Oil Sector and Carbon Emissions in Nigeria: Asymmetry Analysis

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Abstract
The paper investigates the asymmetric effects of the oil sector on carbon emissions per capita in Nigeria through nonlinear autoregressive distributed lag estimations from 1980 to 2020 on yearly data. We consider the oil sector because of the country's high dependence on it. Our results confirm that changes in the oil sector and carbon emissions are asymmetrically associated in both the short and long run. Moreover, the results show that both positive and negative changes in the oil sector lead to a reduction in carbon emissions, but positive shocks have a more profound effect. The results have important policy implications namely expanding the oil sector with strict enforcement of all environmental regulations will reduce carbon emissions. Moreover, an increase in oil prices in the short run will reduce carbon emissions, Finally, carbon emissions from the non-oil sector need to be regulated.

Keywords: Carbon emissions; Oil sector; Nonlinear ARDL; Cointegration; Asymmetry; Nigeria

JEL Classification Codes: C22, O13, P18, Q43

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1. Introduction

Studies on determinants and effects of carbon emissions occupy a substantial part of the economic literature. This follows from the high and increasing amount of carbon emissions in the atmosphere. Available data show that the atmospheric level of carbon dioxide increased from 316.91 parts per million in 1960 to 338.76 parts per million in 1980. The figure steadily increased to 354.45 and 369.71 parts per million in 1990 and 2000, respectively. The atmospheric carbon emissions level reached a high of 414.24 parts per million in 2020, in comparison to 2010 levels which stood at 390 parts per million. The story is not different in Nigeria. The level of carbon emissions increased from 0.34 million metric tons in 1989 to an average of 0.62 million metric tons over the period 2006 and 2020. Prior studies (Xu and Chen, 2016; Environmental Canada, 2013, 2014) have shown that the oil sector is a significant source of air pollution. Emissions of air pollutants occur in all the stages of the oil-gas industry, including mining, refinery, storage, transportation between different storage facilities, and refueling (Xu and Chen, 2016; USEPA, 2015). The common pollutants from the oil-gas industry include volatile organic compounds (VOCs), methane (CH4), polycyclic aromatic hydrocarbon (PAHs), and particulate matter (PM). The health and economic impacts of pollution from the oil-gas industry are profound. Many recent studies show that pollutants from the oil-gas sector are associated with asthma, respiratory and cardiovascular illnesses, liver failure, cancer, headaches, preterm birth, and low birth weight (Denham, et al., 2021; Tang et al., 2021; Gonzalez, et al., 2020; Tran, et al., 2020).

Nigeria is one of the world's most endowed nations in terms of oil reserves. The country's oil reserves represent 3.1 per cent of the world's total ranking as the tenth among countries with oil reserves (Akinlo, 2021). Oil constitutes a major income source in Nigeria. The increase in oil income is argued often leads to increased economic activities and carbon emissions (Saboori et al., 2016; Nwani 2017). Asides, oil has an impactful role in urbanization. It strongly influences urban planning not only because of the number of people working in the sector but also the massive rural-urban migration it engenders. In the literature, several studies have established a positive relationship between urbanization and carbon emissions (Ali et al., 2019; Liang and Yang 2019; Mahmood et al. 2020).

Worldwide previous studies like Roberts et al., 2019; Bekun et al., 2019; Johnston et al., 2019; Mahmood et al., 2020) have examined empirically how the oil sector affects the environmental profile of a country. However, it is missing in the case of Nigeria. Most existing studies on the subject matter in Nigeria are merely narrative and descriptive. The analysis is imperative because both carbon emissions and the oil sector have witnessed increased growth over the years. It is necessary to know how the increasing role of oil in the country affects environmental degradation. Therefore, our study attempts to investigate the effect of the oil sector on carbon emissions in Nigeria, considering the asymmetry in the relationship.

The paper is structured as follows: Section 2 gives a brief review of the theoretical and empirical literature. Section 3 presents the data and methodology adopted in the analysis. Section 4 presents the empirical results. Section 5 contains the conclusion.

