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The Influence of Economic Growth and Electric Consumption on Pollution in South America Countries

Joel Alejandro Rosado[1]*, María Isabel Alvarado Sánchez[2]

[1]Faculty of Social Sciences and Humanities, Escuela Superior Politécnica del Litoral, Campus Gustavo Galindo Km 30.5 Vía, Perimetral, Guayaquil, Ecuador, [2]Faculty of Social Sciences and Humanities, Escuela Superior Politécnica del Litoral, Campus Gustavo Galindo Km 30.5 Vía, Perimetral, Guayaquil, Ecuador. *Email: jarosado@espol.edu.ec

ABSTRACT

This study investigates the influence of electric consumption (ELC) and economic growth on CO_2 emissions in 10 selected South American countries using the period of 1980-2012. Panel data techniques were used in examining the relationships. The Pedroni cointegration results indicated that CO_2 emissions, per capita gross domestic product (GDP), and electricity power consumption were cointegrated. The fully modified ordinary least squares and dynamic ordinary least-squares results revealed that GDP growth and ELC increase CO_2 emissions in the long run. The vector error correction model Granger causality test show the causal flows from energy consumption, electricity consumption and economic growth to CO_2 emissions in South America both short and long-run. Policy recommendations were provided for the South American countries.

Keywords: South American Countries, Pollution, Carbon Dioxide Emissions, Electric Consumption, Economic Growth
JEL Classifications: Q4, Q5, Q53, Q57

1. INTRODUCTION

An important source of energy necessary for the daily activities is the electric energy. The relationship between pollution, economic activities, and electric consumption (ELC) has been thoroughly investigated by different scholars. Using different methodologies several authors found relationships between many variables and CO_2 emission as pollution indicator (Apergis and Payne, 2014; Baek and Pride, 2014; Bella et al., 2014; Hossain, 2011, Zhang and Cheng, 2009; Chandran and Tang, 2013).

This paper contributes the existent literature to consider the relationship between economic growth gross domestic product (GDP), ELC and CO_2 emissions (CO_2) for a panel of South America countries. This study can be defined as a complementary to the previous empirical papers. The main motivation for testing the relationship between environmental quality and economic growth is that it allows policy makers to judge the response of the environment to economic growth which is crucial since the objective function of any economy is to maximize economic growth. However, it differs from the existing literature for some aspects. As being distinguished from the previous works, it employs not only the Pedroni cointegration and Granger causality methods but also the fully modified ordinary least squares (FMOLS) and dynamic ordinary least-squares (DOLS) estimates in order to clarify the direction of relationship with elasticities of ELC.

In the case of the studies that used panel data, Lee and Chang (2007) analyzed the relationship between energy consumption and GDP with the panel vector auto regression method for 1965-2002 period. They found unidirectional causality from GDP growth to energy consumption in developed countries and bidirectional causality in developing countries. Is important to mention that the electricity consumption positively affects and causes GDP, which is crucial for electricity conservation policies (Ghosh, 2002; Narayan and Smyth, 2005; Alege et al., 2016).

An empirical methodology is proposed in four stages. The first step consists in use the panel unit root tests; the second step are the panel co-integration tests. The third step develops the long run relationship using panel FMOLS and panel DOLS estimators. Finally, the last step consists to estimate a panel vector error correction model (VECM) in order to study Granger causality relationships.

In Section 2, we present the data. In the Section 3 we explain the econometrical methodology used. The empirical results and discussion are described in Section 4. Finally, the conclusions and policy implications are provided in Section 5.

2. DATA

In this study, the relationship between ELC and economic growth for a balanced panel of South America countries over the annual period 1980-2012 was analyzed by Pedroni cointegration, FMOLS and DOLS. The countries used are: Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Paraguay, Peru, Uruguay and Venezuela[1]. The variables used are: CO_2 emissions (CO_2) measured in metric tons per capita; income (GDP) using per capita real GDP in constant 2010 US$; and ELC expressed in terms of billion kilowatt hours (kWh). The related data are collected from World Bank Database (World Development Indicators, 2017).

