CO2 EMISSIONS, RENEWABLE ENERGY CONSUMPTION, POPULATION DENSITY AND ECONOMIC GROWTH IN G7 COUNTRIES

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Abstract

This study aims investigating the relationship between CO2 emissions, renewable energy consumption, economic growth, and population density in G7 countries for 1991–2009 period. In this study, Levin, Lin and Chu; Breitung; Im, Pesaran and Shin; ADF- Fisher Chi-square; ADF- Choi Z-stat; PP- Fisher Chi-square and PP- Choi Z-stat panel unit root tests, Johansen-Fisher panel cointegration test, panel Granger causality test, impulse-response test and Panel OLS, fixed effects, random effects tests were employed. As a result of the study we can say that from country to country the relationship between our variables may show difference, but ultimately we have presented evidence that economic growth, renewable energy consumption and population density are the causes of CO2 emissions.

Keywords: Carbondioxide emissions, renewable energy consumption, population density, economic growth, G7.

Introduction

As one of the main problems of economics, economic growth is one of the main objectives of most of the countries for many years. Income growth is vital for achieving economic, social, and even political development. Countries that grow strongly for sustained periods of time are able to reduce their poverty levels significantly, strengthen their democratic and political stability, improve the quality of their natural environment, and even diminish the incidence of crime and violence (Loayza and Soto 2002).

Until the 1970s economic growth and development focused on only increasing per capita incomes and improving the welfare levels, i.e. only on read-economic growth. After this year, starting to expressing the opinion that social development should not limited with only economy, should also cover environment, nature and the needs of future generations, has led to an increase in the criticisms of the traditional development model (Acar 2002). Carbon dioxide (CO2) emissions come in at the beginning of the factors that negatively effect the environment and the nature. CO2 emissions accumulate in the atmosphere and create costly changes in regional climates throughout the world. Due to these losses of CO2 emissions, researchers have interested more in the factors increasing and decreasing CO2 emissions.

In this regard, this study aims investigating the relationship between CO2 emissions and renewable energy consumption, population density and economic growth in G7 countries for 1991–2009 periods. The reason for choosing G7 countries as sample is that, G7 economies have caused 27.7% of World's total CO2 emissions in 2009 (WDI, World Development Indicators 2013).

The paper is organized as follows: Next section is devoted to the literature. Section 3 presents the data, methodology and results. Finally, Section 4 concludes.

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1. Literature Review

The relationship between CO2 emissions, economic growth, renewable energy consumption and population density has been treated in the literature using different methodological approaches. The results have differed significantly depending on the country, period, variables and method used for the analysis.

The studies examining the relationship between economic growth and CO2 emissions have reached three different conclusions. Kim et al. (2010, for linear causality), Ozturk and Acaravci (2010), Jayanthakumaran et al. (2012, for India), Saboori et al. (2012, for short run) concluded that there is no causal relationship between economic growth and CO2 emissions. Lotfalipour et al. (2010), Jayanthakumaran et al. (2012, for China), Saboori et al. (2012, for long run) concluded that there is a unidirectional causality from economic growth to CO2 emissions. Kim et al. (2010, for nonlinear causality), Shahbaz et al. (2013), Park and Hong (2013) and Wang (2013) concluded that there is bidirectional causality between economic growth and CO2 emissions.

Table 1 Summary of recent literature review for economic growth and CO2 emissions

Study	Period	Country	Methodology	Confirmed hypothesis
Kim, Lee and Nam (2010)	1992-2006	Korea	Smooth transition autoregressive model, linear and nonlinear Granger causality tests	Linear causality: no causality; nonlinear causality: two-way causality
Ozturk and Acaravci (2010)	1968-2005	Turkey	ARDL cointegration analysis, Engle Granger causality	Long run relationship; No causality
Lotfalipour, Falahi and Ashena (2010)	1967-2007	Iran	Unit root, Toda-Yamamoto causality	Unidirectional causality from economic growth to CO2 emissions
Jayanthakumaran, Verma and Liu (2012)	1971-2007	China and India	Bounds testing approach to cointegration and the ARDL methodology	In China: growth→CO2 emissions In India: no causal relationship
Saboori, Sulaiman and Mohd (2012)	1980-2009	Malaysia	ARDL methodology, VECM Granger Causality	U shape relationship Short run: no causality Long run: Unidirectional causality from economic growth to CO2 emissions
Arouri, Youssef, M'Henni and Rault (2012)	1981-2005	12 MENA countries	Panel unit root and cointegration tests	Quadratic relationship
Shahbaz, Hye, Tiwari and Leitao (2013)	1975-2011	Indonesia	Unit root, ARDL bounds, VECM Granger causality, innovative accounting approach	Bidirectional causality
Park and Hong (2013)	1991-2011	South Korea	Regression analysis, Markov switching model	Very close correlation, variables are moving identically
Wang (2013)	1971-2007	138 countries	Panel data analysis, quantile regression analysis, short run error correction model	Absolute decoupling Relative decoupling Feedback

The studies examining the relationship between renewable energy consumption and CO2 emissions have reached three different conclusions. Menyah and Wolde-Rufael (2010) have used Granger causality test and generalized impulse response approach for the period 1960-

2007 in US. They concluded that there is no causal relationship between renewable energy consumption and CO2 emissions. Sadorsky (2009), Marques et al. (2010), Shafiei and Salim (2012) and Farhani (2013, for long run) concluded that there is a unidirectional causality from CO2 emissions to renewable energy consumption. Tiwari (2011), Shabbir et al. (2011), Silva et al. (2012), Kulionis (2013) and Farhani (2013, for short run) concluded that there is a unidirectional causality from renewable energy consumption to CO2 emissions.

