Impact of energy consumption and carbon dioxide emissions on economic growth: cointegrated panel data in 79 countries grouped by income level

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Abstract

This paper investigates the existence of causal relationships among primary energy consumption per capita (PEC), carbon dioxide per capita (Co2) and gross domestic product per capita (GDP) in 79 countries grouped by income level for the 1980-2014 period. The countries are classified into high (HIC), upper-middle (UMIC), lower-middle (LMIC), and low (LIC) average per capita income. We apply a model of cointegrated panel data and an error correction mechanism. The estimation is carried out with fully modified ordinary least squares (FMOLS) and dynamic ordinary least squares (DOLS). For the HIC and UMIC groups, there is, in general, a positive relationship between PEC and GDP, and a negative one between GDP and PEC given that they develop new technologies to reduce Co2 emissions. For the LMIC and LIC groups there are mixed results. For instance, the LIC group accepts the null hypothesis in 26% of the cases with FMOLS and 42% with the DOLS. The Granger causality test suggests that for the HIC, UMIC and LMIC groups the variable GDP has a bidirectional relationship with PEC and Co2 in the short and long runs, a bidirectional causal relationship between PEC and Co2 in the long run, and unidirectional from PEC to Co2 in the short run. For the LIC group, PEC and Co2 show a bidirectional relationship, but unidirectional from PEC to Co2 in the short term. We also only detected a bidirectional relationship between Co2 and GDP in the short term for the LIC group.

JEL Classification: O13, H54, O47, C31, C33, L70.

Keywords: Energy consumption, carbon dioxide emission, economic growth, country income classification, time series analysis with panel data.

1. Introducción

Since the seminal article by Kraft and Kraft (1978) was published with empirical evidence of a unidirectional relationship of gross domestic product (GDP) to primary energy consumption (PEC) in the United States in the post-war period, there have been an increasing number of studies, in countries and regions, of causal relationships between GDP and PEC. Subsequently, Grossman and Krueger (1991) found a relationship between economic growth and environmental degradation in the free trade zone in North America. Later, from the signing of the Kyoto protocol in 1997 and the Paris Agreement in 2016, greenhouse gas emissions have been a subject of ongoing debate on climate change. These facts oblige governments to have a better design of economic policy on energy and emissions.

Why it is important to find out about the causal relationships among PEC, Co2, and GDP? Suppose, for instance, that a government is committed to complying with the Paris Agreement and decide to apply an economic policy to reduce the emission of greenhouse gases, particularly Co2. If in addition, there is knowledge of a unidirectional causal relationship from PEC towards Co2 and from PEC towards GDP. Then, if a control policy of energy consumption is applied, economic growth would decrease in favor of complying with the signed agreement, which should be taken into account in the design and implementation of any economic policy devoted to boost sustainable growth.

Many empirical studies have looked for causal relationships after the findings from Kraft and Kraft (1978) and Grossman and Krueger (1991). Some papers that associate PEC with GDP include Asafu-Adjaye (2000), Paul and Bhattacharya (2004), Lee (2005), Hye and Riaz (2008), Ozturk *et al*. (2010) and, more recently, Salahuddin *et al*. (2015) and Narayan (2016). Other researches that link Co2 to GDP comprise Friedl and Getzner (2003), Aldy (2005), Dinda and Coondoo (2008), Ghosh (2010), and Liu (2016). Table 1 summarizes different papers that have investigated for causal relationships among PEC, Co2, and GDP, emphasizing on the used econometric method and the obtained empirical results. Initially, most of them were cross-country studies and later regional studies with diverse econometric techniques and findings. However, for the short run, most papers found unidirectional relationships among the variables under analysis, whereas, for the long run, they detected bidirectional relationships between PEC and GDP, and unidirectional between Co2 and GDP.

Table 1. Comparison of empirical results and causality tests applied to panel data

