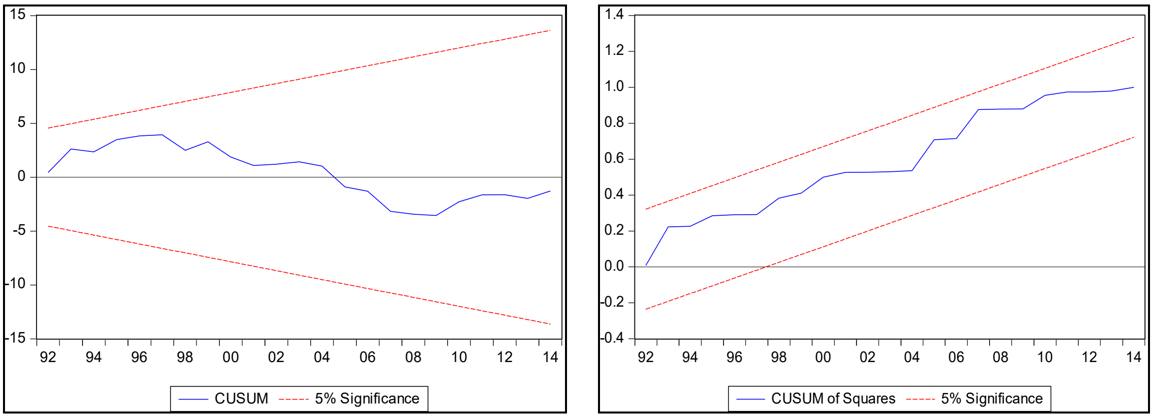
Selected Model: ARDL(2, 1, 0, 1, 0, 0); Dependent Variable is $\Delta lnCO_2$				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Probability**
$\Delta lnCO_2(-1)$	0.241 ***	0.078	3.107	0.005
$\Delta lnGDP$	1.345 ***	0.102	13.240	0.000
$\Delta lnRNE$	−0.332 ***	0.039	−8.507	0.000
ECT(−1)	−0.564 ***	0.101	−5.604	0.000
R^2	0.875	Mean dependent variables		0.036
Adjusted R^2	0.862	Standard Deviation dependent variables		0.056
Standard error of regression	0.021	Akaike info criterion		−4.803
Sum squared residuals	0.012	Schwarz criterion		−4.620
Log likelihood	80.848	Hannan-Quinn criterion.		−4.742
Durbin–Watson statistic	2.118			

Notes: *, **, *** mean the rejection of null hypothesis at the 10%, 5% and 1% level of significance, respectively.

In the short run, the changes in both *lnGDP* and *lnRNE* affect the changes in $lnCO_2$. An increase in GDP per capita brings to an increase in CO_2 emissions per capita. On the contrary, an increase in the share of renewable and nuclear energy brings to a decrease in CO_2 emissions per capita. In the short run, although the direction is reversed, the coefficients of the changes in GDP per capita on the changes in CO_2 emissions per capita is approximately four times greater than that of the changes in the share of renewable and nuclear energy. Meanwhile, the changes in two variables, *lnURBAN* and *lnFDI* didn't affect the changes in $lnCO_2$ in the short run, although two variables would increase $lnCO_2$ in the long-run shown in Section 3.4. The progress of urbanization and the net inflows of FDI affect CO_2 emissions per capita in the long-run but not in the short run.

3.6. Model Stability

The stability test for the estimated parameters of this selected ARDL model is required to avoid misspecification of the functional form, which is due to the volatility of the time variables. To ensure the stability of the ARDL-ECM model, the cumulative sum (CUSUM) and cumulative sum of squares (CUSUMSQ) tests are usually used (Pesaran and Pesaran [31]). The statistics of the CUSUM and CUSUMSQ tests are calculated as the cumulative sum or cumulative sum of the squares of the regression residuals, respectively. If the statistic lies between confidence intervals, then the estimated coefficients is believed to be stable (Brown et al. [42]). According to Figure 4, the left plot (a) shows CUSUM and the right plot (b) shows CUSUMSQ. Both the CUSUM and CUSUMSQ plots lie between the critical lower and upper bounds (red lines) at the 5% significance level. The stability of this selected ARDL model is confirmed by these two tests. Accordingly, the selected model is statistically stable and the parameters corresponding to *lnGDP, lnMV, lnRNE, lnURBAN*, and *lnFDIS* to $lnCO_2$ are reliable.