2. Literature Review

2.1 Theoretical Issues

Several studies have explored the effect of the oil sector on growth and development worldwide (Rosser 2006; Brunnschweiler 2009; Akinlo 2012). Also, a substantial literature has examined how oil price changes impact carbon emissions (Li et al., 2020, Ullah et al., 2020; Musa 2020; Wei 2022; Ebaid et al., 2022) However, the ecological effects of the oil sector have been largely ignored.

There are two broad perspectives on the relationship between the oil sector and carbon emissions. The first viewpoint posits that the oil sector leads to an increase in carbon emissions. The basic argument is that the endowment of oil through mining, refining, and storage leads to increased carbon emissions. Some identified pollutants from the sector include volatile organic compounds (VOCs), methane (CH_4), and polycyclic aromatic hydrocarbons (PAHs) (USEPA 2015, Xu and Chen 2016).

Aside from emissions of pollutants from increased oil production, the huge revenue from the sector when efficiently utilized can lead to increased income and carbon emissions. Studies have documented the positive effects of income on carbon emissions (Samargandi 2017; Raggad 2018; Hakimi and Hamdi 2016; Ahmed et al., 2017; Saboori et al., 2016). The argument is that increased oil income working through increased energy consumption and rising urbanization often lead to increased carbon emissions. Empirically, some studies have reported the positive effect of urbanization (Chen et al., 2019; Wang et al., 2019; Musa 2020) and energy consumption (Apergis et al., 2010, Bulut 2017; Saboori et al., 2016; Nwani 2017) on carbon emissions.

The second perspective on the oil sector - carbon emissions relationship, however, argues that the oil sector may not necessarily lead to increased carbon emissions. It is contended in the literature that where oil production is based on modern and cleaner technologies, carbon emissions may be reduced. Furthermore, some scholars have argued that the abundance of oil does not, in most cases, translate into increased income and energy consumption. According to this school of thought, oil abundance tends to harm economic growth (income). The main transmission mechanisms channel includes the Dutch disease theory, volatility argument, and inefficiency in income allocation argument (see the works of Sachs and Warner 1995, 1999; Neary and Wijnbergen 1986; Leite and Weidermann 1999; Collier and Hoeffler 2004, Rosser 2006).

In general, while there are strong thematic grounds to suspect a broad correspondence between the oil sector and increased carbon emissions, the nature of the relationship is not simple and direct. In an economy where oil production is based on old technologies, carbon emissions will likely increase. In the same way, increased income from oil that leads to increased urbanization and energy consumption may lead to increased carbon emissions. However, where a country adopts modern and cleaner technologies in the mining, refining, and storage of oil coupled with strict environmental regulations to control carbon emissions, the oil sector may not necessarily to increased pollution.

2.2 Empirical Evidence

Many empirical studies have checked the linkage of oil with environmental quality and depicted diverse results. However, the focus of most existing studies has been on the effect of oil price changes or oil price volatility on environmental quality. The effect of the oil sector as a share of the national economy on carbon emissions has been unjustifiably ignored. Most studies on the subject matter are descriptive and highly impressionistic. However, recently few studies have started to emerge on the impact of the oil sector on carbon emissions (Johnston et al., 2019; Mahmood et al., 2020).

Johnston et al. (2019) examine the effect of the upstream oil segment on the environment and public health. They find that oil drilling and extraction activities do raise environmental concerns on a large scale. In like manner, Bambeger et al. (2012) analyze the impact of gas drilling on the environment, and human health, and prove that gas drilling has significant environmental effects. Few other studies that have investigated the effects of oil drilling and gas flaring on the environment and health status include Cushin et al., 2020; Willis et al., 2021; Xu and Chen 2016). In general, all these studies prove that oil drilling, extraction, and gas flaring do raise serious environmental issues.