Authors	Periods	Cross section	Methodology	Causal relationship
Soytas and Sari (2009)	1960-2010	Turkey	VAR and Granger causality test	Long run Co2→PEC
Apergis and Payne (2010)	1992-2004	11 countries of the Commonwealth of Independent States	Panel vector error correction model	Short run PEC→Co2; GDP→Co2 PEC↔GDP Long run Co2↔PEC
Acaravci and Ozturk (2010)	1960-2005	18 European countries	ARDL	Short run GDP→Co2, GDP→PEC Long run PEC→Co2; GDP→PEC
Hossain (2011)	1971-2007	9 Newly industrialized countries	Panel cointegration and Panel ECM	Short run GDP→Co2 GDP→ PEC
Tiwari (2011)	1971-2005	India	VECM	Short run GDP→Co2; PEC↔Co2; Long run GDP→Co2; PEC→Co2
Farhani and Rejeb (2012)	1973-2008	15 MENA countries	Panel cointegration and Panel ECM	Long run GDP→Co2; PEC→Co2
Arouri *et al.* (2012)	1981-2005	12 MENA countries	Bootstrap panel unit root tests and cointegration techniques.	Long run PEC→Co2 GDP→Co2
Saboori and Sulaiman (2013)	1971-2009	5 ASEAN countries	ADRL	Long run PEC↔GDP Co2↔GDP PEC↔Co2
Dritsaki and Dritsaki, (2014)	1960-2009	3 Countries of Southern Europe (Greece, Spain, and Portugal)	Panel cointegration and Panel ECM	Short run PEC↔GDP Co2↔GDP PEC↔Co2 Long run PEC↔GDP PEC→Co2
Ucan *et al.* (2014)	1990-2011	15 European Union countries	Panel cointegration and Panel ECM	Short run PEC→GDP
Kasman and Duman (2015)	1992-2010	27 European Union countries	Panel cointegration and Panel ECM	Short run PEC→Co2 PEC→GDP Long run PEC↔GDP PEC↔Co2
Liu *et al.* (2016)	1997-2010	China	panel VECM	Long run GDP↔Co2
Ahmed *et al.* (2017).	1971-2013	5 South Asian Countries	Panel cointegration, FEVD and IRF	Long run PEC→Co2

Source: Authors' own elaboration.

Econometric methodologies to study causal relationships between variables have strongly evolved. In this regard, Mehrara (2007) classifies the methodologies into four generations according to the type of the econometric model used: the first generation uses VAR models and Granger causality tests (1969); the second one uses the Engle-Granger cointegration methodology (1987); the third one uses the Johansen's methodology (1991); and the fourth generation is based on Engle-Granger (1987) with panel data. Likewise, Breitung and Pesaran (2008) classify the cointegrated panel data models according to the type of unit root and cointegration tests used, since these could take into account cross section independence.

This paper examines the existence of causal relationships with the methodology proposed by Engle-Granger (1987). To do that, we will use a panel cointegration model and the error correction mechanism. First, two unit root tests will be applied one from Levin, Lin and Chun's (2002) paper (LLC), and other from Im, Pesaran and Shin's (2003) work (IPS), whose difference lies in the alternative hypothesis. To look into the stationarity of series, the Pedroni test (1999) and (2004) will be used. The test will help in analyzing the cointegration of variables. The decision between the within-dimension or between-dimension panel data model to be estimated is based on the methods stated in Phillips and Moon (1999) and Pedroni (2000) of fully modified ordinary least squares (FMOLS), and Kao and Chiang (2001) of dynamic ordinary least squares (DOLS). The latter introduced some changes to use it with panel data. Lastly, we examine a sample of 79 countries from several regions that are classified into 4 groups: high income (HIC), upper-middle income (UMIC), lower-middle income (LMIC), and low income (LIC) during the 1980–2014 period.[1]

We assume that the functional relationships among GDP, PEC, and Co2 are in line with the Kuznets curve hypothesis. It is known that the HIC and UMIC groups have two main types of relationships: a positive one between GDP and PEC because they are industrial or service economies, and a negative one between GDP and PEC given that they build up new technologies to reduce Co2 emissions. LMIC and LIC have inverted signs in the GDP-PEC and GDP-Co2 relationships because they are inefficient in energy consumption and do not create new technologies. Nonetheless, it is possible that in less-

[1] It is important to mention that today Chile, Uruguay, and Singapore have high per capita income.

developed countries those relationships have similar signs as in developed countries because the former are receptors of new technologies. On the other hand, according to the International Energy Agency (IEA, 2016) fossil fuels such as coal, natural gas, and crude oil caused 82% of Co2 emissions worldwide in 2014. Therefore, if the relationships have the same signs it indicates inefficiency (otherwise, efficiency) in the use of PEC.

This paper is organized as follows. Section 2 describes the data. Section 3 presents the unit root and panel-data cointegration tests. Section 4 discusses the Engle-Granger test and the error correction mechanism, as well as the panel causality tests. Section 4 concludes.

