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The Impacts of Population Change and Economic Growth on Carbon Emissions in Nigeria

Adewale F. Lukman[*1], Matthew O. Oluwayemi[2]
Joshua O. Okoro[3], Clement A. Onate[4]

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Abstract

The main aim of this study is to investigate the impacts of population total, gross domestic product per capita, urbanization rate and energy use on carbon emissions in Nigeria for a period of 1981-2015 using autoregressive distributed lag approach to co-integration (ARDL). The empirical results revealed evidence of a long run relationship among the variables. The generalized ridge regression was used to correct the presence of multicollinearity among the explanatory variables in the long-run. Results show that population total, gross domestic product per capita, urbanization rate and energy use have a positive impact on carbon emissions. Energy use and urbanization both contributed significantly to increasing carbon emissions in the long and short run respectively. Considering the fact that the factors investigated in this study are of the increasing trend in this nation there is a need to implement policies to curb the increasing rate of carbon emissions in Nigeria.

Keywords: Carbon Emission, Population Growth, Gross Domestic Product, Generalized Ridge
JEL Classification: C01, C33, O44, O53.

1. Introduction

Carbon dioxide (CO_2) is one of the greenhouse gases (GHG) that is mostly affected by human activities and was regarded as the major contributor of GHG with more than 60% of the total of greenhouse

1. Department of Physical Sciences, University of Landmark, Nigeria (Corresponding Author: adewale.folaranmi@lmu.edu.ng).
2. Department of Physical Sciences, University of Landmark, Nigeria (oluwayemi.matthew@lmu.edu.ng).
3. Department of Physical Sciences, University of Landmark, Omu-Aran, Nigeria (okoro.joshua@lmu.edu.ng).
4. Department of Physical Sciences, University of Landmark, Omu-Aran, Nigeria (onate.clement@lmu.edu.ng).

gases (Kaygusuz, 2009). It has increasingly become an issue of global concern because of climate change. Increase in Greenhouse emissions can be attributed to human activities, energy consumption, and fossil fuel combustion. The major source of carbon emission is traceable to the combustion of fossil fuel. Global carbon emissions from fossil fuels have significantly increased from 1900 to date.

This has contributed to the rise of global temperature since half of its emission remains in the atmosphere and other half is absorbed by natural land and ocean carbon reservoirs (Wang et al., 2016).

Top emitters China and the United States started to curb carbon dioxide (CO_2) emissions in 2015 (Oliver et al., 2015). They reduced their emissions by 0.7% and 2.6%, respectively, compared to 2014. Carbon emissions in the Russian Federation and Japan were also reduced by 3.4% and 2.2%, respectively. However, these reductions were counterbalanced by increases in India and European Union by 5.1% and 1.3%, respectively (Oliver *et al*., 2015). The share of the G20 in the global total decreased by 0.4% in 2015, compared to 2014. Over the last 10 years, CO_2 emissions in the G20 increased by 20%, with an annual average of 1.9%. In 2015, the 10 largest CO_2 emitters among the G20 were China, the United States, the European Union, India, the Russian Federation, Japan, South Korea, Canada, Brazil, Indonesia and Saudi Arabia. The eight largest emitting countries among the non-G20 countries are Iran (1.7%), Taiwan (0.8%), Thailand (0.8%), Kazakhstan (0.7%), Malaysia (0.7%), Ukraine (0.6%), Egypt (0.6%) and Nigeria (0.2%). Over the last decade, the CO_2 emissions in these eight countries increased by 10.3%, with an annual average of 1.4%. For the rest of the countries in this group of other countries, the increase was 33%, over the last 10 years, with an annual average increase of 3.2%.

Due to this global issue caused by carbon emissions, the Kyoto Protocol was adopted in Kyoto, Japan, in 1997 and entered into force in 2005. Across countries, climate policy commitments under the Kyoto Protocol have reduced domestic emissions. However, the landmark Paris Agreement on Climate Change by 194 countries and the European Union was adopted in the closed off 2015 (Oliver et al., 2015). This agreement will be fully effected in 2020 to avoid dangerous climate change and limit global warming.

The main aim of this paper is to investigate the impacts of economic growth and population growth on carbon emissions.