Table 2 Summary of recent literature review for renewable energy consumption and CO2 emissions

Study	**Period**	**Country**	**Methodology**	**Confirmed hypothesis**
Sadorsky (2009)	1980-2005	G7	Vector auto regression techniques	Unidirectional causality from CO2 emissions to renewable energy consumption
Menyah and Wolde-Rufael (2010)	1960-2007	US	Granger Causality test, generalized impulse-response approach	No causality
Marques et al. (2010)	1990-2006	24 EU countries	Panel regression techniques	Unidirectional causality from CO2 emissions to renewable energy consumption
Tiwari (2011)	1960-2009	India	Structural Vector Auto Regression Analysis	Unidirectional causality from renewable energy consumption to CO2 emissions
Shabbir et al. (2011)	1971-2010	Pakistan	Clemente-Montanes-Reyes detrended structural break unit root test, ARDL bounds test	Unidirectional causality from renewable energy consumption to CO2 emissions
Silva et al. (2012)	1960-2004	USA, Denmark, Portugal and Spain	Unit root, impulse-response function	Unidirectional causality from renewable energy consumption to CO2 emissions
Shafiei and Salim (2012)	1980-2008	29 OECD countries	STIRPAT model, panel unit root, panel cointegration, panel DOLS and panel causality tests	Unidirectional causality from CO2 emissions to renewable energy consumption
Kulionis (2013)	1972-2012	Denmark	Unit root, Toda-Yomamoto Granger causality, cointegration, impulse response function	Unidirectional causality from renewable energy consumption to CO2 emissions
Farhani (2013)	1975-2008	12 MENA countries	Panel unit root, panel cointegration, panel causality, panel FMOLS and DOLS tests	Short run: unidirectional causality from renewable energy consumption to CO2 emissions Long run: unidirectional causality from CO2 emissions to renewable energy consumption

The studies examining the relationship between population and CO2 emissions have reached four different conclusions. Knapp and Mookerjee (1996) used cointegration analysis, granger causality and ECM causality for the period 1880-1989. They concluded that there is a unidirectional causality from CO2 emissions to population. Dietz and Rosa (1997) and Shi (2001) concluded that there is a unidirectional causality from population to CO2 emissions. Lantz and Feng (2006) used five region panel data analysis for the period 1970-2000 in Canada. They concluded that there is an inverted U-shaped relationship between population and CO2 emissions.

Martinez- Zarzoso et al. (2007) used STIRPAT model, panel OLS, fixed effects and random effects model and Generalized method of moments (GMM) test for the period 1975-1999 in 23 EU countries. Their results show that the impact of population growth on emissions is more than proportional for recent accession countries whereas for old EU members, the elasticity is lower than unity and non significant when the properties of the time series and the dynamics are correctly specified.

Jorgenson and Clark (2010) used cross national panel study for the period 1960-2005 in 86 countries. They concluded that there is a large and stable positive association between population and CO2 emissions.

Table 3 Summary of recent literature review for Population and CO2 emissions

Study	Period	Country	Methodology	Confirmed hypothesis
Knapp and Mookerjee (1996)	1880-1989	World	Cointegration analysis, Granger causality, ECM causality	Unidirectional causality from CO2 emissions to population
Dietz and Rosa (1997)	1989	111 countries	Impact=Population·Affluence·Technology (IPAT) model	Unidirectional causality from population to CO2 emissions
Shi (2001)	1975-1996	93 countries	Descriptive analysis, fixed effects model	Unidirectional causality from population to CO2 emissions
Lantz and Feng (2006)	1970-2000	Canada	Five-region panel data analysis	Inverted U-shaped relationship
Martínez-Zarzoso et al. (2007)	1975-1999	23 EU countries	STIRPAT model, OLS, fixed effects and random effects model, Generalized method of moments (GMM)	The elasticity of emissions-population is much lower for old EU members then recent accession countries
Jorgenson and Clark (2010)	1960-2005	86 countries	Cross-national panel study	a large and stable positive association

This paper analyzes the relationship between CO2 emissions, economic growth, renewable energy consumption and population density.

2. Data, Methodology and Results

2.1. Data

In our study carbon dioxide emissions are in metric tons per capita, representing economic growth GDP is in current US dollars, renewable energy consumption is share of renewable in primary consumption (%), and population density is people per square kilometer of land area. Data set covers 1991–2009 period in G7 countries and attained from Enerdata energy statistical yearbook 2013 and World Bank.

In our study the main model we examine is:

$$\ln CO_{2it} = \alpha + \beta_1 \ln gdp_{it} + \beta_2 reru_{it} + \beta_3 \ln popdens_{it} + e_{it}$$

2.2. Panel Unit Root Test

In panel data models, the leading studies proposed unit root test are Levin, Lin and Chu (2002), Breitung (2000), Im, Pesaran and Shin (2003), Maddala and Wu (1999) and Choi (2001). In our study these unit root tests are applied.