2. Data and descriptive statistics

This study uses time series of 79 countries for the 1980–2014 period. Primary energy consumption (PEC) is measured in kilograms of oil equivalent per capita. GDP per capita (GDP) is expressed in 2010 U.S. dollars and was extracted from the World Bank (WB). Finally, Co2 emissions are in metric tons per capita and were obtained from the Global Carbon Atlas (GCA). The 79 countries were classified by per capita income level into four groups: high income (HIC), upper middle income (UMIC), lower middle income (LMIC), and low income (LIC). This classification agrees with the World Bank's classification.

Table 2. Descriptive statistics

		Mean	Std. Dev.	Skewness	Kurtosis	J-B
	GDP	38075.56	16498.14	1.67	7.03	919.61
HIC	**PEC**	4709.85	2341.38	1.87	9.71	1978.90
	Co2	10.47	4.44	1.68	6.86	879.26
	GDP	11448.25	7547.93	2.43	10.28	1901.42
UMIC	**PEC**	2176.08	2132.74	3.69	19.54	8121.34
	Co2	5.85	5.50	2.83	13.68	3623.45
	GDP	3192.22	1318.17	0.27	2.56	13.23
LMIC	**PEC**	831.23	430.67	2.05	8.45	1289.53
	Co2	2.03	1.49	1.59	6.39	598.55
	GDP	1094.63	548.09	0.81	3.98	100.08
LIC	**PEC**	443.63	158.38	0.81	4.13	108.71
	Co2	0.58	0.48	1.56	5.63	463.04

Source: Authors' own elaboration with *Eviews* 8.0 and data from World Bank.

Table 2 contains the descriptive statistics of the four per capita income groups. It can be observed that the higher the income (GDP), the higher the PEC and Co2 emissions. On average, the HIC group has a per capita income of $38,075 dollars, consumed 4,709 kgs of oil equivalent per capita, and emitted 10.47 tons of Co2 per capita annually between 1980 and 2014. The rest of the groups can be explained in a similar manner. UMIC has the highest variability, which represents 65.9%, 98.0% and 94.0% of the means of GDP, PEC, and Co2, respectively. The HIC group has the lowest variability with around 45% of the mentioned variables. In all the cases the skewness is positive, which indicates that most of the time series are on the left-hand side of the mean and some data on the extreme right-hand side. The UMIC group presents the highest skewness indicating that most of the countries have levels of GDP, PEC, and Co2 below the mean of the group. The series are leptokurtic, especially in the UMIC group having the highest levels of kurtosis; the contrary happens with the LIC group. In general, there are fat tails in the time series. Finally, the Jarque-Bera normality test rejects the null hypothesis of normality in all the groups. From now on, the series of GDP, PEC, and Co2 will be expressed in natural logs in order to homogenize them.

3. Panel data unit root and cointegration

Here we develop some unit root, cointegration and error correction tests for panel data. Table 3 presents unit root tests of Levin, Lin and Chu (LLC) and Im, Pesaran and Shin (IPS), which are based on the Augmented Dickey-Fuller test (1981). The first test proposes as the null hypothesis that all cross sections have a common unit root, and the second test that each cross section has its own unit root. The efficiency of the LLC and IPS tests increases when there are at least N = 10 cross sections with T = 25 observations. In this research, LIC has N = 19 and T = 35; LMIC has N = 19 and T = 35; UMIC has N = 17 and T = 35; and, finally, HIC, N = 23 and T = 35. It is worth mentioning that Maddala and Wu (1999), Breitung (2001) and Choi (2001) argue that the tests lose efficiency when they include a trend and a constant.

Table 3. Panel unit root test

		Test	GDP		PEC		Co2	
			Non-trend	**Trend**	**Non-trend**	**Trend**	**Non-trend**	**Trend**
HIC	**LLC**	Level	-6.37*	0.10	-1.95**	7.04	0.40	6.63
		First Difference	-9.29*	-9.73*	-5.19*	-7.80*	-8.34*	-9.11*
	IPS	Level	-1.43***	1.53	0.71	7.41	1.23	5.45
		First Difference	-10.13*	-9.76*	-11.80*	-13.26*	-12.77*	-12.12*
UMIC	**LLC**	Level	0.45	-4.01*	-0.87	-1.09	-1.93*	-2.26*
		First Difference	-10.43*	-9.17*	-9.59*	-7.71*	-14.56*	-13.07*
	IPS	Level	3.95	-3.26*	2.06	0.10	0.10	-1.91**
		First Difference	-11.53*	-10.04*	-12.40*	-10.67*	-15.62*	-13.99*
LMIC	**LLC**	Level	0.60	-1.62**	0.51	0.39	-1.74*	0.59
		First Difference	-8.21*	-7.19*	-8.94*	-6.86*	-11.11*	-10.01*
	IPS	Level	5.70	0.17	3.46	1.06	0.71	0.51
		First Difference	-9.91*	-8.65*	-11.97*	-10.34*	-14.65*	-13.03*
LIC	**LLC**	Level	6.96	-2.32*	2.57	1.93	-0.82	-0.68
		First Difference	-5.71*	-5.32*	-8.18*	-6.77*	-12.02*	-10.19*
	IPS	Level	8.34	0.75	4.45	2.74	2.05	-0.51
		First Difference	-8.18*	-9.01*	-11.75*	-11.11*	-13.73*	-12.00*