Despite the high dependence on oil as a major source of income and the significant role, the sector plays in Nigeria, no known studies have explored the oil sector-carbon emissions nexus empirically. This is a gap in the literature that needs to be filled. Therefore, this study attempts to examine the asymmetric and symmetric effects of the oil sector on carbon emissions and ascertain the direction of causality between the two phenomena. The findings of this study will help in designing policies to enhance the ongoing economic diversification programme while caring for the environmental effects.

3. Methodology and Data

3.1 Methodology

The study adopts a variant of Dietz and Rosa's (1994) Stochastic Impacts by Regression of Population, Affluence and Technology (STIPAT) model. This is implicitly stated as:

$$CO2_t = (olr_t, nor_t, ent_t, oip_t) \quad (1)$$

Equation is stated explicitly as:

$$CO2_t = \alpha_0 + \alpha_1 olr_t + \alpha_2 nor_t + \alpha_3 ent_t + \alpha_4 oip_t + \varepsilon_t \quad (2)$$

where *CO2* is carbon emissions, *olr* is the natural logarithm of the percentage of oil income in total GDP, *nor* is the natural logarithm of real non-oil gdp per capita, *ent* is energy intensity measured as total energy per unit of the gdp, and *oip* is the natural logarithm of oil price, and ε is the error term.

Following Pesaran et al. (2001), the unrestricted error correction version of equation 2 is given as:

$$\Delta CO2 = \delta_0 + \delta_1 CO2_{t-1} + \delta_2 olr_{t-1} + \delta_3 nor_{t-1} + \delta_4 ent_{t-1} + \delta_5 oip_{t-1} + \sum_{i=1}^{n} \beta_1 \, CO2_{t-i} + \sum_{i=0}^{p} \beta_2 \, olr_{t-i} + \sum_{i=0}^{q} \beta_3 \, nor_{t-i} + \sum_{i=0}^{r} \beta_4 ent_{t-i} + \sum_{i=0}^{s} \beta_5 \, oip_{t-i} + \varepsilon_t \qquad (3)$$

To account for asymmetries, the oil sector is decomposed into positive and negative partial sums (olr_t^+, olr_t^-) following Shin et al. (2014). The partial sums are generated as shown in equation 4:

$$olr_t^+ = \sum_{j=1}^{m} \Delta olr_j^+ = \sum_{j=1}^{m} \max(\Delta olr_j, 0)$$

$$olr_t^- = \sum_{j=1}^{m} \Delta olr_j^- = \sum_{j=1}^{m} \max(\Delta olr_j, 0) \qquad (4)$$

According to Shin et al. (2014), substituting (4) into the linear unrestricted error correction model given as equation (3), we obtain a nonlinear ARDL (NARDL) explicitly stated as:

$$\Delta CO2_t = \delta_0 + \delta_1 CO2_{t-1} + \delta_2^+ olr_{t-1}^+ + \delta_3^- olr_{t-1}^- + \delta_4 nor_{t-1} + \delta_5 ent_{t-1} + \delta_6 oip_{t-1} + \sum_{i=1}^{z} \beta_1 \Delta CO2_{t-i} + \sum_{i=0}^{w} \beta_2 nor_{t-i} + \sum_{i=0}^{x} \beta_3 ent_{t-i} + \sum_{i=0}^{r} \beta_4 \Delta oip_{t-i} + \sum_{i=0}^{s} (\beta_5^+ olr_{t-i}^+ + \beta_5^- olr_{t-i}^-) + \mu_t \qquad (5)$$

where *z, w, x, r,* and s denote the lag orders, while (olr^+, olr^-) represent the decomposed *olr* innovations as earlier defined. These innovations, as included in equation (5), are used to ascertain short- and long-run asymmetric responses of carbon emissions to changes in the oil sector, which is measured as the percentage of oil income in total GDP.