Levin, Lin and Chu (LLC) and Breitung tests assume that there is a common unit root process. And these tests employ a null hypothesis of a unit root. LLC and Breitung tests consider the following basic ADF specification:

$$\Delta y_{it} = \alpha y_{it-1} + \sum_{j=1}^{p_i} \beta_{ij} \Delta y_{it-j} + X'_{it}\delta + \varepsilon_{it} .$$

Here y indicates the series to be done unit root test, Δ indicates the first order difference processor, i indicates cross section units or series, t indicates periods, X'_{it} indicates the exogenous values in the model and ε indicates errors.

The null and alternative hypotheses for the tests may be written as:

$$H_0 : \alpha = 0$$
$$H_1 : \alpha < 0$$

Under the null hypothesis there is a unit root, under the alternative hypothesis there is no unit root (Levin et al., 2002; and Breitung, 2000).

The Im, Pesaran and Shin (IPS) and the Fisher ADF and PP tests assume that there is an individual unit root process. These tests are characterized by the combining of individual unit root tests to derive a panel-specific result.

The null and alternative hypotheses for the IPS test may be written as:

$$H_0 : \alpha_i = 0, \; for \;\; all \;\; i$$
$$H_1 : \begin{cases} \alpha_i = 0, \; for \;\; i = 1,2,\cdots,N_1 \\ \alpha_i < 0, \; for \;\; i = N+1, N+2,\cdots,N \end{cases}$$

which may be interpreted as a non-zero fraction of the individual processes is stationary (Im et al., 2003).

Maddala and Wu (1999) used the Fisher (1932) test results which are based on combining the p-values of the test statistic for a unit root in each cross section. If we define π_i as the p-value from any individual unit root test for cross section i, that π_i are U[0,1] and independent, and $-2\log_e \pi_i$ has a χ^2 distribution with 2 degrees of freedom. The null and alternative hypotheses are the same as in the IPS test. Applying the ADF estimation equation in each cross-section, we can compute the ADF t-statistic for each individual series, find the corresponding p-value from the empirical distribution of ADF t-statistic, and compute the Fisher-test statistics and compare it with the appropriate χ^2 critical value (Hoang and McNown, 2006).

Table 4 Panel Unit Root Tests Results (Level and 1st Differences)

	ln CO_2 Intercept					
	t-stat I(0)	***Prob I(0)***	***t-stat I(1)***	***Prob I(1)***		
Levin, Lin&Chu	4.66757	1.000	-1.66230**	0.0482		
Breitung	7.27365	1.000	2.50097	0.9938		
Im, Pesaran&Shin	3.79564	0.9999	-3.49383***	0.0002		
ADF- Fisher Chi-square	3.75397	0.9968	43.3836***	0.0001		
ADF- Choi Z-stat	3.75701	0.9999	-3.33743***	0.0004		
PP- Fisher Chi-square	7.52691	0.9125	80.2318***	0.0000		
PP- Choi Z-stat	2.03522	0.9791	-5.92149***	0.0000		
	ln gdp Intercept					
	t-stat I(0)	***Prob I(0)***	***t-stat I(1)***	***Prob I(1)***		
Levin, Lin&Chu	-2.11701**	0.0171	-2.03039**	0.0212		
Breitung	3.45887	0.9997	1.84202	0.9673		
Im, Pesaran&Shin	-0.32029	0.3744	-2.81272***	0.0025		
ADF- Fisher Chi-square	16.9440	0.2592	32.2913***	0.0036		
ADF- Choi Z-stat	-0.00049	0.4998	-2.83822***	0.0023		
PP- Fisher Chi-square	8.59552	0.8561	26.3196**	0.0236		
PP- Choi Z-stat	1.72841	0.9580	-1.94202**	0.0261		
	reru Intercept					
	t-stat I(0)	***Prob I(0)***	***t-stat I(1)***	***Prob I(1)***		
Levin, Lin&Chu	8.58829	1.000	-4.32093***	0.0000		
Breitung	4.75817	1.000	2.64456	0.9959		
Im, Pesaran&Shin	6.73913	1.000	-3.49491***	0.0002		
ADF- Fisher Chi-square	8.59941	0.8558	57.7921***	0.0000		
ADF- Choi Z-stat	4.83804	1.000	-2.74780***	0.0030		
PP- Fisher Chi-square	8.51141	0.8610	73.8328***	0.0000		
PP- Choi Z-stat	5.32094	1.000	-6.33904***	0.0000		
	ln popdens Intercept					
	t-stat I(0)	***Prob I(0)***	***t-stat I(1)***	***Prob I(1)***	***t-stat I(2)***	***Prob I(2)***
Levin, Lin&Chu	0.80859	0.7906	0.26981	0.6063	-4.44867***	0.0000
Breitung	0.65140	0.7426	-0.08197	0.4673	-0.86130	0.1945
Im, Pesaran&Shin	2.47330	0.9933	0.88385	0.8116	-3.96956***	0.0000
ADF- Fisher Chi-square	8.47747	0.8630	11.5688	0.6409	42.4301***	0.0001
ADF- Choi Z-stat	2.64783	0.9959	1.02367	0.8470	-4.03917***	0.0000
PP- Fisher Chi-square	43.0116***	0.0001	11.6927	0.6310	43.3055***	0.0001
PP- Choi Z-stat	1.95394	0.9746	1.22269	0.8893	-4.01858***	0.0000

***, **, * indicate significance at the level of 1, 5 and 10 percent, respectively. Optimal lag length is chosen according to the Schwarz information criterion. In LLC and PP tests Bartlett Kernel method is used and the width of Bandwidth is determined by Newey-West method.