* Rejects the null of unit root at the 1% level.
**Rejects the null of unit root at the 5% level.
***Rejects the null of unit root at the 10% level.
Source: Authors' own elaboration with *Eviews* 8.0 and data from World Bank.

In Table 3, the LMIC and LIC groups accept the null hypothesis when the LLC and IPS tests are applied to variables in levels, with the exception of some cases when the trend is added. However, in the first difference, the series become stationary. On the other hand, the HIC and UMIC groups show diverse results in the two tests after these are applied in levels with or without a trend. This indicates that the process is contaminated by problems of autocorrelation and heteroscedasticity. In general, the time series reject the null hypothesis of a unit root in first difference and, therefore, they are stationary. These results coincide with most studies; see, for instance: Lee (2005), Mehrara (2007), and Ozturk *et al.* (2010).

Table 4 displays Pedroni cointegration tests (1999) and (2004) that are based on the two-stage methodology of Engle-Granger (1987). These tests rely on a residual analysis of the panel static regression. The test considers the use of seven tests that are divided into panel cointegration statistics (within-dimension) and group mean cointegration statistics (between-dimension). In turn, these statistics are classified into nonparametric (panel ν, panel ρ, and panel PPP) and parametric (panel ADF, group ρ, group PP, and group ADF). Pedroni (1999) mentions that the efficiency of the tests depends on the sample size (for instance, if $T \leq 20$ and $N \leq 20$, then there is higher distortion in the seven tests and vice versa when $T \rightarrow \infty$ and $N \rightarrow \infty$). The seven cointegration tests have different levels of distortion, being panel ρ, group ρ, and group ADF those with lower levels of distortion. Panel PP, panel ADF, and group PP are in the middle level, and panel ν present acceptable results in most cases. The expected signs of the tests are positive for panel ν and negative for the rest of the statistics (panel ρ, panel PP, panel ADF, group ρ, and group ADF in large sample sizes). We conclude that the null hypotheses are the same for the within-dimension and between-dimension, but they differ with respect to the alternative hypotheses.

Table 4. Residual Cointegration Test

	HIC		UMIC		LMIC		LIC	
	Non-trend	**Trend**	**Non-trend**	**Trend**	**Non-trend**	**Trend**	**Non-trend**	**Trend**
Within Dimension								
Panel v	-0.80	6.88*	1.11	4.65*	-0.02	1.81**	0.66	2.82*
Panel ρ	-0.65	0.32	-1.93**	0.58	-0.69	-1.78**	-1.03	1.68
Panel PP	-2.46*	-4.71*	-2.04**	-1.43***	-1.36***	-4.68*	-2.00**	0.64
Panel ADF	-1.93**	-5.11*	-1.22***	-1.41***	-0.81	-4.20*	-2.38*	1.00
Between dimension								
Group ρ	0.18	2.76	-0.17	1.67	1.08	1.60	-0.62	1.66
Group PP	-1.97*	-0.16	-1.66*	-1.56***	0.03	-1.20***	-2.67*	-0.83
Group ADF	-1.44**	-0.46	-0.56	-1.91**	1.31	-0.97	-3.24*	-1.52***

* Rejects the null of no cointegration at the 1% level.
**Rejects the null of no cointegration at the 5% level.
***Rejects the null of no cointegration at the 10% level.
Source: Authors' own elaboration with *Eviews* 8.0 and data from World Bank.

Several facts can be extracted from Table 4. First, for the tests without a trend, almost 80% of the coefficients have the correct signs (with the trend, 60%). Second, for the HIC, UMIC and LIC groups, four of the seven tests reject the null hypothesis when a trend is not included, even though the opposite occurs with the LMIC group (a trend is necessary). Third, the tests that reject the null hypothesis of no cointegration are panel PP, panel ADF, group PP, and panel ν on seven, six, five and four occasions, respectively (the tests with the lower distortion). As argued by Karaman (2007), panel PP has the lowest distortion. Therefore, there is evidence of cointegration among the study variables and the panel data model within- and between-dimensions. Our results deviate from Ozturk *et al.*

(2010) due to, among other things, the time considered in the sample and the addition of other variables.