To ascertain the long-run asymmetric effect of the oil sector changes in equation 5, we employ the Wald test with the null hypothesis ($\delta_2^+ = \delta_3^-$). The long-run impacts of increased oil sector (olr^+) and decreased oil sector (olr^-) on carbon emissions are obtained as $B^+ = -(\delta_2^+/\delta_1)$, $B^- = -(\delta_3^-/\delta_1)$, respectively. In contrast, we employ the Wald test to verify the asymmetric effect of the stock market development in the short run. The null hypothesis of this test is: ($\beta_5^+ = \beta_5^-$).

The last step entails the use of the nonlinear ARDL model in equation (5) to generate the two dynamic multipliers, m_h^+ and m_h^-. The dynamic multiplier m_h^+ relates to the change in olr_t^+ while m_h^- is connected with the change in olr_t^-:

$$m_h^+ = \sum_{i=0}^{h} \frac{\partial co2_{t+i}}{\partial olr_{t-1}^+}, \qquad m_h^- = \sum_{i=0}^{h} \frac{\partial co2_{t+i}}{\partial olr_{t-1}^-} \qquad h = 0, 1, 2 \qquad (6)$$

$$Note\ that\ as\ h \longrightarrow \infty, \quad m_h^+ \longrightarrow \beta^+, and\ m_h^- \longrightarrow \beta^-$$

To further investigate the oil sector–carbon emissions nexus in Nigeria, we conduct the granger causality test based on the error correction modeling approach. And from the estimations, the impulse response functions (IRFs) and the variance decompositions (VDs) are obtained. The IRF traces the dynamic responses to the effect of a shock on one variable on itself and on the other variables in the model. The VD measures the relative contribution of each random (i.e. one-standard deviation) shock to the endogenous variables.

Next, the unit root properties of the variables are ascertained to preclude the inclusion of I(*2*) variable. Following this, we conduct a cointegration test. This involves testing the null hypothesis of no cointegration (H_0: $\delta_1 = \delta_2 = \ldots = \delta_6 = 0$) against an alternative hypothesis (H_1: $\delta_1 \neq \delta_2 \neq \ldots \neq \delta_6 \neq 0$) using the F-test. The variables are cointegrated when the computed value of the F-statistic falls outside the upper critical value of the two sets of critical values provided by Pesaran, Shin and Smith, (2001).

3.2 Data and Data Sources

We employ annual data from 1980 to 2020 in estimating the specified model. The data on carbon emissions series and energy intensity are obtained from the World Development Indicators database (World Bank). Non-oil income and the percentage of oil income in total GDP are sourced from the Statistical Bulletin 2021 edition (Central Bank of Nigeria). Oil price (US dollar per barrel) is obtained from the BP Statistical Review of World Energy. The variables are used in their natural logarithmic form. Table 1 shows the definitions of variables and data sources.

Table 1: Definition of Variables and data sources

Variables	Definition of variable and data sources
nor	real non-oil GDP per capita. Source: CBN Statistical Bulletin (2021)
oip	oil price (US dollar per barrel). BP Statistical Review of World Energy (2021)
ent	energy intensity. Source World Development Indicators (2021)
olr	percentage of oil income in total GDP as a measure of oil sector development, while + and – denote positive and negative shocks for the oil sector. Source: CBN Statistical Bulletin (2021 edition)
CO_2	carbon emissions measured in millions metric tons. Source: World Development Indicators (2021).

4. Results and Discussion

Table 2 presents the highlights of the descriptive statistics, while Table 3 shows the pair-wise correlation matrix of the variables used in the analysis. As revealed in Table 2, all the series except energy intensity are platykurtic because their kurtosis values are less than 3. This finding simply means that the variables except energy intensity have lighter tails than a normal distribution. The probability value of the Jacque-Bera statistic confirms the normal distribution hypothesis at 5 percent for all the variables. As shown in Table 3, none of the independent variables has a coefficient of correlation greater than 0.7. This obviates the likelihood of multicollinearity between the independent and dependent variables as variables with correlation values greater than 0.7 are considered highly correlated. The pair-wise correlation results reveal that carbon emissions is negatively correlated with increased oil sector (percentage of oil income in total GDP) and energy intensity. Contrariwise, a decreased oil sector and oil price are positively correlated with carbon emissions.

