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The Impact of Renewable Energy Policies on Carbon Dioxide Emissions in the Latin American countries-A PVAR approach[1]

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Abstract

This article analyzes the impact of renewable energy policies on carbon dioxide emissions (CO_2) in nine Latin American countries, in a period of 1991 to 2012. The Panel Vector Auto-Regressive (PVAR) was utilized. The results revealed that the renewable energy policies reduce the environmental degradation (CO_2 emissions) in -0.0109, and the consumption of renewable energy -0.0231, while the economic growth and consumption oil increase the emissions in 0.9082 and 0.1437 respectively. These empirical findings will help the policymakers develop appropriate renewable energy policies, as well as help to advance the literature that approaches the impact of renewable energy policies on environmental degradation in the Latin America region.

Keywords: Environmental degradation; Energy economics; Econometrics; Energy; Environmental; Latin America.

1. Introduction

The increase of fossil fuels consumption and the consequent intensification of the level of Carbon dioxide emissions (CO_2) have set off an alarm signal in the worldwide (Arce et al. 2016). Indeed, 80% of these emissions come from fossil fuels burning, where 44% comes from coal, 36% from oil and 20% from natural gas (IRENA, 2014). Therefore, in order to mitigate these emissions, different policies have been applied to promote the development of renewable energy sources.

The aim of this investigation is to answer the following question: Does renewable energy policies reduce the carbon dioxide emissions? To answer this question, the impact of renewable energy policies on CO_2 emissions will be analyzed in nine countries from Latin America region, in a period between 1991-2012. A Panel Vector Auto-Regressive (PVAR) was utilized as methodology. In the literature, the impact of renewable energy policies on environmental degradation has been widely researched. For instance, several studies have indicated that the renewable energy policies decrease the CO_2 emissions (e.g., Hinrichs-Rahlwes, 2013; Ortega et al. 2013; Verma and Kumar, 2013; Smith and Urpelainen, 2014; Redondo and Collado,2014; Arce and Sauma, 2016;Argenteiro et al. 2015;Carley et al. 2016;Arce et al. 2016;Thapar et al.2016).

This investigation is extremely important because it is necessary to identify whether these policies are effective. Moreover, this article will help the policymakers develop appropriate renewable energy policies that inventive the investments, development, and consumption of alternative sources with the intention of reduce the environmental degradation in the Latin American countries.

The paper is organized as follows. Section 2, presents the literature review. Section 3, presents the data based used, method and preliminary tests. Section 4, presents the empirical results and discussion. Finally, Section 5 presents the conclusions.

2. Literature review

The impact of renewable energy policies on environmental degradation (CO_2 emissions) has been widely researched in the ecological and economic literature. There is evidence in the literature that the renewable energy policies have encouraged the introduction of renewable energy sources in the energy mix and consequently reduce the environmental degradation. Table 1, presents a summary of the literature review.

Table 1. Summary of literature review

Author(s)	Period(s)	Country(ies)	Policy(ies)	Conclusion(s)
Carley et al. (2016)	1990-2010	164 countries	FITs and RPS.	The REP reduces the CO_2 emissions.
Arce et al. (2016)	n. a.	n. a.	Carbon taxes; FITs; Premium payments; Quota obligations.	The REP reduces the CO_2 emissions.
Thapar et al. (2016)	n. a.	India	Grant/subsidies; Accelerate depreciation; Tax concessions/exemptions; Preferential tariffs; Renewable purchase obligations.	The REP reduces the CO_2 emissions.
Arce and Sauma (2016)	n. a.	n. a.	Carbon taxes; FITs; Premium payments and Quota systems.	The REP reduces the CO_2 emissions.
Argenteiro et al. (2015)	1995-2012	15 E.U countries	Tax concessions/exemptions; Preferential tariffs; Renewable purchase obligations.	The REP reduces the CO_2 emissions.
Smith and Urpelainen (2014)	1979-2005	U. S	FITs.	The REP reduces the CO_2 emissions.
Redondo and Collado (2014)	2011	Spain	Premium payments.	The REP reduces the CO_2 emissions.
Ortega et al. (2013)	2002-2011	Spain	FITs.	The REP reduces the CO_2 emissions.
Verma and Kumar (2013)	n. a.	n. a.	Carbon quotas; Cap-and-trade and bilateral IPPs.	The REP reduces the CO_2 emissions.
Stokes (2013)	1997-2012	Canada	FITs.	The REP reduces the CO_2 emissions.
Hinrichs-Rahlwes (2013)	1998-2009	Germany	FITs.	The REP reduces the CO_2 emissions.