3. ECONOMETRICAL METHODOLOGY

The approach consist in shows the long-run relationship between CO_2 emissions (CO_2), income (GDP) and electric power consumption (ELC), the variables was presented in its natural logarithm; the econometric model can be presented as follows:

$$\ln CO_{2i,t} = \alpha_0 + \alpha_1 \ln GDP_{i,t} + \alpha_2 \ln ELC_{i,t} + u_{i,t} \tag{1}$$

The econometric analysis for this study posed four stages. It begins with panel unit root test to examine the integration of each variable as first step; following with the panel co-integration tests as second step. The third step implemented the analysis of the long run relationship using panel FMOLS and panel DOLS estimators. Finally, the last step was estimate a panel VECM to study Granger causality relationships.

3.1. Panel Unit Root Test Analysis

The econometric analysis begins with panel unit root test to examine the integration of each variable. Three types of panel unit root tests were utilized, namely Breitung proposed by Breitung (2001), Levin, Lin and Chu t*, proposed by Levin et al. (2002) and Im, Pesaran and Shin W-stat proposed by Im et al. (2003) for robustness.

In the case of Breitung (2001), the inference is carried out based on the following test statistic:

$$\lambda = \frac{\frac{1}{\sigma_i^2}\sum_{i=1}^{N} W_i^{*}{}'x_i^{*}{}'}{\sqrt{\frac{1}{\sigma_i^2}\sum_{i=1}^{N} x_i^{*}{}'A'x_i^{*}}} \tag{2}$$

From the equation $W_{i,t} = \alpha_{i,t} + \sum_{j=1}^{k+1}\beta_{i,j}\Delta X_{i,t-j} + \varepsilon_k$ and if $W_{i,t}$ is stationary. Also, using the transformed vectors $w_i^* = AW_i = \left[w_{i1}^*, w_{i2}^*, \ldots, w_{iT}^*\right]'$ and $x_i^* = AX_i = \left[X_{i1}^*, X_{i2}^*, \ldots, X_{iT}^*\right]'$.

1 Does not include the countries of Guyana, Suriname and French Guiana because data for electricity consumption do not exist.

From the following equation:

$$\Delta X_{i,t} = \alpha_i + \beta_i X_{i,t-1} + \delta_i t + \sum_{j=1}^{k}\gamma_{i,j}\Delta X_{i,t-j} + \nu_{i,t} \tag{3}$$

Where, Δ is the first difference operator, $X_{i,t}$ is the dependent variable, $v_{i,t}$ is a white - noise disturbance with a variance of σ^2, i=1,2,…N depending of the number of countries and t=1,2,…T considering the time.

Levin et al. (2002) proposed a panel unit root based on augmented Dickey-Fuller (ADF) test. Expanding this analysis, considering all panel units, assumed cross-sectional independence and that there is homogeneity in the dynamics of the autoregressive coefficients. Im et al. (2003) proposed a test based on the mean group approach considering the average of the $t_{\beta i}$ statistics of the Equation 3 using the next $\bar{Z}$ statistic:

$$\bar{Z} = \sqrt{N}\left[\bar{t} - E\left(\bar{t}\right)\right] / \sqrt{V\left(\bar{t}\right)} \tag{4}$$

Where $\bar{t} = \left(1/N\right)\sum_{i=1}^{N} t_{\beta i}$, $E(\bar{t})$ is the mean of $t_{\beta i}$ statistics and $V\left(\bar{t}\right)$ is the variance generated by simulations. $\bar{Z}$ converges to a standard normal distribution and $\bar{t} = \left(1/N\right)\sum_{i=1}^{N} t_{\beta i}$ taking account the test is based on the average of the individual unit root test and permits heterogeneity in the dynamics of the autoregressive coefficients.

The three above panel unit root tests work under the null hypothesis of a panel unit root (non-stationary variables) and the alternative hypothesis of no unit root (stationary variables).