Table 2: Descriptive Statistics

	Co2	*olr*$^+$	*olr*$^-$	*nor*	*ent*	*oip*
Mean	0.6048	4.4212	-1.5838	4.1777	6.5155	3.5122
Median	0.5878	4.2957	-0.3840	3.7309	6.5324	3.3687
Maximum	0.9282	9.4214	-0.3659	8.4608	6.6829	4.6955
Minimum	0.3256	0.0000	-3.4769	1.0578	5.8111	2.5080
Std.Dev	0.1705	3.3316	0.7838	2.5772	0.1584	0.6476
Skewness	0.0227	0.0843	-0.6602	0.1606	-3.2313	0.3591
Kurtosis	2.0386	1.5682	2.9714	1.4981	14.0208	1.9610
Jarque-Bera	1.5825	3.4643	2.9069	4.0295	278.8384	2.7254
Probability	0.4533	0.1769	0.2338	0.1334	0.0000	0.2560
Sum	24.7953	176.8481	-63.3517	171.2872	267.1367	143.9999
Sum Sq.Dev	1.1625	432.8823	23.9602	265.6713	1.0042	16.7752

Table 3: Pairwise-Correlation Matrix

Variable	*Co2*	*olr*$^+$	*olr*$^-$	*nor*	*ent*	*oip*
CO2	1.0000					
olr$^+$	-0.2198	1.0000				
olr$^-$	0.2195	-0.9896	1.0000			
nor	-0.1326	0.9711	-0.9631	1.0000		
ent	-0.3495	0.6569	-0.6165	0.6026	1.0000	
oip	0.2367	0.6846	-0.6905	0.7301	0.4571	1.0000

The results of Augmented Dickey-Fuller (ADF intercept only) and Phillips-Peron unit root tests are shown in Table 4. The results suggest that the variables are all stationary at first differences.

Table 4: Unit Root Tests

	ADF		PP	
Variable	Level	1st diff	Level	1st diff
CO2	-2.0819	-4.1352***	-0.1385	-6.1398***
olr$^+$	-0.0154	-5.1685***	0.1910	-5.7508***
olr$^-$	1.2595	-4.4188***	1.1187	-6.6383***
nor	0.8875	-4.3157**	0.4973	-8.1509***
ent	-2.2422	-3.2335***	-2.3040	-7.3388***
oip	-1.3109	-4.6697***	-1.3374	-5.8727***

Note:***, ** and * denote 1%, 5% and 10% significant levels respectively. For the ADF test, critical values are:-3.6104, -2.9390 and -2.6079 at 1%, 5% and 10% respectively. For the PP test, critical values are: -3.6056, -2.9369 and -2.6069 at 1%, 5% and 10% respectively.

The result of the cointegration test, shown in table 5, shows that the F- statistic values (F_{pss} = 4.361) for linear and (F-pss = 3.696) for nonlinear models lie above the upper bound of the critical values at a 5% significance level. Therefore, the null hypothesis of no cointegration can be rejected. This simply means that the variables are cointegrated in both the linear and nonlinear models.

Table 5: Bounds test for cointegration in the linear and nonlinear specifications

Dependent Variable: $\Delta Co2$	F-PSS	95% Lower bound	95% Upper bound	Result
Linear ARDL	4.361**	2.39	3.38	Cointegration
Non-Linear ARDL[a]	3.696**	2.27	3.28	Cointegration

Bound Test at 5%

[a]The exact specification of the asymmetric ARDL model is presented in Tables 6 and 7

F-PSS indicates the *PSS F*-statistic testing the model hypothesis of no cointegration.