Notes: n. a. denotes 'not available'. The abbreviations are as follows: Feed-in tariffs (FITs), Independent Power Producers (IPPs), Carbon Dioxide Emissions (CO_2); Renewable Energy Resources (RPS); Renewable Energy Policies (REP); Europe Union (E.U); United States (U.S).

3. Data and method

This section is divided into three parts. In the first one, the variables and data used are described. The second contains the method that will be used. The third shows the preliminary tests.

3.1 Data

Annual data from 1991 to 2012 was used for a panel of nine Latin American countries, namely: Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Mexico, Peru, and Uruguay. The choice of these countries and time series are due to the availability of existing data. After the presentation of the object of this study, the variables that will be used are presented in Table 2 below.

Table 2. Variables description and summary statistics

Variables	Definition(s)	Source (s)	Obs	Mean	Std. Dev	Min	Max
LCO_2	Consumption of energy in million metric tons.	Energy Information Administration (EIA).	189	-13.1235	0.4819	-14.1656	-12.2740
LPOL	Include economic instruments, information, and education, policy support, regulatory instruments, research, development and deployment (RD&D) voluntary approaches.	International Energy Agency (IEA).	189	1.1554	1.0622	0.0000	3.5554
LRE	Net generation in billion Kilowatt-hours, from hydroelectric, geothermal, wind, solar, tide, wave, biomass, and waste.	Energy Information Administration (EIA).	189	-14.0800	0.7164	-15.5654	-12.7685
LO	Consumption of oil consumption in million metric tons.	Energy Information Administration (EIA).	189	-11.4646	0.4673	-12.5180	-10.7145
LY	GDP in constant local currency unity (LCU).	The World Bank Data (WBD).	189	10.8891	2.8139	7.7480	16.0930

Notes: n. a. denotes 'not available'. The prefix (L) denotes natural logarithms. The Stata command *sum* was used.

These variables were chosen considering the following criteria: (i) they have had renewable and fossil consumption over a long period; and (ii) they have data available for the entire period. The total population of each country of this study was used to transform the variables (LCO_2, LRE, LO, and LY) into *per capita* values with the purpose of control the disparities in the population growth among the Latin American countries. The option to use constant Local Currency Unit

(LCU) in the variable LY, allowed the influence of exchange rates to be circumvented. The Stata 15.1 was used in the econometric analyzes.

3.2 Method

The Panel data Vector Autoregressive (PVAR) developed by (Holtz-Eakin et al. 1988) was used to analyze the causal relationship between all variables. The PVAR model used in this empirical analysis follow the specification of Eq. (1):

$$Y_{it} = Y_{it-1}A_1 + Y_{it-2}A_2 + \cdots + Y_{it-p+1}A_{p-1} + Y_{it-p}A_p + X_{it}B + u_i + e_{it} \quad (1)$$

where Y_{it} is a vector of dependent variable; X_{it} is a vector of exogenous covariates; u_i and e_{it} are a vector of dependent variable-specific panel fixed-effects and idiosyncratic errors, respectively. The matrices $A_1, A_2, \ldots, A_{p-1}, A_p$ and B are parameters to be estimated.

So, before the realization of PVAR regression, it is advisable to verify the properties of the variables. To this end, some preliminary tests were applied, namely: (i) Variance Inflation Factor (VIF) test to check the presence of multicollinearity (O'Brien, 2007);(ii) Pesaran CD test to identify of cross-section dependence (Pesaran, 2004);(iii) 2nd generation of unit root tests (CIPS-test) to check the presence of cross-section dependence (Pesaran,2007); (iv) Hausman test to verify whether the panel has random effects (RE) or fixed effects (FE);and (v) Lag-order selection statistics for PVAR (Hansen,1982) that reports the model overall coefficient of determination.