3.2. Panel Cointegration Tests Analysis

The next step was to examine whether a long-run relationship between the variables exists using Pedroni (1999; 2004) panel cointegration tests who based on residuals of the Engle and Granger (1987), considering the next equation:

$$W_{i,t} = \propto_i + \lambda_i t + \sum_{j=1}^{m}\beta_{j.i}X_{j.i.t} + \zeta_{i,t} \tag{5}$$

Where $W_{i,t}$ and $X_{j.i.t}$ are integrated of the order one.

Engle and Granger (1987) cointegration test explain whether the residual of each variable is stationary at level which means that the variables are cointegrated, or I(1) which indicates that the variables are not cointegrated. This approach has been used in several studies for the panel cointegration test analysis (Pesaran et al., 1999; Sebri and Ben-Salha, 2014; Al-Mulali and Ozturk 2015; Bilgili and Ozturk, 2015; Al-Mulali et al., 2015a; Al-Mulali et al., 2015b; Al-Mulali et al., 2015c; Bilgili and Ozturk, 2015; Hamit-Haggar, 2012; Rosado, 2017). There are two parts of panel cointegration tests which contains a panel cointegration tests based on the within dimension approach and a group mean panel cointegration tests based on the between dimension approach Pedroni (1999; 2004).

Following the terminology in Pedroni (1999), we will refer to the within-dimension based statistics simply as panel cointegration statistics, and the between-dimension based statistics as group mean panel cointegration statistics. The first of the simple panel cointegration statistics is a type of non-parametric variance ratio statistic. The second is a panel version of a non-parametric statistic that is analogous to the familiar Phillips and Perron rho-statistic. The third statistic is also non-parametric and is analogous to the Phillips and Perron t-statistic. Finally, the fourth of the simple panel cointegration statistics is a parametric statistic which is analogous to the familiar ADF t-statistic.

The other three panel cointegration statistics are based on a group mean approach. The first of these is analogous to the Phillips and Perron rho-statistic, and the last two are analogous to the Phillips and Perron t-statistic and the ADF t-statistic respectively. Again, the comparative advantage of each of these statistics will depend on the underlying data-generating process, and the reader is referred to Pedroni (1999) for a detailed analysis based on the bivariate regression case. The panel cointegration statistics are detailed in the Table 1.

3.3. Panel FMOLS and DOLS Estimates

If cointegration is concluded among the variables, to analyze the long-run cointegration relationship between the dependent and the independent variables will be implemented the panel FMOLS and the panel DOLS. The FMOLS estimator was proposed by Phillips and Hansen (1990) and the DOLS estimator was proposed by Saikkonen (1991), Stock and Watson (1993), Phillips and Hansen (1990).

The FMOLS estimator is presented below:

$$\widehat{\beta^*_{FMOLS}} = \frac{1}{N}\sum_{i=1}^{N}\left[\left(\sum_{t=1}^{T}\left(X_{i,t}-\overline{X}_i\right)^2\right)^{-1}\left(\sum_{t=1}^{T}\left(X_{i,t}-\overline{X}_i\right)W^*_{i,t}-T\hat{\gamma}_i\right)\right] \tag{6}$$

Where $W^*_{i,t} = W_{i,t} - \overline{W}_i - \left(\hat{\Omega}_{2,1,i}/\hat{\Omega}_{2,2,i}\right)\Delta X_{i,t}$ and

$$\hat{\gamma}_i = \hat{\Gamma}_{2,1,i} + \hat{\Omega}^0_{2,1,i} - \left(\frac{\hat{\Omega}_{2,1,i}}{\hat{\Omega}_{2,2,i}}\right)\left(\frac{\hat{\Gamma}_{2,2,i}}{\hat{\Omega}^0_{2,2,i}}\right)$$

According to Kao and Chiang (2001) and Mark and Sul (2003) the panel DOLS estimator can be defined as:

$$\widehat{\beta^*_{DOLS}} = \frac{1}{N}\sum_{i=1}^{N}\left[\left(\sum_{t=1}^{T} Z_{i,t}Z_{i,t}'\right)^{-1}\left(\sum_{t=1}^{T} Z_{i,t}\tilde{w}_{i,t}\right)\right] \tag{7}$$

Where $Z_{i,t} = \left[X_{i,t}-\hat{X}_i, \Delta X_{i,t-k_i,\ldots,} X_{i,t+K_i}\right]$ is vector of regressors, and $\tilde{w}_{i,t} = W_{i,t} - \overline{W}_i$.