The results of the linear model presented in table 6 show that the coefficient of lagged CO2 is significant (β = -0.458, ρ-value = 0.002). The coefficient of the oil sector measured as a share of oil income in GDP is positive and significant in the long run. However, the reverse is the case in the short run. This finding suggests that the increased oil sector reduces carbon emissions in the short run but increases it in the long run. Non-oil GDP has a significant negative effect in the long run but a positive impact in the short run. Energy intensity has a significant negative effect in the long run. This simply suggests that increasing energy efficiency reduces carbon emissions in the long run.

Table 6: Results of Linear Model

Oil sector-pollution: ARDL Linear Estimation

Variable	Coefficient	t-statistics	P-value
Constant	35.533	3.681	0.001
$co2_{t-1}$	-0.458***	-3.500	0.002
olr_{t-1}	0.526***	3.897	0.001
nor_{t-1}	-0.408***	-3.359	0.003
ent_{t-1}	-5.550***	-3.692	0.001
oip_{t-1}	-0.116	-1.482	0.153
Δolr_t	-0.049	-0.645	0.526
Δolr_{t-1}	-0.567***	-4.674	0.0001
Δolr_{t-2}	-0.226**	-2.579	0.018
Δolr_{t-3}	-0.235***	-3.375	0.003
Δnor_t	-0.048	-0.565	0.584
Δnor_{t-1}	0.284***	3.379	0.003
Δent_t	-0.199	-0.985	0.336
Δent_{t-1}	4.938***	3.600	0.002
Δoip_t	0.049	0.535	0.598
Δoip_{t-1}	0.296***	2.988	0.007
Statistics and diagnostic tests			
X^2_{Norm} = 0.971(0.615)		X^2_{Het} = 0.482(0.924)	
X^2_{SC} = 1.373(0.277)		X^2_{FF} = 0.903(0.353)	

Note: *** and ** indicate significance levels for 1% and 5%, respectively.
χ^2_{SC}, χ^2_{HET}, χ^2_{NORM} and χ^2_{FF} refer to LM test for serial correlation, normality, functionality form and heteroscedasticity, respectively.

However, to explore more deeply the association between the oil sector and carbon emissions and comprehend the possibility of asymmetry in the relationship, we estimate equation 5. The estimated results are shown in Table 7. As shown in Table 7, the asymmetric impact is established both in the short and long run using the Wald test. The outcomes confirm a significant asymmetric relationship between oil sector growth (measured as oil income share of GDP) and carbon emissions both in the short and long run. The numerical values of the Wald test, 2.921 in the short run and 3.816 in the long run are statistically significant. The result confirms that carbon emissions react differently to an increasing oil sector compared to a decreasing oil sector in the two periods. By implication, nonlinearity and asymmetry should be considered when analyzing the carbon emissions-oil sector nexus in Nigeria.

With the confirmation of an asymmetric relationship between the oil sector and carbon emissions, we focus on the long and short-run estimates. The coefficients of positive (olr^{+}) and negative (olr^{-}) partial sums decomposition of oil sector growth are both negative. However, only the coefficient of an increasing oil sector is significant in the long run. This result shows that an expanding oil sector will reduce carbon emissions in the long run. Non-oil GDP increases carbon emissions in the long run with an insignificant effect in the short run. The oil price has no significant impact on carbon emissions in the long run. In the short run, oil price reduces carbon emissions only after two lags. Energy intensity tends to increase carbon emissions both in the short and long run. However, the effect is not significant in both periods.