After the PVAR regression, it is necessary to apply the specification tests to verify the characteristics of the model. To this end, some diagnostics tests by Abrigo and Love (2015) will be applied, namely: (i) Eigenvalue stability condition to verify the stability in the PVAR model;(ii) Granger causality Wald test to check the casual relationship between variables of model;(iii) Forecast-error variance decomposition (FEVD) that compute the forecast-error variance decomposition based on the Cholesky decomposition of the underlying PVAR model. In this test, the standard errors and the confidence intervals are based on Monte Carlos simulation; and (iv) Impulse-response function that calculates the plots impulse-response functions (IRF). The confidence bands of IRFs are estimated using Gaussian approximation and base on Monte Carlo simulation.

3.3 Preliminary tests

This section shows the results of preliminary tests. To check the presence of multicollinearity and cross-section dependence in the variables, the Variance Inflation Factor (VIF) test and Pesaran CD test were performed. The results of both tests can be seen in Table 3.

Table 3. VIF and Pesaran CD-tests

Variables	VIF	1/VIF	CD-test	p-value	Corr	Abs (corr)
LCO_2	n.a	n.a	17.02	0.000	0.605	0.615
LPOL	1.01	0.9867	22.82	0.000	0.811	0.811
LRE	1.31	0.7608	8.43	0.000	0.299	0.403
LO	1.15	0.8660	8.93	0.000	0.317	0.674
LY	1.19	0.8398	25.68	0.000	0.912	0.912
Mean VIF	1.17					
$DLCO_2$	n.a	n.a	3.03	0.002	0.110	0.194
DLPOL	1.02	0.9833	1.04	0.298	0.038	0.169
DLRE	1.11	0.8970	-0.33	0.745	-0.012	0.226
DLO	1.29	0.7778	4.94	0.000	0.180	0.236
DLY	1.21	0.8230	11.17	0.000	0.406	0.406
Mean VIF	1.16					

Notes: n. a. denotes ‘not available’. The Stata command *xtcd* was used. Hereafter the prefixes (L) and (D) denote the variables in the natural logarithms and first-differences respectively.

The values of the mean of VIFs was 1.17 in levels (natural logarithms) and in the first differences was 1.16. The low VIFs statistics than benchmark 10% support the argument that multicollinearity is not a great problem in the model. Moreover, the Pesaran CD-test points to the presence of cross-section dependence (CSD) in the variables in levels and in first-differences except for the variables (DLPOL and DLRE) in the first-differences. After the realization of VIF and Pesaran CD-test, it is necessary to apply the 2^{nd} generation unit root test (CIPS-test) to verify the stationarity of variables. The null hypothesis rejection of this test is that all variables are I(1) that is stationary. Table 4, shows the results of unit root test.

Table 4. Unit roots test

2nd Generation unit root test CIPS (Zt-bar)				
Variables	Specification without trend		Specification with trend	
	Zt-bar	p-value	Zt-bar	p-value
LCO_2	-2.045	0.020	-1.413	0.079
LPOL	0.259	0.602	0.721	0.764
LRE	-3.556	0.000	-2.490	0.006
LO	-0.662	0.254	0.932	0.824
LY	-1.833	0.033	-2.061	0.020
$DLCO_2$	-10.120	0.000	-9.176	0.000
DLPOL	-7.108	0.000	-6.464	0.000
DLRE	-11.934	0.000	-10.567	0.000
DLO	-7.980	0.000	-6.635	0.000
DLY	-8.072	0.000	-6.466	0.000

Notes: The Stata command *multipurt* was used.

The 2nd generation unit root test (CIPS-test) was used with lag length (1), and with the specifications without trend and with the trend. The results of the CIPS-test indicate that the variables in level are I (0) except the variables (LCO_2, LRE, and LY), and the variables in the first differences are I(1).

The Hausman test was performed to determine whether the panel has random effects (RE) or fixed effects (FE). The null hypothesis of this test that the best model is RE. Table 5, reveals the coefficients of Hausman test.