3.4. Panel Granger Causality Test

If cointegration is confirmed among the variables, there might be a causal relationship between the variables, at least in one direction. Therefore, the Granger causality was utilized. If cointegration exists, then the Granger causality based on VECM will be used. The VECM Granger causality can capture the short-run causality based on the F-statistic and the long-run causality based on the lagged error correction term (ECT). The VECM Granger causality is presented below:

Table 1: Panel cointegration statistics

Test	Statistic
Panel υ-statistic:	$T^2N^{3/2}Z_{\hat{\upsilon}N,T} \equiv T^2N^{3/2}\left(\sum_{i=1}^{N}\sum_{t=1}^{T}\hat{L}^{-2}_{11i}\hat{e}^{-2}_{i,t-1}\right)^{-1}$
Panel ρ-statistic:	$T\sqrt{N}Z_{\hat{\rho}N,T-1} \equiv T\sqrt{N}\left(\sum_{i=1}^{N}\sum_{t=1}^{T}\hat{L}^{-2}_{11i}\hat{e}^{-2}_{i,t-1}\right)^{-1}\sum_{i=1}^{N}\sum_{t=1}^{T}\hat{L}^{-2}_{11i}\left(\hat{e}_{i,t}\Delta\hat{e}_{i,t}-\hat{\lambda}_i\right)$
Panel t-statistic: (Non-parametric)	$Z_{tN,T} \equiv \left(\tilde{\sigma}^2_{N,T}\sum_{i=1}^{N}\sum_{t=1}^{T}\hat{L}^{-2}_{11i}\hat{e}^{-2}_{i,t-1}\right)^{-1/2}\sum_{i=1}^{N}\sum_{t=1}^{T}\hat{L}^{-2}_{11i}\left(\hat{e}_{i,t}\Delta\hat{e}_{i,t}-\hat{\lambda}_i\right)$
Panel t-statistic: (Parametric)	$Z^*_{tN,T} \equiv \left(\tilde{s}^{*2}_{N,T}\sum_{i=1}^{N}\sum_{t=1}^{T}\hat{L}^{-2}_{11i}\hat{e}^{*2}_{i,t-1}\right)^{-1/2}\sum_{i=1}^{N}\sum_{t=1}^{T}\hat{L}^{-2}_{11i}\hat{e}^{*}_{i,t-1}\Delta\hat{e}^{*}_{i,t}$
Group ρ-statistic:	$TN^{-1/2}\tilde{Z}_{\hat{\rho}N,T^{-1}} \equiv TN^{-1/2}\sum_{i=1}^{N}\left(\sum_{t=1}^{T}\hat{e}^2_{i,t-1}\right)^{-1}\sum_{t=1}^{T}\left(\hat{e}_{i,t}\Delta\hat{e}_{i,t}-\hat{\lambda}_i\right)$
Group t-statistic: (Non-parametric)	$N^{-1/2}\tilde{Z}_{\hat{\rho}N,T} \equiv N^{-1/2}\sum_{i=1}^{N}\left(\hat{\sigma}^2_i\sum_{t=1}^{T}\hat{e}^2_{i,t-1}\right)^{-1/2}\sum_{t=1}^{T}\left(\hat{e}_{i,t}\Delta\hat{e}_{i,t}-\hat{\lambda}_i\right)$
Group t-statistic: (Parametric)	$N^{-1/2}\tilde{Z}^*_{\hat{\rho}N,T} \equiv N^{-1/2}\sum_{i=1}^{N}\left(\sum_{t=1}^{T}\hat{s}^{*2}_i\hat{e}^{*2}_{i,t-1}\right)^{-1/2}\sum_{t=1}^{T}\hat{e}^{*}_{i,t-1}\Delta\hat{e}^{*}_{i,t}$