2. Literature Review

According to Jiang and Hardee (2011) in the past 200 years, population, gross domestic product and carbon emissions have been on the increased globally. Recent statistics show that in some developed countries residential energy consumption contributed more to carbon emissions than industrial factors (Jiang and Hardee, 2011). Consequently, researches on the impacts of population growth and residential energy consumption on carbon emissions are of increasing trend by researchers (Druckman and Jackson, 2009; Qin and Xizhe, 2012; Jong-Chao and Chih-Hsiang, 2017). The impacts of population, urbanization level, per capita GDP, industrialization level, and energy intensity were studied by Lin et al. (2009) on the environment in China using STIRPAT (Stochastic impacts by regression on population, affluence and technology) model covering a period of 1978 to 2006. Wang et al. (2016) estimate the relationship between the carbon emissions, population, GDP per capita, electricity and energy consumptions.

An amount of literature has examined the contribution of population growth to CO2 emissions. Engelman (1994) found that both emissions and population have grown at similar rates since 1970 by plotting the long-term trends in global carbon dioxide emissions and population. Consequently, he hypothesizes that population growth has been a major force in driving up global emissions over recent decades. Meyerson (1998) claimed that the global increase in carbon emissions was attributed to population growth over the last 25 years. Satterthwaite (2009) found that population contributes to CO2 emissions through its effect on production and consumption activities. A large proportion of studies confirmed a positive relationship between population growth and CO2 emissions (Shi, 2003; Cole and Neumayer, 2004; Morales-Lage et al., 2006; Muhammad et al., 2011; Hossain, 2012). Some considered population density as an alternative to population growth (Panayotou, 1993; Nguyen, 1999; Panayotou, 2000; Muhammad *et al.*, 2011). Ehrlish and Holdren (1971), Cole and Nuemayer (2004) used the IPAT identity (impacts by regression on population, affluence, and technology) to examine the impact of population growth on carbon emission. Shi (1993) examined the impact of population change on carbon emissions for 93 countries covering a period of 1975 to 1996 using the IPAT model. He concluded that the impact of population change is more pronounced in developing countries than in developed countries.

Increase in CO2 has been attributed to urbanization by some researchers. Zhu and Peng (2012) claimed that urbanization increases residential consumption and energy demand, which in turn increases CO2 emissions. In addition, they concluded that urbanization increases demand for houses, which increases demand for housing materials such as cement, which also is an important source of CO2 emissions. Increase in the demand for houses leads to deforestation require the clearing of trees and grasslands conversion, which releases the carbon stored in the trees increasing CO2 emissions. The impact of urbanization on CO2 emissions in Sub-Saharan Africa have not been intensively explored.

Table 1: CO_2 Emissions in 2015 (a Million Tones CO_2) and CO_2/cap Emissions, 1990–2015 (Tones CO_2 per Person)

Country	Emis- sions 2015	CO2 / cap in 1990	CO2 / cap in 2000	CO2 / cap in 2010	CO2 / cap in 2013	CO2 / cap in 2014	CO2 / cap in 2015	Change '90-'15	Change '90-'15 in %	Change in CO2 1990-2015 in %	Change in population 1990-2015 in %
China *	10,720	2.0	2.9	6.7	7.7	7.8	7.7	5.7	281%	355%	19%
United States *	5,180	19.8	20.8	17.8	16.6	16.6	16.1	-3.7	-19%	3%	27%
European Union *	3,470	9.2	8.4	7.7	7.2	6.8	6.9	-2.3	-25%	-21%	6%
Germany *	*780*	*12.9*	*10.5*	*10.1*	*10.1*	*9.6*	*9.6*	*-3.3*	*-25%*	*-24%*	*2%*
United Kingdom*	*400*	*10.2*	*9.3*	*7.9*	*7.1*	*6.5*	*6.2*	*-4.0*	*-39%*	*-31%*	*13%*
Italy*	*350*	*7.5*	*8.0*	*7.1*	*6.1*	*5.6*	*5.9*	*-1.6*	*-21%*	*-17%*	*5%*
France*	*330*	*6.7*	*6.7*	*6.1*	*5.6*	*5.1*	*5.1*	*-1.6*	*-24%*	*-14%*	*13%*
Poland	*300*	*9.5*	*8.2*	*8.4*	*7.9*	*7.5*	*7.6*	*-1.9*	*-20%*	*-19%*	*1%*
Spain	*260*	*5.9*	*7.6*	*6.1*	*5.4*	*5.3*	*5.7*	*-0.2*	*-3%*	*14%*	*18%*
Netherlands	*170*	*10.7*	*10.8*	*11.0*	*10.1*	*9.5*	*9.8*	*-0.9*	*-9%*	*3%*	*13%*
India1	2,470	0.8	1.0	1.5	1.7	1.8	1.9	1.1	147%	272%	51%