The long-run coefficient of positive changes in the oil sector (olr^{+}) is -0.694, while the negative is –0.113. This outcome shows that a 1 percent increase in the oil sector will lead to a 0.694 percent decrease in carbon emissions. In the same way, a 1 percent decrease in the oil sector will lead to a 0.113 percent reduction in carbon emissions. However, the coefficient is not significant.
The results show that the expansion of the oil sector reduces carbon emissions in Nigeria. This outcome contradicts the results of Mahmood et al. (2020) for Saudi Arabia. There are two probable reasons for this finding. First, it could mean that the sector is adopting cleaner technologies that help to reduce carbon emissions as oil production increases. Second, oil refining has more or less stopped following the collapse of the refineries in the country over the years. The country only

Table 7: NARDL Estimation Results

Dependent variable: CO_2

Variable	Coefficient	t-statistics	ρ-value
Constant	-0.741	-0.278	0.786
$co2_{t-1}$	-0.569***	-2.994	0.010
olr^{+}_{t-1}	-0.395*	-1.951	0.073
olr^{-}_{t-1}	-0.064	-0.199	0.845
nor_{t-1}	0.551**	2.499	0.027
ent_{t-1}	0.005	0.012	0.991
oip_{t-1}	0.014	0.134	0.895
Δolr^{+}_{t}	-0.256*	-1.843	0.088
Δolr^{+}_{t-1}	0.002	0.015	0.988
Δolr^{+}_{t-2}	-0.120	-1.008	0.331
Δolr^{+}_{t-3}	-0.402***	-3.570	0.003
Δolr^{-}_{t}	0.310	1.554	0.144
Δolr^{-}_{t-1}	0.518	1.404	0.184
Δolr^{-}_{t-2}	0.806**	2.057	0.060
Δolr^{-}_{t-3}	0.836**	2.171	0.049
Δnor_{t}	0.290**	2.513	0.026
Δnor_{t-1}	-0.032	-0.268	0.792
Δnor_{t-2}	-0.154	-1.561	0.143
Δent_{t}	0.259	0.781	0.449
Δoip_{t}	0.043	0.392	0.701
Δoip_{t-1}	0.035	0.268	0.793
Δoip_{t-2}	-0.411***	-3.179	0.007
Δoip_{t-3}	-0.259*	-1.940	0.074

Long run (LR) asymmetric coefficient	Long and Short run asymmetric tests
LR^{+}_{olr} = -0.694* (0.065)	$W_{LR,olr}$ = 3.816**(0.0511)
LR^{-}_{olr} = -0.113 (0.849)	$W_{SR,olr}$ = 2.921** (0.049)
Statistics and diagnostic tests	
X^2_{Norm} = 1.563 (0.458)	X^2_{Het} = 0.751 (0.732)
X^2_{SC} = 0.567 (0.583)	X^2_{FF} = 2.836 (0.118)

*, ** and ***, indicate significance level for 10%, 5%, and 1%, respectively.

W_{LR}, W_{SR} and wald test for the null of long and short-run symmetry, respectively

χ^2_{SC}, χ^2_{NORM}, χ^2_{HET} and χ^2_{FF} symbolize LM test for serial correlation, normality, functional form and heteroscedasticity, respectively.

exports crude-oil while importing refined oil. This development coupled a massive reduction in gas flaring following the government's embankment on gas utilization, and commercialization projects, might have reduced carbon emissions in the country.

The diagnostic tests, reported in the lower panel of tables 6 and 7, reveal that the residuals of the estimated linear and nonlinear model pass all the diagnostic tests. This confirms well-specified estimated models. The stability of the estimated coefficients ascertained using both the cumulative sum of squares (CUSUMQ) and cumulative sum (CUSUM) tests confirm model stability. The results, shown in figs 1 &2 for the linear model and figs 3 & 4 for the nonlinear model, confirm the stability of the coefficients of the nonlinear model.