(a) **(b)**

Figure 4. Plot of cumulative sum (CUSUM) (**a**) and cumulative sum of squares (CUSUMSQ) (**b**).

4. Discussion and Conclusions

This study analyzed the effects of foreign direct investment, renewable and nuclear energy, urbanization, industrial structure incorporating economic growth on Korean GHG emissions over the period from 1981 to 2014. The econometric methodology used in this paper is the Autoregressive distributed lag model because this is for one country and the data is relatively short. According to ARDL bounds test, the long-run equilibrium among the variables is confirmed. After that, the long-run and short-run coefficients were estimated using ARDL-ECM.

In the long run, the net inflow of FDI slightly contributed to the increase of GHG emissions. However, the coefficient is negligible. Hence, it is difficult to conclude that Korea has become a pollution haven or that the halo effect has occurred in Korea. Therefore, when seeking to attract FDI, an analysis of the impact on GHG emissions should also be taken into account. So far, there is no previous study analyzing the impact of FDI on CO_2 emissions in Korea, so it is difficult to compare these findings with previous studies. Meanwhile, the empirical results show that as urbanization progressed, CO_2 emissions in Korea increased accordingly. Comparing the results of previous studies on other countries, these findings are similar to the results of previous studies on developing countries as in Martinez-Zarzoso and Maruotti [12], Zhu et al. [13], and Sadorsky [14]. The lifestyle changes due to urbanization have played a role in increasing CO_2 emissions. As previously predicted, the renewable and nuclear energy have played an important role in the reduction of CO_2 emissions. These findings are consistent with most previous studies on other countries as shown in Table A2. Especially in Korea, this result seems to be due to the high proportion of nuclear energy. However, the increase in the share of the manufacturing industry has resulted in the reduction of CO_2 emissions, which is the opposite of what was predicted earlier. This may be related to changes in the industrial structure of manufacturing industry, not just an increase in CO_2 emissions as a result of increased share of the manufacturing industry in GDP.

In the short run, economic growth has caused an increase in greenhouse gases, while renewable and nuclear energy have caused a reduction in CO_2 emissions. Urbanization industrial structure and FDI did not cause CO_2 emissions in the short run. Therefore, the policies relating to industrial restructuring and net FDI inflows aimed at GHG emissions reduction should be made with long term view. As shown in the analysis results, the roles of renewable energy and nuclear energy are important for CO_2 emissions reduction. According to the Third Energy Basic Plan established in 2019, the Korean government decided to increase the share of renewable energy in the power generation sector by 30~35% by 2030. However, this plan didn't provide a concrete vision for the share of nuclear power. To reduce CO_2 emissions, long-term targets for renewable energy and nuclear energy should be set. In order to reduce CO_2 emissions, the energy efficiency of the industrial sector should be continuously improved, and the manufacturing sector should be upgraded to a low carbon industry. Recently, Korea is trying to improve the energy efficiency of the manufacturing sector by expanding factory energy management system. In particular, in order to prevent the increase of CO_2 emissions caused by FDI inflows, the level of CO_2 emissions should be considered when attracting FDI. This study considered various factors affecting GHG emissions including foreign direct investment, renewable and nuclear energy, urbanization incorporating economic growth and industrial structure. However, the use of eco-friendly vehicles such as electric vehicles and hydrogen vehicles is increasing in Korea. In future analysis, the proportion of eco-friendly cars in transportation sector should be considered as one of factors affects GHG emissions. This will be left for further study.