Where, $\hat{\lambda}_i \equiv \frac{1}{T}\sum_{s=1}^{k_i}\left(1-\frac{s}{k_i+1}\right)\sum_{t=s+1}^{T}\hat{\mu}_{i,t}\hat{\mu}_{i,t-s}$, $\hat{s}^2_i \equiv \frac{1}{T}\sum_{t=1}^{T}\hat{\mu}^2_{i,t}$, $\hat{\sigma}^2_i \equiv \hat{s}^2_i + 2\hat{\lambda}_i$, $\tilde{\sigma}^2_{N,T} \equiv \frac{1}{T}\sum_{i=1}^{N}\hat{L}^{-2}_{11i}\hat{\sigma}^2_i$ $\hat{s}^{*2}_i \equiv \frac{1}{t}\sum_{t=1}^{T}\hat{\mu}^{*2}_{i,t}\hat{s}^{*2}_{N,T} \equiv \frac{1}{N}\sum_{i=1}^{N}\hat{s}^{*2}_i$, $\hat{L}^2_{11i} \equiv \frac{1}{T}\sum_{t=1}^{T}\hat{\eta}^2_{i,t} + \frac{2}{T}\sum_{s=1}^{k_i}\left(1-\frac{s}{k_i+1}\right)\sum_{t=s+1}^{T}\hat{\eta}_{i,t}\hat{\eta}_{i,t-s}$. And where the residuals $\hat{\mu}_{i,t}$, $\hat{\mu}^*_{i,t}$ and $\hat{\eta}_{i,t}$ are obtained from the following regressions: $\hat{e}_{i,t} \equiv \hat{\gamma}_i\hat{e}_{i,t-1} + \hat{\mu}_{i,t}$, $\hat{e}_{i,t} \equiv \hat{\gamma}_i\hat{e}_{i,t-1} + \sum_{k=1}^{k_i}\hat{\gamma}_{i,k}\Delta\hat{e}_{i,t-k} + \hat{u}^*_{i,t}$, $\Delta y_{i,t} \equiv \sum_{m=1}^{M}\hat{b}_{mi}\Delta x_{mi,t} + \hat{\eta}_{i,t}$. All statistics are from Pedroni (1997a)

$$\begin{pmatrix}\Delta\ln CO_{2_{i,t}}\\ \Delta\ln GDP_{i,t}\\ \Delta\ln GDP^2{}_{i,t}\\ \Delta\ln ELC_{i,t}\end{pmatrix} = \begin{pmatrix}\phi_{i,1}\\ \phi_{i,2}\\ \phi_{i,3}\\ \phi_{i,4}\end{pmatrix} + \sum_{l=1}^{m}\begin{pmatrix}\theta_{1,1,k} & \theta_{1,2,k} & \theta_{1,3,k} & \theta_{1,4,k}\\ \theta_{2,1,k} & \theta_{2,2,k} & \theta_{2,3,k} & \theta_{2,4,k}\\ \theta_{3,1,k} & \theta_{3,2,k} & \theta_{3,3,k} & \theta_{3,4,k}\\ \theta_{4,1,k} & \theta_{4,2,k} & \theta_{4,3,k} & \theta_{4,4,k}\end{pmatrix}$$

$$\begin{pmatrix}\Delta\ln CO_{2_{i,t-k}}\\ \Delta\ln GDP_{i,t-k}\\ \Delta\ln GDP^2{}_{i,t-k}\\ \Delta\ln ELC_{i,t-k}\end{pmatrix} + \begin{pmatrix}\gamma_1\\ \gamma_2\\ \gamma_3\\ \gamma_4\end{pmatrix} ECT_{i,t-1} + \begin{pmatrix}\omega_{1,i,t}\\ \omega_{2,i,t}\\ \omega_{3,i,t}\\ \omega_{4,i,t}\end{pmatrix} \tag{8}$$