Table 5. Hausman test

Variables	(a) Fixed	(b) Random	(a-b) Difference	Sqrt (diag(V_a-V-b)) S.E.
LCO_2	-0.5283	-0.0530	-0.4753	0.0654
LPOL	-0.0073	0.0006	-0.0079	0.0071
LRE	-0.0279	-0.0080	-0.0199	0.0364
LO	0.2796	0.0442	0.2354	0.0586
LY	0.3125	0.0006	0.3120	0.0766
DLPOL	0.0118	0.0178	-0.0060	n.a
DLRE	-0.0947	-0.0994	0.0048	0.0115
DLO	0.3599	0.4255	-0.0656	n.a
DLY	0.5315	0.3937	0.1378	n.a
Chi2 (9)			54.63***	

Notes: n. a. denotes ‘not available’. *** denotes statistical significance level of 1%.

The results of Hausman test point to the selection of (FE) model, where the result is statistically significant at 1% ($\chi_9^2 = 54.63$***). After the realization of the Hausman test, the PVAR lag-order selection was used to report the model overall coefficients of determination. The overall coefficient of determination (CD), Hansen´s J statistic (J), p-value (Jp-value), moment model selection criteria (MMSC) - Bayesian information criterion (MBIC), MMSC-Akaike information criterion (MAIC), and MMSC-Hannan and Quinn information criterion (MQIC) were applied. Table 6, shows the results of lag-order selection.

Table 6. Lag order selection on estimation

Lags	CD	J	Jp-value	MBIC	MAIC	MQIC
1	0.2439	77.7339	0.3917	-295.0021	-72.2661	-162.7734
2	0.2697	50.1867	0.4660	-198.3039	-49.8133	-110.1515
3	0.5016	19.7235	0.7612	-104.5219	-30.2766	-60.4457
4	0.3539	-	-	-	-	-

Notes: The Stata the command *pvarsoc* was used.

One lag was used in the PVAR model, totalizing 144 observations, 9 panels, and an average of number T of 16.000. The estimations result of the Hansen´s J statistic (J) is higher at one lag, and the MBIC, MAI, and MQIC estimations are lower at one lag.

4. Empirical results and discussion

The results of PVAR model, Eigenvalue Stability Condition, Granger Causality Wald test, Forecast-Error Variance Decomposition (FEVD), and Impulse-response function will show in this section. Table 7, shows the results of the PVAR with one lag.

Table 7. PVAR model results

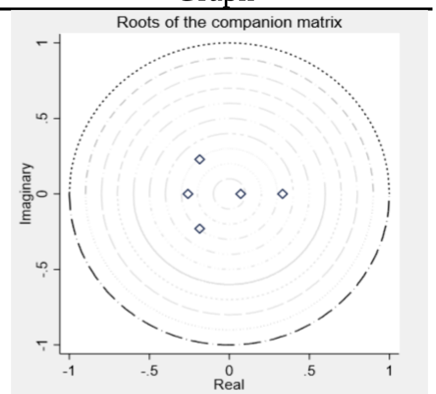
Response of	Response to				
	$DLCO_2$	DLPOL	DLRE	DLO	DLY
$DLCO_2$	-0.3429 (-12.17) 0.000	-0.2794 (-4.12) 0.000	0.5293 (8.38) 0.000	-0.1795 (-12.53) 0.000	0.0483 (3.09) 0.002
DLPOL	-0.0109 (-2.07) 0.038	0.0718 (3.79) 0.000	0.0004 (0.03) 0.972	-0.0096 (-2.01) 0.044	-0.0088 (-4.04) 0.000
DLRE	-0.0231 (-2.24) 0.025	-0.2208 (-10.83) 0.000	-0.3109 (-18.05) 0.000	0.0200 (2.59) 0.010	-0.0157 (-3.13) 0.002
DLO	0.1437 (5.56) 0.000	-0.2770 (-4.27) 0.000	-0.8014 (-12.99) 0.000	-0.0831 (-4.08) 0.000	-0.1247 (-5.53) 0.000
DLY	0.9082 (15.22) 0.000	0.4551 (2.83) 0.005	-0.8554 (-8.10) 0.000	1.1259 (27.54) 0.000	0.4378 (9.37) 0.000
N obs	171				
N panels	9				

Notes: The Stata command *pvar*, with one lag was used.