Country	Emis-	CO2 /	CO2 /	CO2 /	CO2 /	CO2 /	CO2 /	Change	Change	Change	Change in
Russian Federation*	1,760	16.2	11.5	12.1	12.7	12.7	12.3	-4.0	-24%	-26%	-3%
Japan*	1,260	9.5	10.0	9.6	10.4	10.1	9.9	0.4	4%	8%	4%
Canada*	680	20.1	23.8	20.3	20.0	19.8	19.0	-1.1	-5%	23%	30%
Iran	630	3.6	5.3	7.7	7.8	8.0	8.0	4.4	123%	214%	41%
South Korea*	620	6.3	10.4	12.2	12.3	12.2	12.1	5.9	93%	129%	17%
Saudi Arabia*	510	10.2	12.2	15.0	15.2	15.8	16.0	5.8	56%	201%	93%
Indonesia*	500	0.9	1.4	1.8	1.8	1.9	2.0	1.1	122%	214%	42%
Brazil*	490	1.5	1.9	2.1	2.4	2.5	2.3	0.9	60%	120%	38%
Mexico*	470	3.4	3.7	3.8	3.9	3.8	3.7	0.3	10%	63%	48%
Australia*	450	16.3	18.8	19.0	18.4	18.6	18.6	2.3	14%	60%	40%
South Africa*	420	7.7	7.1	8.4	7.9	8.0	7.7	0.0	0%	47%	48%
Turkey*	360	2.8	3.6	4.3	4.3	4.5	4.5	1.7	60%	132%	46%
Taiwan	280	6.2	10.6	11.8	11.9	12.0	11.9	5.7	92%	121%	16%
Thailand	280	1.6	2.7	3.7	4.0	4.1	4.1	2.5	151%	200%	20%
Kazakhstan	270	15.2	9.2	15.3	15.6	15.8	15.2	0.0	0%	7%	7%
Malaysia	250	3.0	5.3	7.3	7.9	7.9	8.1	5.1	168%	345%	67%
Ukraine	230	16.0	8.0	7.0	7.0	6.1	5.1	-10.9	-68%	-72%	-13%
Egypt	230	1.6	1.8	2.6	2.5	2.5	2.5	0.9	55%	152%	62%
Argentina*	190	3.3	3.9	4.5	4.4	4.4	4.4	1.1	32%	75%	33%
Nigeria	90	0.7	0.7	0.5	0.5	0.5	0.5	-0.2	-34%	26%	91%
Global total	36,250	4.3	4.2	4.9	5.0	5.0	4.9	0.7	15%	60%	38%
G20	29,530	5.0	5.1	6.1	6.3	6.4	6.3	1.3	25%	60%	28%
Non-G20	6,720	2.2	1.9	2.1	2.1	2.1	2.1	-0.1	-4%	59%	62%

*. Member of the Group of Twenty (G20). The European Union (EU-28) is also a member.

Poumanyvong and Kaneko (2010) examined the impact of urbanization on energy use and CO2 emissions by considering different development stages using the STIRPAT model along with balanced panel dataset covering the period 1975-2005 and concluded that urbanization positively affect CO2 emissions which are also confirmed by a number of studies (Cole and Neumayer, 2004; Liddle and Lung, 2010).

In Nigeria, energy serves as the engine of growth for all sectors of the economy. The output of the energy sector usually electricity and the petroleum products usually consolidate the activities of the other sectors. Population changes have affected and continued to influence the Nigerian energy use and consequently increase carbon emissions. In this study, population structure (age structure, urbanization level) was incorporated into the STIRPAT model to investigate the impacts of population size, population structure and energy use on carbon emissions.