As can be seen from table 1, according to the unit root tests results, applied to the levels of variables, t stats and probability results indicate that CO2 emissions series that will be used in the econometric analysis is not stationary in its level [I(0)]. For this reason, the first difference of the series is researched, and looking at the first difference of CO2 emissions series, it is seen that its first difference [I(1)] is stationary according to all of the unit root tests results except Breitung.

It is seen that economic growth series is stationary in its level [I(0)] according to the LLC test, but according to the other unit root tests results it is not stationary. For this reason, the first difference of the series is researched, and looking at the first difference of economic growth series, it is seen that its first difference [I(1)] is stationary according to all of the unit root tests results except Breitung.

It is seen that renewable energy consumption series is not stationary in its level [I(0)] according to unit root tests. For this reason, the first difference of the series is researched, and looking at the first difference of renewable energy consumption series, it is seen that its first difference [I(1)] is stationary according to all of the unit root tests results except Breitung.

And lastly, it is seen that population density series is stationary in its level [I(0)] according to the PP-Fisher Chi-Square test, but according to the other unit root tests results it is not stationary. For this reason, the first difference of the series is researched, and looking at the first difference of population density series, it is seen that its first difference [I(1)] is not stationary according to all of the unit root tests results. Then the second difference of the series is researched, and looking at the second difference of population density series, it is seen that its second difference [I(2)] is stationary according to all of the unit root tests results except Breitung.

2.3. Panel Cointegration Test

In our study Johansen Fisher panel cointegration analysis was used after investigating unit roots in order to investigate if in the long term there is a mutual relation between the series. Johansen Fisher panel cointegration test is developed by Maddala and Wu (1999). As an alternative test for cointegration in panel data, Maddala and Wu used Fisher's result to propose a method for combining tests from individual cross-sections to obtain a test statistic for the panel data. Two kinds of Johansen Fisher tests have been developed: the Fisher test from the trace test and the Fisher test from the maximum eigen-value test (Sheigeyuki and Yoichi, 2009).

We did not use population density variable in cointegration analysis because while other variables are stationary in their first level, population density variable is not stationary in its first level.

Table 5 Johansen Fisher Panel Cointegration Test Results

$$\ln CO_{2it} = \alpha + \beta_1 \ln gdp_{it} + \beta_2 reru_{it} + e_{it}$$

Johansen Fisher Panel Cointegration Test Results

Hypothesized No. of CE(s)	Fisher Stat.* (from trace test)	Prob.	Fisher Stat.* (from max-eigen test)	Prob.
None	157.2***	0.0000	143.6***	0.0000
At most 1	37.32***	0.0007	35.20***	0.0014
At most 2	20.25	0.1223	20.25	0.1223

***, **, * indicate significance at the level of 1, 5 and 10 percent, respectively. Lag interval is chosen as 1 to 2.

According to the table it can be said that both the hypothesis of there is no cointegration and the hypothesis of there is at most one cointegration are rejected. And the hypothesis of there is at most two cointegration is accepted. So the conclusion to be drawn here is there is a cointegration relationship between CO2 emissions, economic growth and renewable energy consumption. In this context, in the long term in G7 countries CO2 emissions, economic growth and renewable energy consumption series move together.

Table 6 Johansen Fisher Panel Cointegration Test Individual Cross Section Results

Individual cross section results				
	Trace Test		Max-Eign Test	
Cross Section	Statistics	Prob.**	Statistics	Prob.**
Hypothesis of no cointegration				
1	38.7263	0.0036	26.7949	0.0072
2	45.6466	0.0004	32.7952	0.0008
3	73.9613	0.0000	46.3935	0.0000
4	78.1071	0.0000	63.4586	0.0000
5	57.2212	0.0000	41.0669	0.0000
6	33.8914	0.0160	28.0140	0.0046
7	71.0897	0.0000	62.8626	0.0000
Hypothesis of at most 1 cointegration relationship				
1	11.9314	0.1603	10.9533	0.1566
2	12.8514	0.1204	11.5769	0.1276
3	27.5678	0.0005	22.6508	0.0019
4	14.6485	0.0668	13.8582	0.0579
5	16.1543	0.0397	15.5818	0.0308
6	5.8774	0.7100	4.5932	0.7920
7	8.2270	0.4414	7.5673	0.4244
Hypothesis of at most 2 cointegration relationship				
1	0.9781	0.3227	0.9781	0.3227
2	1.2745	0.2589	1.2745	0.2589
3	4.9170	0.0266	4.9170	0.0266
4	0.7903	0.3740	0.7903	0.3740
5	0.5725	0.4493	0.5725	0.4493
6	1.2842	0.2571	1.2842	0.2571
7	0.6597	0.4167	0.6597	0.4167
**MacKinnon-Haug-Michelis (1999) p-values				

When we look at the individual cross section results, according to both the trace test and max-eigen test, in all the countries there is at most two cointegration relationships between economic growth, CO2 emissions and renewable energy consumption.