Funding: This work was supported by 2019 Hongik University Research Fund.

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

Appendix A

Table A1. The studies on urbanization and GHG emissions.

	Countries	Periods	Methods
Martinez-Zarzoso and Maruotti [12]	88 developing countries	1975–2003	Stochastic Impacts by Regression on Population, Affluence and Technology (STIRPAT) model
Zhu et al. [13]	20 emerging economies	1992–2008	semi-parametric panel data model
Sadorsky [14]	Emerging economies	1971–2009	STIRPAT model
Dogan and Turkekul [15]	USA	1960–2010	Autoregressive distributed lags (ARDL)
Ali et al. [16]	Singapore	1970–2015	Autoregressive distributed lags (ARDL)
He et al. [17]	China, regional	1995–2013	STIRPAT model
Bekhet and Othman [18]	Malaysia	1971–2015	VECM
Pata [19]	Turkey	1974–2013	Autoregressive distributed lags (ARDL)
Pata [20]	Turkey	1974–2014	Autoregressive distributed lags (ARDL), FMOLS

Table A2. The studies on clean energy and GHG emissions.

	Countries	Periods	Methods
Menyah and Wolde_Rufael [21]	US	1960–2007	Vector Auto regression
Apergis et al [22]	19 developed and developing countries	1984–2007	Panel error correction model
Iwata et al. [23]	France	1960–2003	ARDL
Shafiel and Salim [24]	29 OECD [1] countries	1980–2011	STIRPAT model
Jaforullah and King [25]	US	1965–2012	VECM
Bilgili et al [26]	17 OECD countries	1977–2010	Panel FMOLS, Panel DOLS
Dogan and Seker [27]	European Union	1980–2012	Panel Dynamic Ordinary Least Squares
Ito [28]	42 developing countries	2002–2011	GMM and PMG
Zoundi [29]	25 selected African countries	1980–2012	Panel cointegration (Dynamic OLS, System GMM, etc.)

Notes: [1] OECD means Organization for Economic Cooperation and Development.

References

1. Intergovernmental Panel on Climate Change. Climate Change 2014: Impacts, Adaptation, and Vulnerability Part A: Global and Sectoral Aspects. In *Working Group II Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, 1st ed.; Field, C.B., Barros, V.R., Eds.; Cambridge University Press: New York, NY, USA, 2014.