Table 2: Panel unit root test results

Test	$\ln CO_2$	ΔlnGDP	lnELC
Breitung			
Level	−0.61451 (0.2694)	0.76718 (0.7785)	−5.37097 (0.0000)
Δ	−8.13356* (0.0000)	−5.79477* (0.0000)	−4.80658* (0.0000)
Levin, Lin and Chu t*			
Level	0.97734 (0.8358)	−1.67466** (0.0470)	−7.33413 (0.0000)
Δ	−7.39502* (0.0000)	−7.22077* (0.0000)	−4.23468* (0.0000)
Im, Pesaran and Shin W-stat			
Level	0.73676 (0.7694)	−0.11141 (0.4556)	−0.10276 (0.4591)
Δ	−9.92562* (0.0000)	−6.55565* (0.0000)	−6.42062* (0.0000)

Δ is the first difference operator. The null hypothesis of Breitung, LLC and IPS tests examines non-stationary. Lag selection (automatic) is based on SIC, *statistical significance at the 1% level (P-values are presented in parentheses), **statistical significance at the 5% level (P-values are presented in parentheses), ***statistical significance at the 10% level (P-values are presented in parentheses), SIC: Schwarz Information Criteria, GDP: Gross domestic product, ELC: Electric consumption

Table 3: Pedroni (1999; 2004) panel cointegration results

Test	Statistic	P	Weighted statistic	P
Within-dimension				
Panel v-statistic	2.402844*	(0.0081)	2.453796**	(0.0349)
Panel rho-statistic	−4.037455*	(0.0000)	−1.801876*	(0.0044)
Panel PP-statistic	−5.449203*	(0.0000)	−3.199726*	(0.0001)
Panel ADF-statistic	−3.394701*	(0.0003)	−2.256147*	(0.0016)
Between-dimension				
Group rho-statistic	−1.707399**	(0.0439)		
Group PP-statistic	−3.932641*	(0.0000)		
Group ADF-statistic	−3.009145*	(0.0013)		

The null hypothesis of Pedroni test examines the absence of cointegration. Lag selection (automatics) is based on SIC with a max lag of 7. *Statistical significance at the 1%, **statistical significance at the 5%, ADF: Augmented Dickey-Fuller

The term Δ denotes first differences; $\varnothing_{i,j}$ (j = 1,2,3,4) present the fixed country effect; l (l = 1,…,m) is the optimal lag length determined by the Schwarz Information Criterion, and $ECT_{i,t-1}$ is the estimated lagged ECT derived from the long-run cointegrating relationship. The term γ_j is the adjustment coefficient; and $\omega_{j,i,t}$ is the disturbance term, which assumed to be uncorrelated with zero means. The lagged residuals estimated are defined in the next model as ECT:

$$ECT_{i,t} = \Delta \ln CO_{2_{i,t}} - \hat{\alpha}_{1.i} \ln GDP_{i,t} - \hat{\alpha}_{2.i} \ln GDP_{i,t}^{2} - \hat{\alpha}_{3.i} \ln ELC_{i,t} \quad (9)$$

4. EMPIRICAL RESULTS AND DISCUSSION

The first step consists to examine the stationarity of the variables using Breitung (2001), Levin et al. (2002) and Im et al. (2003) unit root tests. The panel unit root tests results are displayed in Table 2. The null hypothesis of the panel unit root is rejected at the first difference because all the variables are significant at the 1% significance level.

The Pedroni (1999; 2004) panel cointegration results are reviewed in Table 3. The long-run relationships between $\ln CO_2$, lnGDP and lnELC is confirmed considering that all statistics are significant and we can reject the null hypothesis of no cointegration. Several studies are consistent with this results, because the long-run relationships between CO_2 and other determinants were found by Chandran and Tang (2013), Al-mulali (2014) and so forth.

The panel FMOLS and panel DOLS were utilized to examine the positive as well as the negative long-run relationship between the independent and dependent variables. The panel FMOLS results are shown in Table 4 and the panel DOLS results are shown in the Table 5. The results indicate that GDP growth and ELC increase CO_2 emissions in the long run.