3. Econometrical Model

Following the STIRPAT model by Qin and Xizhe (2012), carbon emissions (C_t) represent the dependent variable while population total (P_t), urbanization rate (U_t), gross domestic product per capita (G_t). Energy use is included as one of the independent variables in this study. The data is used in its logarithmic form so as to provide efficient and consistent results (Qin and Xizhe, 2012). The econometric model is defined as follows:

$$lC_t = f\left(lP_t, lU_t, lG_t, lE_t\right) \quad (1)$$

The functional of the model is as follows:

$$lC_t = \beta_0 + \beta_1 lP_t + \beta_2 lU_t + \beta_3 lE_t + \beta_4 lG_t + \varepsilon_t$$

where C_t refers to carbon emissions measured in kt, P_t denotes population size measured in billions, U_t is the rate of urbanization expressed in percentage, E_t is the energy use expressed in kg of oil equivalent per capita and G_t is gross domestic product per capita measured in current US$, t is the time trend, ε_t is the random error term that is assumed to be normally distributed with mean zero and variance, σ^2.

3.1 Data Description

The study data covers a period from 1981–2015 in Nigeria. Table 2 presents the variables used and their expected sign. All data were sourced from the World Bank Development.

Table 2: Variable Description

Variables	Symbol	Measure	Expected Sign
Carbon emission	C_t	CO2 emissions in kt	N/A
Economic growth	G_t	GDP per capita in constant 2010 US$	±
Population	P_t	population size measured in billions	+
Energy consumption	E_t	Energy used in kg of oil equivalent per capita	±
Urbanization	U_t	expressed in percentage	+

Note: N/A implies not applicable since CO2 is the dependent variable.

Table 3: Descriptive Statistics

Variables	N	Minimum	Maximum	Mean	Std. Deviation
lC_t	35	10.41	11.56	11.13	.358
lP_t	35	18.14	19.02	18.59	.263
lG_t	35	5.03	8.07	6.34	.895
lU_t	35	3.12	3.87	3.52	.215
lE_t	35	6.51	6.68	6.57	0.05

Source: Authors' calculation using SPSS

Table 4: Correlation Matrix

	lC_t	lP_t	lG_t	lU_t	lE_t
lC_t	1	$.572^{**}$	$.703^{**}$	$.537^{**}$	$.712^{**}$
lP_t	$.572^{**}$	1	$.752^{**}$	$.997^{**}$	$.880^{**}$
lG_t	$.703^{**}$	$.752^{**}$	1	$.716^{**}$	$.832^{**}$
lU_t	$.537^{**}$	$.997^{**}$	$.716^{**}$	1	$.870^{**}$
lE_t	$.712^{**}$	$.880^{**}$	$.832^{**}$	$.870^{**}$	1

Source: Authors' calculation using SPSS; **significant at 1%

3.2. Discussion of Empirical Results

3.2.1 Descriptive and Unit Roots Test

Table 3 summarizes the statistics for the variables used in this study. Population total and urbanization rate have the lowest and highest mean respectively. Table 4 shows the correlation matrix between the variables examined in this study. There exist positive correlations between all the variables.

Figure 1 shows that the population size in Nigeria has been increasing sporadically from year to year. The same is applicable to the rate of urbanization growth over the years. The plot shows that the minimum GDP per capita in the country is experienced in 1993 after which there has been an increasing trend to date. There has been a form of an upward and downward trend in carbon emissions. The lowest was in 1995 while the highest so far is in 2005. Also, there has been a form of an upward and downward trend in energy use. The lowest was in 1986 while the highest so far is in 2012.