2. Pao, H.T.; Tsai, C.M. Multivariate Granger causality between CO_2 emissions, energy consumption, FDI (foreign direct investment) and GDP (gross domestic product): Evidence from a panel of BRIC (Brazil, Russian Federation, India, and China) countries. *Energy* **2011**, *36*, 685–693. [CrossRef]
3. Seker, F.; Ertugrul, H.M.; Cetin, M. The impact of foreign direct investment on environmental quality: A bounds testing and causality analysis for Turkey. *Renew. Sustain. Energy Rev.* **2015**, *52*, 347–356. [CrossRef]
4. Zhu, H.; Duan, L.; Guo, Y.; Yu, K. The effects of FDI, economic growth and energy consumption on carbon emissions in ASEAN-5: Evidence from panel quantile regression. *Econ. Model.* **2016**, *58*, 237–248. [CrossRef]
5. Behera, S.R.; Dash, D.P. The effect of urbanization, energy consumption, and foreign direct investment on the carbon dioxide emission in the SSEA (South and Southeast Asian) region. *Renew. Sustain. Energy Rev.* **2017**, *70*, 96–106. [CrossRef]
6. Tang, C.F.; Tan, B.W. The impact of energy consumption, income and foreign direct investment on carbon dioxide emissions in Vietnam. *Energy* **2015**, *79*, 447–454. [CrossRef]
7. Mert, M.; Bolok, G. Do foreign direct investment and renewable energy consumption affect the CO_2 emissions? New evidence from a panel ARDL approach to Kyoto Annex countries. *Environ. Sci. Pollut. Res.* **2016**, *23*, 21669–21681.
8. Abdouli, M.; Hammami, S. Investigating the causality links between environmental quality foreign direct investment and economic growth in MENA countries. *Int. Bus. Rev.* **2017**, *26*, 264–278. [CrossRef]
9. Merican, Y.; Yusop, Z.; Mohd Noor, Z.; Law, S.H. Foreign direct investment and the pollution in Five ASEAN Nations. *Int. J. Econ. Manag.* **2007**, *1*, 245–261.
10. Peng, H.; Tan, X.; Li, Y.; Hu, L. Economic growth, foreign direct investment and CO_2 emissions in China: A panel granger causality analysis. *Sustainability* **2016**, *8*, 233. [CrossRef]
11. Zhang, C.; Zhou, X. Does foreign direct investment lead to lower CO_2 emissions? Evidence from a regional analysis in China. *Renew. Sustain. Energy Rev.* **2016**, *58*, 943–951. [CrossRef]
12. Martinez-Zarzoso, I.; Maruotti, A. The impact of urbanization on CO_2 emissions: Evidence from developing countries. *Ecol. Econ.* **2011**, *70*, 1344–1353. [CrossRef]
13. Zhu, H.-M.; You, W.-H.; Zeng, Z.F. Urbanization and CO_2 emissions: A semi-parametric panel data analysis. *Econ. Lett.* **2012**, *117*, 848–850.
14. Sadorsky, P. The effect of urbanization on CO_2 emissions in emerging economies. *Energy Econ.* **2014**, *41*, 147–153. [CrossRef]
15. Dogan, E.; Turkekul, B. CO_2 emissions, real output, energy consumption, trade, urbanization and financial development: Testing the EKC hypothesis for the USA. *Environ. Sci. Pollut. Res.* **2016**, *23*, 1203–1213. [CrossRef]
16. Ali, H.S.; Abdul-Rahim, A.S.; Ribadu, M.B. Urbanization and carbon dioxide emissions in Singapore: Evidence from ARDL approach. *Environ. Sci. Pollut. Res.* **2017**, *24*, 1967–1974. [CrossRef]
17. He, Z.; Xu, S.; Shen, W.; Long, R.; Chen, H. Impact of urbanization on energy related CO_2 emission at different development levels: Regional difference in China based on panel estimation. *J. Clean. Prod.* **2017**, *140*, 1719–1730. [CrossRef]
18. Bekhet, H.A.; Othman, N.S. Impact of urbanization growth on Malaysia CO_2 emissions: Evidence form the dynamic relationship. *J. Clean. Prod.* **2017**, *154*, 374–388. [CrossRef]
19. Pata, U.K. The effect of urbanization and industrialization on carbon emissions in Turkey: Evidence form ARDL bounds testing procedure. *Environ. Sci. Pollut. Res.* **2018**, *25*, 7740–7747. [CrossRef]
20. Pata, U.K. Renewable energy consumption, urbanization, financial development, income and CO_2 emissions in Turkey: Testing EKC hypothesis with structural breaks. *J. Clean. Prod.* **2018**, *187*, 770–779. [CrossRef]
21. Menyah, K.; Wolde-Rufael, Y. CO_2 emissions, nuclear energy, renewable energy and economic growth in the US. *Energy Policy* **2010**, *38*, 2911–2915. [CrossRef]
22. Apergis, N.; Payne, J.E.; Menyah, K.; Wolde-Rufael, Y. On the causal dynamics between emissions, nuclear energy, renewable energy, and economic growth. *Ecol. Econ.* **2010**, *69*, 2255–2260. [CrossRef]
23. Iwata, H.; Okada, K.; Samreth, S. Empirical study on the environmental Kuznets curve for CO_2 in France: The role of nuclear energy. *Energy Policy* **2010**, *38*, 4057–4063. [CrossRef]
24. Shafiei, S.; Salim, R.A. Non-renewable and renewable energy consumption and CO_2 emissions in OECD countries: A comparative analysis. *Energy Policy* **2014**, *66*, 547–556. [CrossRef]
25. Jaforullah, M.; King, A. Does the use of renewable energy sources mitigate CO_2 emissions? A reassessment of the US evidence. *Energy Econ.* **2015**, *49*, 711–717.