Table 4: Panel FMOLS results

Depend variable: $\ln CO_2$			
Variable	Coefficient	Standard error	T-statistic
Constant	−5.815212	0.636517	−9.135981*
lnGDP	0.493002	0.183444	2.687477*
lnELC	0.315809	0.167176	1.889075**

*Statistical significance at the 1%, **statistical significance at the 5%, FMOLS: Fully modified ordinary least squares, GDP: Gross domestic product, ELC: Electric consumption

Table 5: Panel DOLS results

Depend variable: $\ln CO_2$			
Variable	Coefficient	Standard error	T-statistic
Constant	−5.746931	0.361051	−1.591722*
lnGDP	0.471632	0.108668	4.340106*
lnELC	0.331937	0.100166	3.313864*

*Statistical significance at the 1%, DOLS: Dynamic ordinary least-squares, GDP: Gross domestic product, ELC: Electric consumption

The coefficients from panel FMOLS estimation are 0.493002 and 0.315809 for lnGDP and lnELC respectively. This means that a 1% increase in percapita real GDP increases CO_2 emissions per capita by 0.493002%; and a 1% increase in electric power consumption increases CO_2 emissions per capita by 0.315809%. However, the coefficients from panel DOLS estimation are 0.471632 and 0.315809 for lnGDP and lnELC respectively. This means that a 1% increase in percapita real GDP increases

Table 6: Panel causality test results

Dependent variable	Short run sources of causation (independent variable)			Long run
EKC	$\Delta lnCO_2$	ΔlnGDP	ΔlnELC	ECT
$\Delta lnCO_2$	#	5.959128** (0.0152)	3.000441*** (0.0842)	−0.000203** [−2.359391]
ΔlnGDP	0.001093 (0.9736)	#	0.017222 (0.8957)	−0.000212* [−3.136513]
ΔlnELC	4.434014 (0.0360)**	5.837789 (0.0162)**	#	0.000102 [1.527604]

Short-run causality is determined by statistical significance of the partial F-statistics associated with the right hand side variables. Long-run causality is reveled by the statistical significance og the respective error correction terms using a t-test. P values are listed in parentheses and t-statistics are presented in brackets. *Statistical significance at the 1%, **statistical significance at the 5%, ***statistical significance at the 10%, GDP: Gross domestic product, ELC: Electric consumption

CO_2 emissions per capita by 0.471632%; and a 1% increase in electric power consumption increases CO_2 emissions per capita by 0.331937%.

Since the variables are cointegrated, the Granger causality based on the VECM was utilized. The results are presented in Table 6. The short-run causality shows a bidirectional relationship between CO_2 emissions and electric power consumption. Moreover, an unidirectional causality was also found from GDP to CO_2 emissions and from per capita GDP to electric power consumption. This finding is consistent with Jaunky (2011), whose results shows unidirectional causality running from per capita GDP to per capita CO_2 emissions in 36 high-income countries. The long-run causality shows a bidirectional relationship between CO_2 emissions and per capita GDP. Moreover, an unidirectional causality was also found from electric power consumption to CO_2 emissions and from electric power consumption to per capita GDP.

5. CONCLUSIONS AND POLICY IMPLICATIONS

The main goal of this study was prove the influence of economic growth and ELC on Pollution in South America Countries. According to that, the results revealed that GDP growth and ELC increase CO_2 emissions in the long run. The outcome from the Pedroni cointegration indicated the existence of a long-run relationship between CO_2 emission, per capita GDP and electric power consumption. In addition, the FMOLS and DOLS results revealed that with the selected variables in this study we reject the EKC hypothesis, and the means of FMOLS and DOLS coefficients are 0.482314 and 0.323873 for lnGDP and lnELC, respectively.

Moreover, the VECM Granger causality showed that per capita GDP is the most significant determinant that has positive causal effect on CO_2 emission. The long-run causality shows a bidirectional relationship between CO_2 emissions and per capita GDP and unidirectional causality was also found from electric power consumption to CO_2 emissions and per capita GDP.

From the outcome of this study, a number of policy recommendations can be provided for the investigated countries. Since GDP and ELC increase CO_2 emission, it is important to increase projects and investments that promote the role of renewable energy by providing incentives to the renewable manufactories and promoting new research in renewable energy technologies.

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