2.4. Panel Granger Causality Test Findings and Evaluation

In our study Panel Granger causality test is used to examine if there is causality between CO2 emissions, economic growth, renewable energy consumption and popdens variables. Panel Granger causality test is developed by Granger (1969) for the question of whether x causes y. Granger's method aims to see how much of the current y can be explained by past values of y and then to see whether adding lagged values of x can improve the explanation. If x helps in the prediction of y or if the coefficients on the lagged x's are statistically significant then y is said to be Granger-caused by x. There can be also bi-directional causality, x Granger causes y and y Granger causes x (Granger, 1969). There are many ways to examine for Granger causality because of the assumptions of heterogeneity across countries and time (Chen et al., 2013).

The simple two-variable causal model is as follows:

$$X_t = \sum_{j=1}^{m} a_j X_{t-j} + \sum_{j=1}^{m} b_j Y_{t-j} + \varepsilon_t$$

$$Y_t = \sum_{j=1}^{m} c_j X_{t-j} + \sum_{j=1}^{m} d_j Y_{t-j} + \eta_t$$

Here X_t and Y_t are two stationary time series with zero means. ε_t and η_t are two uncorrelated white-noise series.

The null hypothesis is that x does not Granger-cause y in the first regression and that y does not Granger-cause x in the second regression (Granger, 1969).

Table 7 Pairwise Granger Causality Test Results

Null Hypothesis:	Obs	F-Statistic	Prob.
LNGDP does not Granger Cause LNCO2	**91**	**4.56114*** **	**0.0005**
LNCO2 does not Granger Cause LNGDP		1.78087	0.1139
LNPOPDENS does not Granger Cause LNCO2	91	0.36724	0.8976
LNCO2 does not Granger Cause LNPOPDENS		0.78067	0.5876
RERU does not Granger Cause LNCO2	91	0.37439	0.8932
LNCO2 does not Granger Cause RERU		1.04162	0.4051

*** indicate significance at the level of 1 percent. Lag length is chosen as 6.

As can be seen from table, according to the Panel Granger Causality Test Results, economic growth is Granger Cause of CO2 emissions at the 1% significance level, but there is no causal relationship between other variables.

Country base Granger Causality is presented in the following tables.

Table 8 Granger Causality Test Results for Canada

Null Hypothesis:	Obs	F-Statistic	Prob.
LNGDP does not Granger Cause LNCO2	**14**	**17.2890** **	**0.0202**
LNCO2 does not Granger Cause LNGDP		0.54955	0.7395
RERU does not Granger Cause LNCO2	14	0.96463	0.5481
LNCO2 does not Granger Cause RERU		2.67025	0.2242
LNPOPDENS does not Granger Cause LNCO2	14	5.06508	0.1061
LNCO2 does not Granger Cause LNPOPDENS		2.27283	0.2655

** indicate significance at the level of 5 percent. Lag length is chosen as 5.

In Canada, according to the Granger Causality Test Results, economic growth is Granger Cause of CO2 emissions at the 5% significance level, but there is no causal relationship between other variables.

Table 9 Granger Causality Test Results for France

Null Hypothesis:	Obs	F-Statistic	Prob.
LNGDP does not Granger Cause LNCO2	14	0.71429	0.6545
LNCO2 does not Granger Cause LNGDP		**9.99890** **	**0.0434**
RERU does not Granger Cause LNCO2	14	0.66741	0.6775
LNCO2 does not Granger Cause RERU		0.59828	0.7131
LNPOPDENS does not Granger Cause LNCO2	14	1.98221	0.3042
LNCO2 does not Granger Cause LNPOPDENS		3.63059	0.1588

** indicate significance at the level of 5 percent. Lag length is chosen as 5.

In France, according to the Granger Causality Test Results, CO2 emissions is Granger Cause of economic growth at the 5% significance level, but there is no causal relationship between other variables.

Table 10 Granger Causality Test Results for Germany

Null Hypothesis:	Obs	F-Statistic	Prob.
LNGDP does not Granger Cause LNCO2	14	1.69435	0.3524
LNCO2 does not Granger Cause LNGDP		1.78588	0.3358
RERU does not Granger Cause LNCO2	14	4.83561	0.1124
LNCO2 does not Granger Cause RERU		0.75764	0.6342
LNPOPDENS does not Granger Cause LNCO2	14	3.76133	0.1523
LNCO2 does not Granger Cause LNPOPDENS		**149.636*** **	**0.0009**

*** indicate significance at the level of 1 percent. Lag length is chosen as 5.

In Germany, according to the Granger Causality Test Results, CO2 emissions is Granger Cause of population density at the 1% significance level, but there is no causal relationship between other variables.