The Engle-Granger methodology (1987) is divided into two parts. The first part consists in estimating the long-run equilibrium relationship and the second one in applying the error-correction mechanism. The latter links the short- and long-run dynamics which, in turn, determines the estimation errors of the first part for the first part of the methodology. We use the following equation for each of the cross section and the panel data model:[2]

$$GDP_{i,t} = \alpha_i + \beta_i PEC_{i,t} + \phi_i Co2_{i,t} + \varepsilon_{i,t} \tag{1}$$

where $GDP_{i,t}$ is the gross domestic product of country i at time t, $i = 1,2,\dots,N$, $t = 1,2,\dots,T$. $PEC_{i,t}$ y $Co2_{i,t}$ are defined similarly. Moreover, α_i is the constant term in each regression and $\varepsilon_{i,t}$ is the residual term from the regressions that is normally distributed with zero mean and constant variance, σ_i^2 .

The hypothesis about among the variables is that they are positively related because the higher PEC, the higher GDP and, therefore, the higher Co2. To produce most goods is needed some amount of the PEC variable, which, in turn, induces some proportion of Co2. This is a consequence of the sources that make up the variable PEC such as crude oil, natural gas, and coal among others. Worldwide, these sources are the ones that contribute the most to Co2. According to IEA (2014), these three fossil fuels generated worldwide, respectively, 42%, 21%, and 37% of Co2 emissions. On the other hand, there are other combinations in which PEC, GDP and Co2 can be related. If PEC is positively related with GDP and Co2 is negatively related with GDP, we may assume efficiency in energy consumption, and the contrary would indicate some degree of dependence on PEC. For example, if the country is an exporter and/or importer of energy, and therefore depends mostly on energy prices. Finally, if the two relationships are negative that would indicate dependence and high consumption of energy.

[2] Breitung and Pesaran (2008) extend the unit root and cointegration tests as well as the estimation method for panel data models.

Equation (1) is estimated via the fully modified ordinary least squares (FMOLS) proposed by Phillips and Hansen (1990) for structural models. The method was modified independently by Phillips and Moon (1999) and Pedroni (2000) for panel data. The second method of estimation is the dynamic ordinary least squares (DOLS) which was proposed by Saikkonen (1991) and generalized by Stock and Watson (1993) and Kao and Chiang (2001) that adapted it to panel data.[3]

Table 5. Panel FMOLS and DOLS test results for LMIC and LIC

LMIC					LIC				
	FMOLS		DOLS			FMOLS		DOLS	
	PEC	Co2	PEC	Co2		PEC	Co2	PEC	Co2
Algeria	0.60*	-0.14	0.59*	-0.01	Bangladesh	1.80*	-0.29*	1.84*	-0.30*
China	-2.51*	3.67**	-3.40*	4.48*	Benin	0.04	0.17*	-0.08	0.19*
Colombia	0.33	-0.09	0.90	-0.73	Bolivia	0.82*	-0.08	0.98*	-0.18***
Cote d'Ivoire	0.06	0.48*	0.07	0.46*	Cameroon	0.33	0.19**	0.49	0.26**
Cuba	-0.60**	1.08*	-0.43***	0.94*	Egypt	0.27*	0.63**	0.12	0.74*
Dominican Republic	0.60	0.65***	0.55	0.66	Ghana	-0.32***	0.88*	-0.30	0.89*
Ecuador	0.73*	0.25*	0.63*	0.33**	Honduras	0.80*	0.10*	0.93*	0.07**
El Salvador	0.37*	0.38*	0.22*	0.45	India	2.04*	-0.08	2.09*	-0.11
Guatemala	0.47*	0.13*	0.45*	0.15*	Kenya	1.87*	0.05	2.24*	0.05
Indonesia	0.11	0.73*	-0.07	0.86*	Myanmar	3.07**	1.47*	4.34	1.28***
Iran	-0.57	1.04**	-0.83	1.33	Nepal	1.34*	0.22*	1.38*	0.23*
Iraq	-0.64	1.14**	-0.73	1.20	Nicaragua	0.49	0.29	0.18	0.38
Jamaica	0.93*	-0.46***	1.47*	-0.97***	Pakistan	-1.03***	1.30*	-1.71*	1.66*
Morocco	0.30	0.62	0.54	0.39	Philippines	-2.35*	0.88*	-2.57*	0.86*
Nigeria	4.62*	0.24***	4.92*	0.19	Sri Lanka	2.01*	0.03	2.21**	-0.08
Paraguay	0.30*	0.32**	0.26*	0.32***	Sudan	-2.27*	0.51*	-2.69*	0.44*
Peru	0.09*	0.88	0.24*	0.79	Togo	-0.69*	0.35**	-0.62*	0.30
Thailand	0.68*	0.15	0.91*	-0.04	Zambia	-2.79	0.77	0.62	0.03
Tunisia	0.85*	0.46***	0.82*	0.53	Zimbabwe	1.24	0.29	0.33	0.61
Panel Results					Panel Results				
Within	0.28*	0.60*	0.26*	0.54*	Within	0.42*	0.41*	0.19	0.50*
Between	0.35*	0.61*	0.37**	0.60*	Between	0.35***	0.40*	0.51	0.39*