26. Bilgili, F.; Koçak, E.; Bulut, Ü. The dynamic impact of renewable energy consumption on CO_2 emissions: A Revisited Environmental Kuznets Curve approach. *Renew. Sustain. Energy Rev.* **2016**, *54*, 838–845. [CrossRef]
27. Dogan, E.; Seker, F. Determinants of CO_2 emissions in the European Union: The role of renewable and non-renewable energy. *Renew. Energy* **2016**, *94*, 429–439. [CrossRef]
28. Ito, K. CO_2 emissions, renewable and non-renewable energy consumption, and economic growth: Evidence from panel data for developing countries. *Int. Econ.* **2017**, *151*, 1–6. [CrossRef]
29. Zoundi, Z. CO_2 emissions, renewable energy and the Environmental Kuznets Curve, a panel cointegration approach. *Renew. Sustain. Energy Rev.* **2017**, *72*, 1067–1075. [CrossRef]
30. Fernández, V.C.; Fernández, J.T. The long run impact of foreign direct investment, exports, imports and GDP: Evidence for Spain from an ARDL approach. *EHES Work. Pap.* **2018**, *128*, 1–21.
31. Talukdar, D.; Meisner, C.M. Does the private sector help or hurt the environment? Evidence from carbon dioxide pollution in developing countries. *World Dev.* **2001**, *29*, 827–840.
32. Pesaran, M.H.; Pesaran, B. *Working with Microfit 4.0: Interactive Econometric Analysis*; Oxford University Press: Oxford, UK, 1997.
33. Pesaran, M.H.; Shin, Y. An autoregressive distributed lag modelling approach to cointegration analysis. In *Econometrics and Economic Theory in the 20th Century: The Ranger Frisch Centennial Symposium*; Strom, S., Holly, A., Diamond, P., Eds.; Cambridge University Press: Cambridge, UK, 1999.
34. Pesaran, M.H.; Shin, Y.; Smith, R.J. Bounds testing approaches to the analysis of level relationships. *J. Appl. Econom.* **2001**, *16*, 289–326. [CrossRef]
35. Engle, R.F.; Granger, C.W.J. Co-integration and Error Correction: Representation, Estimation, and Testing. *Econometrica* **1987**, *55*, 251–276. [CrossRef]
36. Johansen, S.; Juselius, K. Maximum likelihood estimation and inference on cointegration with applications to the demand for money. *Oxf. Bull. Econ. Stat.* **1990**, *52*, 169–210. [CrossRef]
37. Shrestha, M.B.; Bhatta, G.R. Selecting appropriate methodological framework for time series data analysis. *J. Financ. Data Sci.* **2018**, *4*, 71–89. [CrossRef]
38. Harris, R.; Sollis, R. *Applied Time Series Modeling and Forecasting*; Wiley: Somerset, NJ, USA, 2003.
39. World Bank DataBank. Available online: https://databank.worldbank.org/home.aspx (accessed on 1 September 2019).
40. Korea Energy Statistical Information System. Available online: https://www.kesis.net/ (accessed on 1 September 2019).
41. Narayan, P.K. The saving and investment nexus for China: Evidence from cointegration tests. *Appl. Econ.* **2005**, *37*, 1979–1990. [CrossRef]
42. Brown, R.L.; Durbin, J.; Evans, J.M. Techniques for Testing the Constancy of Regression Relations over Time. *J. R. Stat. Soc.* **1975**, *37*, 149–163.