The outputs of PVAR indicate that the renewable energy policies reduce the CO_2 emissions in -0.0109, and consumption of renewable energy in -0.0231. Additionally, the economic growth and consumption of oil (fossil fuels) increase the emissions in 0.9082 and 0.1437, respectively. Indeed, to check the stability condition of PVAR estimates, the eigenvalue stability condition was computed. Table 8, display the graph of eigenvalue stability condition.

Table 8. Eigenvalue stability condition

Eigenvalue			Graph
Real	Imaginary	Modulus	
0.3332	0.000	0.3332	
-0.1862	-0.2295	0.2956	
-0.1862	0.2295	0.2956	
-0.2585	0.0000	0.2585	
0.0704	0.0000	0.0704	



Notes: The Stata command *pvarstable* was used.

The eigenvalues indicate that the PVAR is stable because all eigenvalues are inside of unity circle. Moreover, to observe the presence of causalities and their direction was the Granger causality Walt test was computed. Table 9, show the results of Granger causality Walt test.

Table 9. Results of Granger causality Wald test

Equation \ Excluded		chi2	Df.	Prob > chi2
$DLCO_2$	DLPOL	4.304	1	0.038
	DLRE	5.011	1	0.025
	DLO	30.903	1	0.000
	DLY	231.715	1	0.000
	ALL	477.662	4	0.000
DLPOL	$DLCO_2$	16.999	1	0.000
	DLRE	117.296	1	0.000
	DLO	18.201	1	0.000
	DLY	8.004	1	0.005
	ALL	138.435	4	0.000
DLRE	$DLCO_2$	70.162	1	0.000
	DLPOL	0.001	1	0.972
	DLO	168.749	1	0.000
	DLY	65.686	1	0.000
	ALL	424.096	4	0.000
DLO	$DLCO_2$	156.915	1	0.000
	DLPOL	4.051	1	0.044
	DLRE	6.699	1	0.010
	DLY	758.582	1	0.000
	ALL	1085.129	4	0.000
DLY	$DLCO_2$	9.566	1	0.002
	DLPOL	16.322	1	0.000
	DLRE	9.795	1	0.002
	DLO	30.625	1	0.000
	ALL	57.642	4	0.000

Notes: The Stata command *pvargranger* was used.

The Granger causality Wald test show the presence of a bi-directional causality between all variables in the study. Certainly, after estimation by PVAR the forecast error variance decomposition (FEVD) will be applied. The FEVD is computed when exogenous variables are included in the underlying PVAR model. Table 10, show the outputs of FEVD-test.

Table 10. Forecast-error variance decomposition (FEVD)