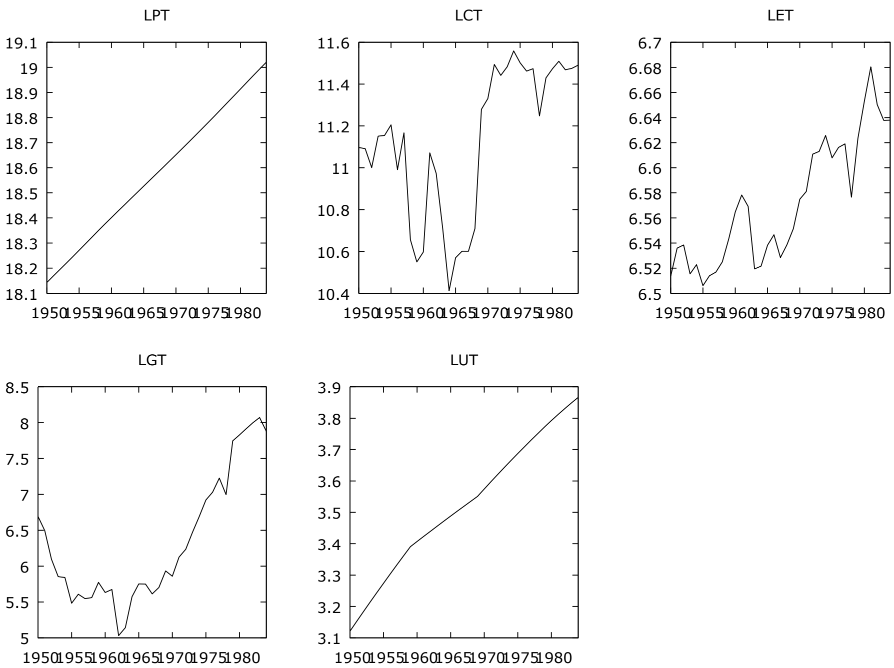

Figure 1: Time Series Plot of All the Variables

It is necessary to ascertain the order of integration of the variables before adopting autoregressive distributed lag (ARDL) bounds methodology. This method is used when all the variables are stationary at the original level I(0) or first difference I(1) or a mixture of both. Consequently, there is a need to check the unit root property of each variable. The augmented Dickey-Fuller (ADF) test was adopted. The result is presented in Table 5. None of the variables is stationary at the second difference. Therefore, it is appropriate to examine the co-integration relationship between the variables using ARDL method.

Table 5: Result of the Unit Root Test of the Variables

Variable Status	Variable Name	Indicator	ADF TEST		Result
			Intercept	Trend and Intercept	
Original	Carbon emissions	C_t	-1.43	-2.12	Non Stationary
	Population total	P_t	-0.81	-4.7**	I(0)
	Urbanization rate	U_t	-0.67	-6.43***	Non Stationary
	Gdp per capita	G_t	0.07	-2.71	Non Stationary
	Energy use	E_t	-1.13	-2.73	Non Stationary
First difference	Carbon emissions	ΔC_t	-5.63***	-5.59***	I(1)
	Population total	ΔP_t	-3.74***	-3.71 **	I(1)
	Urbanization rate	ΔU_t	-5.82 ***	-5.85 ***	I(1)
	Gdp per capita	ΔG_t	-5.34 ***	-6.17***	I(1)
	Energy use	ΔE_t	-5.53***	-5.47***	I(1)

Note: I(0) denote the variable is stationary in the original level, while I(1) denote the variable is stationary after the first difference, *,**,*** denote statistical significance at the 10%, 5% and 1% level respectively.

3.2.2 ARDL Bounds Test

Basically, ARDL co-integration approach involves two steps. Firstly, there is a need to check if there is a long run relationship among the variables via F-statistic. Consequently, if F-statistic confirms the existence of co-integration in the long-run and short run coefficients will be computed. According to the bound test introduced by Peseran et al. (2001), two types of bounds are considered. The lower bound in case the variables are I(0) and upper bound in case the variables are I(1). The null hypothesis of no long-run relationship is rejected if the calculated F-statistic is greater than the upper bound, which implies there is long run co-integration among the variables. The results of the bound test are presented in Table 6. The F-statistic (4.0912) is greater than the upper bound test value at four different level of significance (1%, 2.5%, 5% and 10%). Therefore, there is a long run relationship among the variables.

Table 6: Bound Test Co-integration

F-Bounds Test — Null Hypothesis: No levels relationship

Test Statistic	Value	Signif.	I(0)	I(1)
F-statistic	3.991731	10%	2.08	3
k	5	5%	2.39	3.38
		2.5%	2.7	3.73
		1%	3.06	4.15

Source: Authors' Output from Eview 9

Figure 2 shows the plots of the cumulative sum of recursive residuals (CUSUM) and the cumulative sum of squares of recursive residuals (CUSUMSQ) tests. The plots show that the error correction model is stable during the studied period as they are within the critical bounds of 5%.