* Rejects the null of significance at the 1% level.
**Rejects the null of significance at the 5% level.
***Rejects the null of significance at the 10% level.
Source: Authors' own elaboration with *Eviews* 8.0 and data from World Bank.

[3] Fidrmuc (2009) concludes that better estimates are obtained with the DOLS method.

Table 5 shows the associated parameters to variables PEC and Co2 where most of them are positive. This indicates that as the former increase so does the GDP. On the other hand, the fact that the two parameters have positive signs implies that PEC has been misused. However, there are some exceptions whose parameters have a negative sign. For example, China and Cuba belong to the LMIC group, and Ghana, Pakistan, the Philippines, Sudan, and Togo are included in the LIC group. The negative sign implies that these countries have some dependence on the consumption of primary energy. In other words, China is the second country worldwide with the highest imports of crude oil and liquefied gas with 13.3% and 8.13%, respectively (BP, 2014).

The difference in results between the estimation methods can also be observed in Table 5 given the particular form of correction to the ordinary least squares (OLS). The FMOLS method rejects the null hypothesis on more occasions than its DOLS counterpart. Also, the model was estimated as within-dimension and between-dimension panel data. In the two cases and for the LMIC group, it was obtained that the coefficients of the variables are positive and statistically significant at different levels. On the other hand, there are mixed results for the LIC group because the DOLS estimation method rejects the estimators of the parameters associated with PEC in within- and between-dimensions.

Table 6 Panel FMOLS and DOLS test results for HIC and UMIC

HIC					**UMIC**				
	FMOLS		**DOLS**			**FMOLS**		**DOLS**	
	PEC	**Co2**	**PEC**	**Co2**		**PEC**	**Co2**	**PEC**	**Co2**
Australia	2.43*	-0.23	1.66*	0.49	**Argentina**	1.18*	0.20	1.18*	0.19
Austria	1.97*	-0.52*	1.89*	-0.45***	**Brazil**	1.33*	-0.30*	1.33*	-0.29**
Belgium	1.95*	-0.92*	1.92*	-0.85*	**Chile**	1.29*	-0.19*	1.28*	-0.17*
Canada	4.74*	-1.98**	4.65*	-1.67**	**Costa Rica**	1.35*	-0.59**	1.35*	-0.57**
Denmark	3.84*	-1.96*	4.64**	-2.12**	**Gabon**	1.08*	0.80	1.05*	1.07
Finland	2.30*	-0.85*	2.42*	-0.98*	**Hong Kong**	1.30*	0.22*	1.27*	0.33*
France	1.27*	-0.68*	1.42*	-0.73*	**Malaysia**	1.23*	-0.29*	1.23*	-0.28*
Germany	1.12*	-2.06**	0.81	-1.85*	**Malta**	1.31*	-0.07	1.29*	-0.01
Greece	2.32*	-1.42*	2.53*	-1.55*	**Mexico**	1.22*	0.07	1.22*	0.05
Iceland	0.34*	0.44**	0.34*	0.39	**Oman**	1.72*	-1.84*	1.68*	-1.71*
Ireland	6.67*	-4.02*	5.71*	-3.12*	**Panama**	1.27*	0.26**	1.27*	0.25***