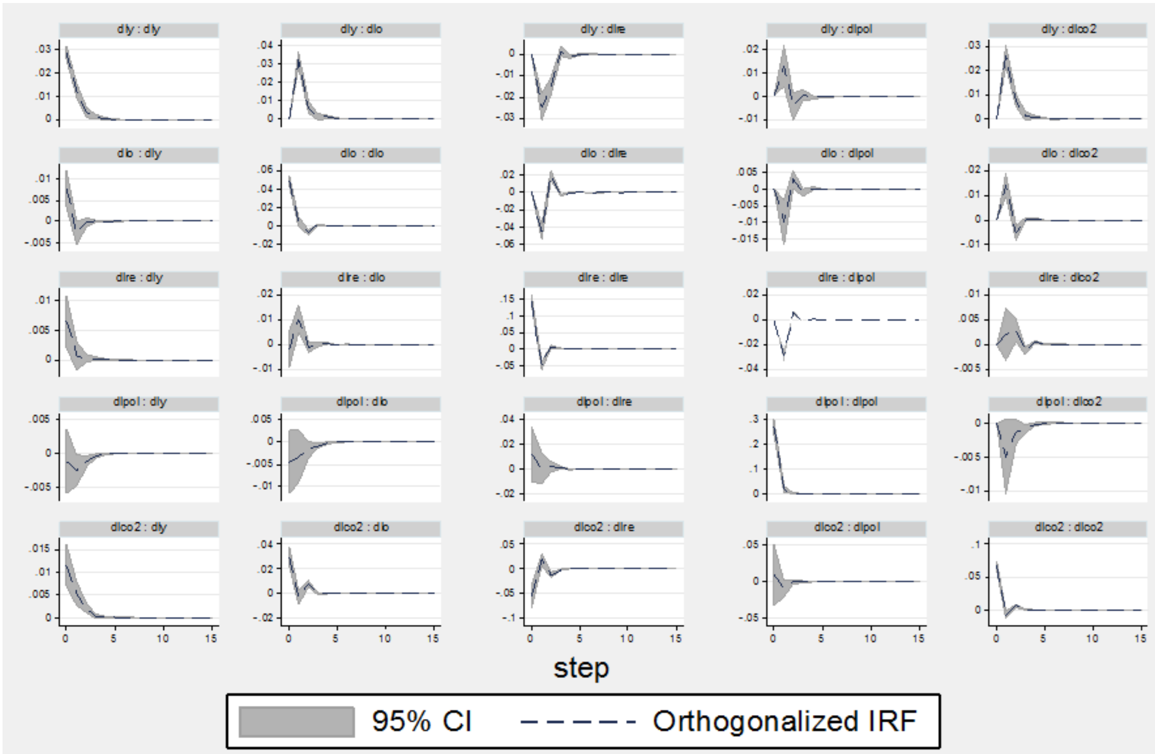
Response variable and Forecast Impulse Variable Horizon	Impulse variable				
	$DLCO_2$	DLPOL	DLRE	DLO	DLY
$DLCO_2$					
0	0	0	0	0	0
1	1	0	0	0	0
2	0.8374	0.0044	0.0008	0.0354	0.1220
5	0.8239	0.0047	0.0026	0.0395	0.1292
10	0.8239	0.0047	0.0026	0.0395	0.1292
15	0.8239	0.0047	0.0026	0.0395	0.1292
DLPOL					
0	0	0	0	0	0
1	0.0013	0.9987	0	0	0
2	0.0024	0.9826	0.0114	0.0013	0.0023
5	0.0024	0.9817	0.0119	0.0014	0.0025
10	0.0024	0.9817	0.0119	0.0014	0.0025
15	0.0024	0.9817	0.0119	0.0014	0.0025
DLRE					
0	0	0	0	0	0
1	0.1191	0.0061	0.8749	0	0
2	0.1095	0.0050	0.7985	0.0674	0.0196
5	0.1112	0.0050	0.7786	0.0786	0.0265
10	0.1112	0.0050	0.7786	0.0786	0.0265
15	0.1112	0.0050	0.7786	0.0786	0.0265
DLO					
0	0	0	0	0	0
1	0.2731	0.0062	0.0011	0.7196	0
2	0.2018	0.0070	0.0249	0.5319	0.2343
5	0.2091	0.0077	0.0244	0.5238	0.2350
10	0.2091	0.0077	0.0244	0.5238	0.2350
15	0.2091	0.0077	0.0244	0.5238	0.2350
DLY					
0	0	0	0	0	0
1	0.1253	0.0013	0.0391	0.0572	0.7770
2	0.1283	0.0063	0.0333	0.0536	0.7786
5	0.1303	0.0073	0.0329	0.0530	0.7765
10	0.1303	0.0073	0.0329	0.0530	0.7765
15	0.1303	0.0073	0.0329	0.0530	0.7765

Notes: Stata command *pvarfevd* was used.

The FEVD show that the $DLCO_2$ two periods after a shock explains the FEVD in 84%, DLPOL in fifteen periods explaining 0.04%, DLRE 0.03%, DLO 4% and DLY 13%. DPOL in one period after a shock explains the FEVD in 100 %, $DLCO_2$ in fifteen periods explaining 0.02%, DLRE 2%, DLO 0.01%, and DLY 0.03%. DLRE in one period after a shock explaining the FEVD in 88%, $DLCO_2$ in fifteen periods explaining 11%, DLPOL 0.5%, DLO 8%, and DLY 3%. DLO in one period after shocks explains the FEVD in 72%, $DLCO_2$ in 27%, DLPOL in fifteen periods explaining in 0.08%, DLY 24%, and DLRE in two periods 3%. DLY in one period after a shock explains the FEVD in 78%, $DLCO_2$ in fifteen periods explaining in 13%, DLPOL 0.07%, DLRE in one period explaining 4%, DLO in 6%.