The results reported in Table 7 and 8 shows the long-run and short-run analysis alongside the robust analysis of the long-run analysis impacts of carbon emission on population total, urbanization rate, gross domestic product per capita and energy use in Nigeria. Results in Table 7 show that in the long-run analysis population total and energy use have a significant and positive influence on carbon emission while in the short run analysis, all the independent variables have a positive impact on carbon emission but only energy use is significant. In addition, from the long-run result in Table 7, urbanization rate and gross domestic product per capita both have a negative impact on carbon emission. The results obtained for urbanization level negates the expected sign. This might be due to the presence of multicollinearity. According to Lukman and Ayinde (2017), a regression coefficient might exhibit a wrong sign if there are relationships among the explanatory variables. The diagnostic check, in the long-run, shows that the model suffers two violations in the assumptions of the classical linear regression model. The maximum variance inflation factor greater than 10 shows the presence of serious multicollinearity while the Durbin-Watson test shows that the error term is correlated. Consequently, the long run analysis shows that the data suffers both problems of multicollinearity and autocorrelation. This necessitates the use of generalized least squares and generalized ridge regression (GRR) provided in Table 8. According to Arowolo et al. (2016), GRR is used to handle the simultaneous effect of autocorrelation and multicollinearity. The result of GRR is provided in Table 8. Results show that population total, urbanization level, gross domestic product per capita and energy use positively influenced carbon emissions in Nigeria. This result agrees with the expected sign in Table 2. The contribution of energy use to carbon emission is highest followed by population total. The short-run results are also in

Table 7: Estimated Long Run and Short Run Analysis Results

Long run Analysis Result Dependent variable=lC_t				**Short Run Analysis Result Dependent variable=ΔlC_t**			
Variable	**Coefficient**	**Std error**	**t-stat**	**Variable**	**Coefficient**	**Std error**	**t-stat**
c	-117.07	42.41	-2.76***	ΔlP_t	1.29	5.84	0.83
lP_t	6.25	2.66	2.35*	ΔlU_t	1.46	6.71	0.83
lU_t	-7.88	3.14	-2.51**	ΔlG_t	0.06	0.13	0.46
lG_t	-0.03	0.11	-0.25	ΔlE_t	3.18	1.53	2.08**
lE_t	6.08	2.07	2.94***	ECT(-1)	-0.48	0.16	-2.99***
diagnostic tests			statistics	diagnostic tests			
J-B Normality test			2.72(0.26)	J-B Normality test			2.56 (0.28)
Durbin-Watson test			0.75 (0.00)	Durbin-Watson test			1.79 (0.19)
Maximum Variance Inflation Factor			317.993	Maximum Variance Inflation Factor			1.66
Breusch Pagan test			5.93 (0.20)	Breusch Pagan test			1.58 (0.81)

Note: ** shows significance at 5% respectively, P-value enclosed in parenthesis

Source: Gretl output

line with the a priori assumptions since all the variables positively influence carbon emissions. In addition, as expected, the sign of the estimate of the lagged error term, i.e., ECT(-1) is negative and statistically significant at 1 per cent level of significance. The coefficient of ECT(-1) is -0.48 implying that ΔlC_t adjusts towards its long-run equilibrium at the rate of 45 per cent each year. The diagnostic tests for both the short run model show that there is no violation of assumption. Energy use contributed more to carbon emissions in the short run.