Israel	1.81*	-0.76***	2.17*	-1.07*	**Singapore**	1.32*	-0.28***	1.32*	-0.29***
Italy	1.59*	-0.66*	1.45*	-0.49**	**South Africa**	1.18*	-0.22	1.14*	-0.08
Japan	0.26	1.07*	0.53	0.65	**Trinidad and Tobago**	1.22*	-0.55***	1.22*	-0.53
Luxembourg	5.11*	-3.47*	5.88*	-3.52*	**Turkey**	1.30*	-0.12*	1.30*	-0.11**
Netherlands	3.25*	-1.87*	3.12*	-1.64*	**Uruguay**	1.35*	-0.27*	1.35*	-0.18***
Norway	1.80*	-0.01	1.81*	0.11	**Venezuela**	1.34*	-0.48*	1.36*	-0.57**
Portugal	1.25*	-0.57*	1.22*	-0.53*	**Panel Results**				
Saudi Arabia	-0.19	0.65**	0.05	0.28	**Within**	1.37*	-0.67*	1.36*	-0.61*
Spain	1.51*	-0.68*	1.44*	-0.59*	**Between**	1.29*	-0.21*	1.28*	-0.17*
Sweden	0.82*	-1.22*	1.13*	-1.43*					
United Kingdom	3.28*	-3.20*	2.96*	-2.71*					
United States	-11.97*	8.05*	-9.94*	6.96*					
Panel Results									
Within	1.04*	-0.37*	1.05*	-0.25*					
Between	2.17*	-1.02*	2.22*	-0.95*					

* Rejects the null of significance at the 1% level.
**Rejects the null of significance at the 5% level.
***Rejects the null of significance at the 10% level.
Source: Authors' own elaboration with *Eviews* 8.0 and data from World Bank.

Table 6 shows the results of the higher income groups, HIC and UMIC, which were estimated under the same conditions as in Table 5 and it is highlighted that there are differences in all cases. Although these per capita income groups consume more energy (as indicated in Table 2), it is used efficiently since it has an inverse relationship with the endogenous variable (except the United States whose parameters are statistically significant and where the PEC sign is negative and the Co2 sign is positive). In general terms, energy consumption leads to an increase in GDP per capita, while decreases in emissions have the same positive effect on GDP. A higher level of rejection of the null hypothesis of the parameters for the HIC group is observed because with both methods the significance of the parameters is 90%. However, the results are varied for the UMIC group, because while for the PEC variable all null hypotheses are rejected, for the parameters of the Co2 variable 71% is rejected. In conclusion, for the panel data model, it is observed that both variables are statistically significant with the two estimation methods within- and between-dimensions at 1%.

Tables 5 and 6 show several differences. The first difference is that in the higher income groups there is a positive relationship between primary energy consumption (PEC) and per capita income, and an inverse relationship with CO2 emissions with per capita income. Secondly, the countries with the lowest income LIC and LMIC are the ones that make the worst use of primary energy. Third, some countries have a high dependence on energy, and among the most important are China and the United States of America that make 29.5% of oil imports worldwide (BP, 2014). On the other hand, low-income groups have greater problems than their counterparts (HIC and UMIC) because there is a higher percentage of acceptance of the null hypothesis. For example, for the LIC group and with the FMOLS method, 42% of the coefficients are statistically significant, which coincides with the DOLS method.

4. Error correction

For the second part of the methodology from Engle and Granger (1987), the calculation of the error correction model is required, for which the following three equations are defined:

$$\begin{aligned}
\Delta LGDP_{i,t} &= \alpha_{a,i} + \varphi_{a,i} ECM_{i,t-1} + \beta_{a1,i}\Delta LPEC_{i,t-1} + \phi_{a1,i}\Delta LCo2_{i,t-1} + \lambda_{a1,i}\Delta LGDP_{i,t-1} + \varepsilon_{ai,t} \\
\Delta LPEC_{i,t} &= \alpha_{b,i} + \varphi_{b,i} ECM_{i,t-1} + \beta_{b1,i}\Delta LPEC_{i,t-1} + \phi_{b1,i}\Delta LCo2_{i,t-1} + \lambda_{b1,i}\Delta LGDP_{i,t-1} + \varepsilon_{bi,t} \\
\Delta LCo2_{i,t} &= \alpha_{c,i} + \varphi_{c,i} ECM_{i,t-1} + \beta_{c1,i}\Delta LPEC_{i,t-1} + \phi_{c1,i}\Delta LCo2_{i,t-1} + \lambda_{c1,i}\Delta LGDP_{i,t-1} + \varepsilon_{ci,t}
\end{aligned} \tag{2}$$

where Δ is the first difference operator, $ECM_{i,t-1}$ is the residuals from Equation (1) with the FMOLS method and its associated parameter that represents the long-run causality. The parameters associated with $PEC_{i,t-1}\ Co2_{i,t-1}\ GDP_{i,t-1}$ of the model represent the short-run causality. Finally, $\varepsilon_{ai,t}$, $\varepsilon_{bi,t}$ and $\varepsilon_{ci,t}$ are random perturbances with zero mean and constant variance.