Table 11 Granger Causality Test Results for Italy

Null Hypothesis:	Obs	F-Statistic	Prob.
LNGDP does not Granger Cause LNCO2	**14**	**14.8039** **	**0.0252**
LNCO2 does not Granger Cause LNGDP		1.61867	0.3671
RERU does not Granger Cause LNCO2	14	2.85623	0.2084
LNCO2 does not Granger Cause RERU		1.41896	0.4111
LNPOPDENS does not Granger Cause LNCO2	**14**	**71.4824*** **	**0.0026**
LNCO2 does not Granger Cause LNPOPDENS		0.18950	0.9477

*** and ** indicate significance at the level of 1 and 5 percent, respectively. Lag length is chosen as 5.

In Italy, according to the Granger Causality Test Results, economic growth is Granger Cause of CO2 emissions at the 5% significance level, and population density is granger cause of CO2 emissions at the %1 significance level, but there is no causal relationship between CO2 emissions and renewable energy consumption variables.

Table 12 Granger Causality Test Results for Japan

Null Hypothesis:	Obs	F-Statistic	Prob.
LNGDP does not Granger Cause LNCO2	14	2.17733	0.2773
LNCO2 does not Granger Cause LNGDP		1.17759	0.4763
RERU does not Granger Cause LNCO2	14	0.52534	0.7530
LNCO2 does not Granger Cause RERU		1.02632	0.5258
LNPOPDENS does not Granger Cause LNCO2	14	1.78411	0.3361
LNCO2 does not Granger Cause LNPOPDENS		0.41317	0.8182

Lag length is chosen as 5.

In Japan according to the Granger Causality Test Results, there is no causal relationship between our variables.

Table 13 Granger Causality Test Results for United Kingdom

Null Hypothesis:	Obs	F-Statistic	Prob.
LNGDP does not Granger Cause LNCO2	14	3.49891	0.1658
LNCO2 does not Granger Cause LNGDP		1.19795	0.4702
RERU does not Granger Cause LNCO2	14	0.46082	0.7900
LNCO2 does not Granger Cause RERU		1.71513	0.3485
LNPOPDENS does not Granger Cause LNCO2	14	2.85877	0.2082
LNCO2 does not Granger Cause LNPOPDENS		0.66821	0.6771

Lag length is chosen as 5.

In United Kingdom, according to the Granger Causality Test Results, there is no causal relationship between our variables.

Table 14 Granger Causality Test Results for United States

Null Hypothesis:	Obs	F-Statistic	Prob.
LNGDP does not Granger Cause LNCO2	14	1.63128	0.3646
LNCO2 does not Granger Cause LNGDP		3.10145	0.1902
RERU does not Granger Cause LNCO2	**14**	**8.88998***	**0.0509**
LNCO2 does not Granger Cause RERU		1.61871	0.3671
LNPOPDENS does not Granger Cause LNCO2	14	3.39554	0.1716
LNCO2 does not Granger Cause LNPOPDENS		3.27460	0.1789

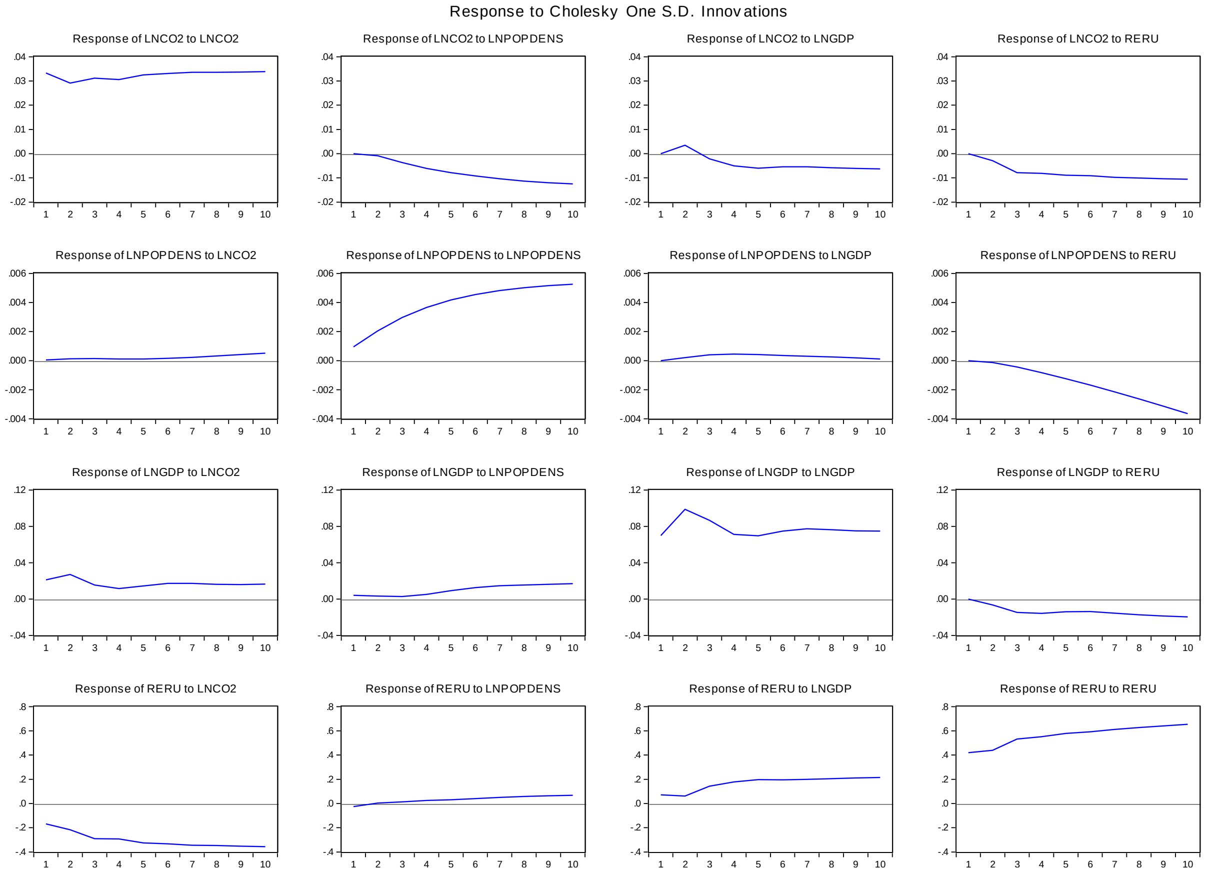
* indicate significance at the level of 10 percent. Lag length is chosen as 5.