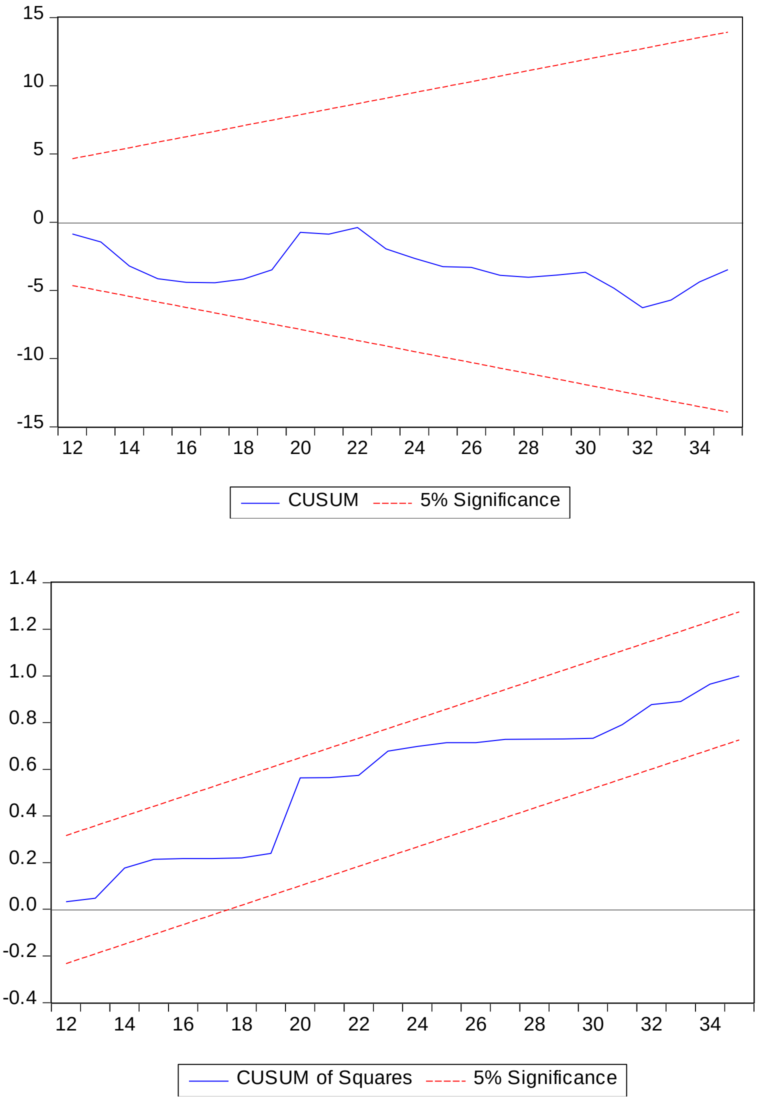

Figure 2: Residual Stability Test Using CUSUM and CUSUMSQ Graph

Table 8: Robust Analysis of Long Run Regression Coefficients

Long run Result using Generalized Least Squares Dependent variable=$logC_t$				Long Run Result using Generalized Ridge Estimator Dependent variable=ΔC_t	
Variable	**Coefficient**	**Std error**	**t-stat**	**Variable**	**Coefficient**
c	-126.53	51.91	-2.44**	c	2.2507
lP_t	7.53	3.38	2.23**	lP_t	0.1645
lU_t	-9.01	3.93	-2.29**	lU_t	0.0737
lG_t	-0.08	0.12	-0.65	lG_t	0.1327
lE_t	4.56	1.74	2.62**	lE_t	2.3337
Diagnostic tests			**statistics**	**Diagnostic tests**	**Statistics**
J-B Normality test			0.99 (0.61)	J-B Normality test	-
Durbin-Watson test			1.81 (0.20)	Durbin-Watson test	-
Maximum Variance Inflation Factor			627.03	Maximum Variance Inflation Factor	-
Breusch Pagan test			3.93 (0.41)	Breusch Pagan test	-

Note: ** shows significance at 5% respectively, P-value enclosed in parenthesis, (-) means test is not available
Source: Gretl output

4. Conclusions and Policy Recommendation

The STIRPAT model was employed to examine the impacts of population total, gross domestic product per capita, urbanization rate and energy use on carbon emissions in Nigeria for a period of 1981-2015. The ARDL bounds testing approach for co-integration revealed evidence of a long run relationship among the variables. The generalized ridge regression was used to correct the negative influence of multicollinearity among the explanatory variables. In the long and short run, the four variables considered have positive impacts on carbon emissions. Energy use and urbanization both contributed significantly to increasing carbon emissions in the long and short run respectively. Considering the fact that the Nigerian population has continued to increase this, in turn, has often led to increases in the rate of urbanization. In addition, since Nigerian economy is majorly centered on energy use especially from oil, there is a need to adopt policies to curb increasing carbon emissions.

Alternative energy policies such as developing the energy conservation strategies, reduced energy intensity, etc. should be adopted. In addition, the country has to adopt other alternative energy sources with less carbon emission. The country should put in place policies that will reduce the rate of urbanization should be considered.

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