Table 7 Panel causality tests

	Dependent variable	Source of causation (independent variable)			
		Short run			Long run
		ΔGDP	**ΔPEC**	**ΔCo2**	**ECM**
HIC	**ΔGDP**		8.07*	2.19***	18.97*
	ΔPEC	19.05*		0.38	15.29*
	ΔCo2	5.12*	2.57***		13.59*
		ΔGDP	**ΔPEC**	**ΔCo2**	**ECM**
UMIC	**ΔGDP**		9.78*	8.38*	13.49*
	ΔPEC	4.66*		0.32	5.56*
	ΔCo2	2.07***	11.04*		11.86*
LMIC		**ΔGDP**	**ΔPEC**	**ΔCo2**	**ECM**
	ΔGDP		10.86*	9.99*	15.20*

	ΔPEC	4.31**		0.80	6.36*
	ΔCo2	2.81***	13.42*		13.49*
		ΔGDP	**ΔPEC**	**ΔCo2**	**ECM**
LIC	**ΔGDP**		0.18	2.41***	1.35
	ΔPEC	13.26*		0.42	6.03*
	ΔCo2	7.33*	3.72**		8.74*

* Rejects the null of y does not Granger cause x at the 1% level.
**Rejects the null of y does not Granger cause x at the 5% level.
***Rejects the null of y does not Granger cause x at the 10% level.
Source: Authors' own elaboration with Eviews 8.0 and data from World Bank.

Table 7 shows the results of the Granger causality test for panel data. First, it is observed that the HIC and UMIC groups present similar results in the short and long term in the studied variables, and the estimated parameters are statistically significant at different levels. Secondly, the causal relationship in Granger's sense is bidirectional between GDP and PEC, that is, in both short and long term, the changes generated by primary energy consumption produce positive changes in per capita income and *vice versa*. However, this also brings with it higher levels of Co2 emissions that also have a bidirectional relationship in both income groups, although mainly in the UMIC group (note that the HIC group countries are at the limit of the rejection of the null hypothesis). On the other hand, it is observed that higher levels of primary energy consumption generate higher levels of Co2 emission, although the opposite is not true given the existence of a unidirectional causal relationship, as in the LMIC group.

For the LIC group, we found a unidirectional relationship between the GDP and PEC variables. Therefore, as the per capita output increases, primary energy consumption increases, which coincides with the results in Table 4. This is the only group where the PEC variable was statistically insignificant in 42% of the cases at the individual level and panel data. On the other hand, the levels of Co2 and GDP maintain a causal relationship of a bidirectional type, that is, the higher the level of per capita income, the higher the Co2 emissions and vice versa. Therefore, the causal relationship is as follows for this group: an increase in per capita domestic product (GDP) results in an increase in primary energy consumption (PEC), which translates into an increase in Co2 levels and the opposite also happens.

5. Conclusions

In the present work, we find that during the period 1980-2014, the variable GDP has a bidirectional relationship with PEC and Co2 in the short and long runs for the HIC, UMIC and LMIC groups, a bidirectional causal relationship between PEC and Co2 in the long run and unidirectional from PEC to Co2 in the short run. For the LIC group, it was found that in the long run, PEC and Co2 show a bidirectional relationship, but unidirectional in the short term. We only detected a bidirectional relationship between Co2 and GDP in the short run.

In this study, the Engle-Granger (1987) cointegration methodology was applied to panel data, which initially consisted of applying unit root tests (LLC and IPS, with and without trend) to the study variables. The results suggest that GDP, PEC, and Co2 are stationary in first difference in both tests. Subsequently, the cointegration test developed by Pedroni (1999 and 2004) was applied, which is divided into within-dimension and between-dimension. In most cases, the non-parametric version of the Phillips-Perron (1988) (PP) panel and group *t*-test, respectively, reject the hypothesis of no cointegration (the other tests present mixed results).

Due to the mentioned results, it was concluded that the study variables were cointegrated and, therefore, that there was a long-run equilibrium relationship. With the aforementioned results, we then proceeded to estimate the equation that specifies that GDP is the exogenous variable and the rest of the variables are endogenous individually and collectively (panel data within-dimension and between-dimension). The FMOLS and DOLS methods were used to obtain the long-term equilibrium relationship. As a consequence, it was found that PEC and Co2 are statistically significant in most cases at the individual and aggregated level (panel data). Finally, a causality test was applied to prove the existence of causal relationships between the study variables.

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