In United States, according to the Granger Causality Test Results, renewable energy consumption is Granger Cause of CO2 emissions at the 10% significance level, but there is no causal relationship between other variables.

2.5. Impulse-Response Test

Impulse-response function shows the effect of shocks on the variables and shows in which time and how a change occurs in impulse. With impulse-response analysis it is examined that in which variable shocks have occurred and how other variables will react to these shocks (Hamilton, 1994). In order to determine how the shocks will occur, the movements of variables for 10 periods are analyzed. The responses of other variables against a one unit change in shocks occurs in the series used in this study are shown in the following graphs.

Graph 1 Impulse-Response Function Tests



The impact of a shock of one standard deviation in economic growth on CO2 emissions initially increases up to 0.0035, then becomes negative in third period, and beginning from the fourth period continuously fluctuates between -0.005 and -0.006.

The impact of a shock of one standard deviation in population density and renewable energy consumption on CO2 emissions monitors a negative course and gradually decreases.

2.6. OLS, Fixed Effects Model and Random Effects Model

In our study three different models for panel data are used to estimate the coefficients of relationship between female labor force participation and national competitiveness. First model is ordinary least squares. If z_i contains only a constant term, then ordinary least squares provides consistent and efficient estimates of the common α and the slope vector β. But if z_i is unobserved, but correlated with x_{it}, then the least squares estimator of β is biased and inconsistent as a consequence of an omitted variable. However, in this instance, fixed effects model provides consistent and efficient estimations. Fixed effects model can be written as follows:

$$y_{it} = x'_{it}\beta + \alpha_i + \varepsilon_{it}$$

Here $\alpha_i = z'_i\alpha$ embodies all the observable effects and indicates an estimable conditional mean. Fixed effects approach takes α_i as a group-specific constant term in the regression model.

If the unobserved individual heterogeneity can be assumed to be uncorrelated with the included variables then random effects model provides consistent and efficient estimations. Random effects model may be formulated as follows:

$$\begin{aligned} y_{it} &= x'_{it}\beta + E[z'_i\alpha] + \{z'_i\alpha - E[z'_i\alpha]\} + \varepsilon_{it} \\ & x'_{it}\beta + \alpha + u_i + \varepsilon_{it} \end{aligned}$$

This formulation shows that as a linear regression model with a compound disturbance that may be consistently estimated by least squares. Random effects model indicates that u_i is a group-specific random element, similar to ε_{it} except that for each group, there is a single draw that enters the regression identically in each period (Greene, 2010).

Our model is $\ln CO_{2it} = \alpha + \beta_1 \ln gdp_{it} + \beta_2 reru_{it} + \beta_3 \ln popdens_{it} + e_{it}$

Table 15 OLS, cross section fixed effects and cross section random effects tests results

	OLS	Cross Section Fixed Effects	Cross Section Random Effects
Constant	-0.613279 (0,3751)	*4.012734* *(0.0000)*	*3.867214* *(0.0000)*
LNGDP	**0.166028** **(0.0000)**	-0.013380 (0.6676)	-0.010939 (0.5305)
RERU	**-0.048305** **(0.0000)**	**-0.020754** **(0.0000)**	**-0.021435** **(0.0000)**
LNPOPDENS	**-0.326125** **(0.0000)**	-0.257234 (0.2439)	**-0.239373** **(0.0001)**
R^2	0.795526	0.988257	0.366977
F	167.2956 (0.0000)	1150.167 (0.0000)	24.92804 (0.0000)

According to table, all three models gave statistically significant results. To investigate which one of these models is appropriate, we employed Hausman (1978) and Likelihood Ratio Tests. Under the null hypothesis that the unobservable, individual-specific effects and the regressors are orthogonal, Hausman specification test is based on the idea that the set of coefficient estimates obtained from the fixed-effects estimation should not differ systematically from the set obtained from random-effects estimation. If the test results suggest rejecting the equality of both coefficient sets, then it can be said that fixed effects estimation results is more appropriate than random effects estimation results. If this is the case than random effects estimations are ignored (Frondel and Vance, 2010).