The impulse-response was computed to analysis the IRFs and dynamic multipliers after PVAR. Figure 1, shows the impulse-response function of variables. The impulse-response function was computed following the Cholesky procedure. The procedure was repeated 1000 times to compute the 5^{th} and the 95^{th} percentiles of the impulse responses.

Figure 1. Impulse-response function



Notes: The Stata *pvarirf* command was used.

The impulse-response function it is in concordance with FEVD and shows that all variables converge to equilibrium, supporting that variables are I (1). Additionally, the shock of DPOL on $DLCO_2$ is very small (See Figure 1).

The results of PVAR model show that the renewable energy policies have the capacity to mitigate the CO_2 emissions. This result is related to efficient of these policies that to promote the introduction of renewable energy sources on energy matrix, as well as, the consumption of this kind of source. Moreover, the fast growth of RES policies in the Latin American countries could be attributed to the interrelated energy challenges. The region will need a substantial amount of new electricity generation to meet growth in demand, and replace aging infrastructure. Currently, many countries in the Latin America region has energy mixes that expose them to fossil fuel price instability. This could significantly affect their national budgets through pass-through provisions in electricity supply contracts, and/or climate variability. These factors have incentive the creation of new policies. The results point too that the consumption of fossil fuels increase the CO_2

emissions and that economic growth promotes the consumption of fossil fuels. This result is due to some countries of Latin America region are major fossil fuels producers such as Argentina, Brazil, Colombia, Ecuador, Peru, and Mexico, or depend on imports of this kind of source, such as Chile.

5. Conclusion

The impact of renewable energy policies on CO_2 emissions was investigated. This article focused on nine countries from Latin America region in a period of 1991 to 2015. The results of preliminary tests proved the presence of multicollinearity, cross-section dependence between the variables, unit roots, the fixed effects in the model, and the need to use the lag length (1) in the PVAR regression.

The results of PVAR regression pointed that the renewable energy policies reduce the environmental degradation (CO_2 emissions) in -0.0109, and the consumption of renewable energy -0.0231, while the economic growth and consumption oil increase the emissions in 0.9082 and 0.1437 respectively.

The negative impact of renewable energy policies on environmental degradation proved that these policies are effective in reduce the CO_2 emissions. Indeed, these policies are able to promote the investments and development in green technologies, and consumption of alternative sources. Moreover, the negative impact of consumption of alternative sources is the reflection of the effectiveness of renewable energy policies.

So, the positive effect of economic growth and consumption of oil (fossil sources) on environmental degradation in the Latin America region is due to the higher economic growth that will further increase the consumption of energy from fossil sources and consequently increase the environmental degradation. Another explanation for this is that the Latin American countries have a high economic dependency on fossil fuels due to that some countries of this region are major fossil fuel energy producers (e.g., Argentina, Brazil, Colombia, Ecuador, Peru, and Mexico) and others are major imports of this kind of source (e.g., Chile). Indeed, this high economic dependency on fossil fuels exerts a negative impact on the environment.

Based on these results, it is necessary to create more renewable energy policies that reduce the consumption of fossil fuels in the Latin American countries; Create conservation policies that reduce the consumption of energy, nonetheless that these policies do not retard the economic growth; Reduce the bureaucracy in institutions and lobbies that discourage the renewable energy foreign investments. These policies and changes are able to increase the consumption of alternative sources and economic growth due to the new investments, development, and production of this kind of source, and also reduce the consumption of fossil fuels and energy, and consequently the environmental degradation.

Finally, these empirical findings will help the policymakers develop appropriate renewable energy policies, as well as help to advance the literature that approaches the impact of renewable energy policies on environmental degradation in the Latin America region.

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