In panel data models, to test the validity of the classic model (OLS); i.e. there is whether the unit and/or time effects, likelihood ratio test can be applied. Likelihood ratio test, that is used to test classical model against the fixed effects model, is applied to determine in which model framework the equation will be estimated. Likelihood ratio test research if standard errors of unit effects are equal to zero; in other words, if the basic hypothesis that classical model is appropriate ($H_0 : \sigma_\mu = 0$). If H_0 is rejected than it can be said that classical model is not appropriate (Gerni et al., 2012).

Likelihood ratio and Hausman tests have been applied to find the fittest of these models. Likelihood ratio test has been applied to find the appropriate one of the OLS model and fixed effects model. Hausman test has been applied to decide to use which one of the fixed effects and random effects models. It is examined if the difference between the two model's parameters is statistically significant. Accordingly the results of the likelihood ratio test under the null hypothesis of "the OLS estimator is correct" and the Hausman test under the null hypothesis of "the random effects estimator is correct" are shown in the following table.

Table 16 Likelihood Ratio and Hausman Test Results

Test Summary	Statistic	d.f.	Prob.
Cross-Section F	336.460807	6.123	0.0000
Cross-Section Chi-Square	380.007747	6	0,0000
Cross-Section Random	4.101222	3	0.2507

When we look at the likelihood ratio test results, H_0 hypothesis is rejected because the probability is less than 0. Because of this, fixed effects model is more favorable for this dataset. And if the Hausman test results are taken into account, as the probability is higher than 0.05, H_0 hypothesis is accepted. So the random effects model is more appropriate for the dataset. According to both Hausman and likelihood ratio tests, random effects model is more appropriate.

According to the cross section random effect model, R^2 is lower than average and the equation is like that:

$$\ln CO_{2it} = 3.867214 - 0.010939 \ln gdp_{it} - 0.021435 reru_{it} - 0.239373 \ln popdens_{it} + e_{it}$$

The coefficients except economic growth are statistically significant at the 1%, 5% and 10% significance level. A one category increase in renewable energy consumption leads to a decrease of 2.1435% in CO2 emissions, and a one category increase in population density leads to a decrease of 23.9373% in CO2 emissions.

Conclusion

This study aims investigating the relationship between CO2 emissions, renewable energy consumption, economic growth, and population density in G7 countries for 1991–2009 period. In this study, Levin, Lin and Chu; Breitung; Im, Pesaran and Shin; ADF- Fisher Chi-square; ADF- Choi Z-stat; PP- Fisher Chi-square and PP- Choi Z-stat panel unit root tests, Johansen-Fisher panel cointegration test, panel Granger causality test, impulse-response test and Panel OLS, fixed effects, random effects tests were employed.

According to the unit root tests results, applied to the levels of variables, t stats and probability results indicate that CO2 emissions, GDP and renewable energy consumption series are not stationary in their level [I(0)]. Looking at the first difference of these series, it is seen that CO2 emissions, GDP and renewable energy consumption's first difference [I(1)] is stationary according to all of the unit root tests results except Breitung. But also it is seen that population density's first difference [I(1)] is not stationary but second difference [I(2)] is stationary according to all of the unit root tests results except Breitung.

According to Johansen Fisher panel cointegration test results there is a cointegration relationship between CO2 emissions, economic growth and renewable energy consumption. In this context, in the long term in G7 countries CO2 emissions, economic growth and renewable energy consumption series move together.

According to Pairwise Granger Causality Test Results, economic growth is Granger Cause of CO2 emissions at the 1% significance level, but there is no causal relationship between other variables. Looking at the country base Granger Causality test it is seen that in Canada economic growth is Granger Cause of CO2 emissions at the 5% significance level, but there is no causal relationship between other variables. In France CO2 emissions is Granger Cause of economic growth at the 5% significance level, but there is no causal relationship between other variables. In Germany, CO2 emissions is Granger Cause of population density at the 1% significance level, but there is no causal relationship between other variables. In Italy, economic growth is Granger Cause of CO2 emissions at the 5% significance level, and population density is granger cause of CO2 emissions at the %1 significance level, but there is no causal relationship between CO2 emissions and renewable energy consumption variables. In Japan and United Kingdom, there is no causal relationship between our variables. In United States, according to the Granger Causality Test Results, renewable energy consumption is Granger Cause of CO2 emissions at the 10% significance level, but there is no causal relationship between other variables.

According to impulse-response test, the impact of a shock of one standard deviation in economic growth on CO2 emissions initially increases up to 0.0035, then becomes negative in third period, and beginning from the fourth period continuously fluctuates between -0.005 and -0.006. The impact of a shock of one standard deviation in population density and renewable energy consumption on CO2 emissions monitors a negative course and gradually decreases.

Lastly panel OLS, fixed effects and random effects tests were employed. And likelihood ratio and Hausman tests have been applied to find the fittest of these models. According to both Hausman and likelihood ratio tests, random effects model is more appropriate. According to the results of cross section random effect model, a one category increase in renewable energy consumption leads to a decrease of 2.1435% in CO2 emissions, and a one category increase in population density leads to a decrease of 23.9373% in CO2 emissions.

To sum up, we can say that from country to country the relationship between our variables may show difference, but ultimately we have presented evidence that economic growth, renewable energy consumption and population density are the causes of CO2 emissions.

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