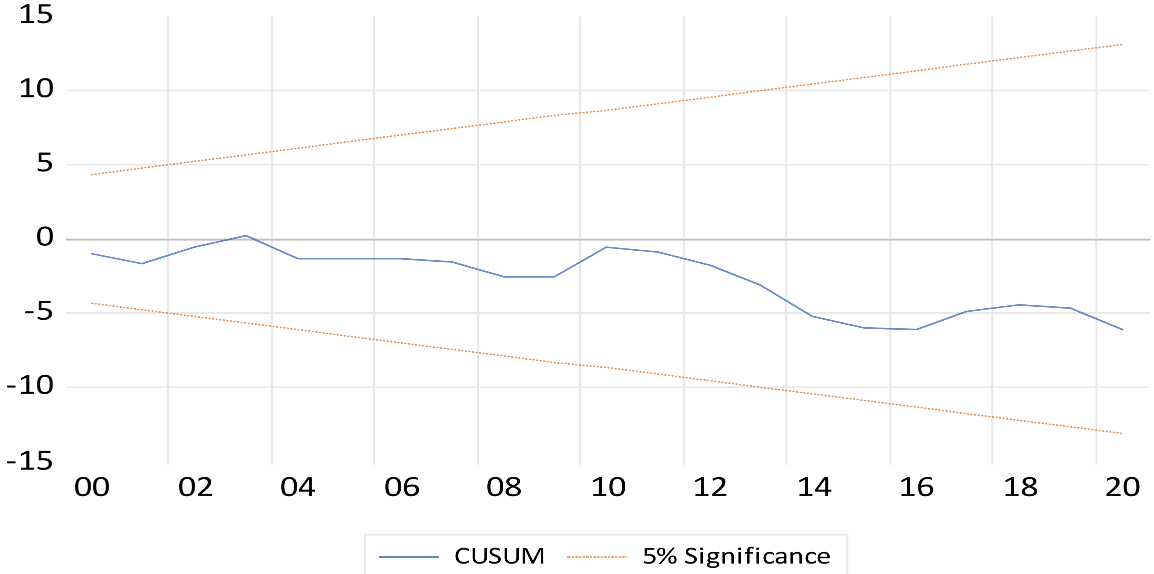

Fig 1: Plot of CUSUM test for the linear ARDL model

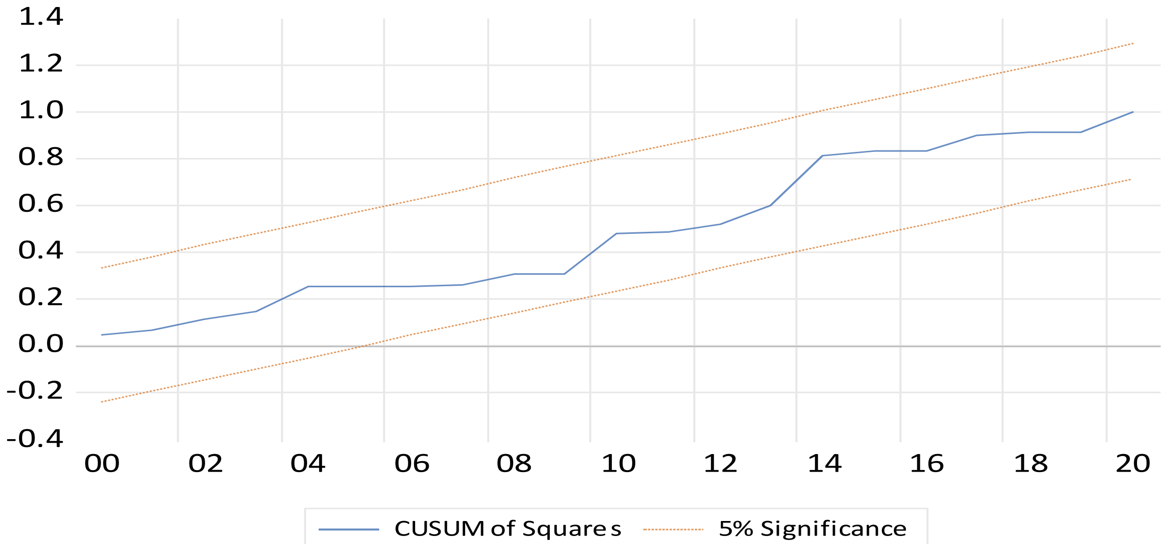

Fig.2: Plot of COSUMQ test for the linear ARDL model

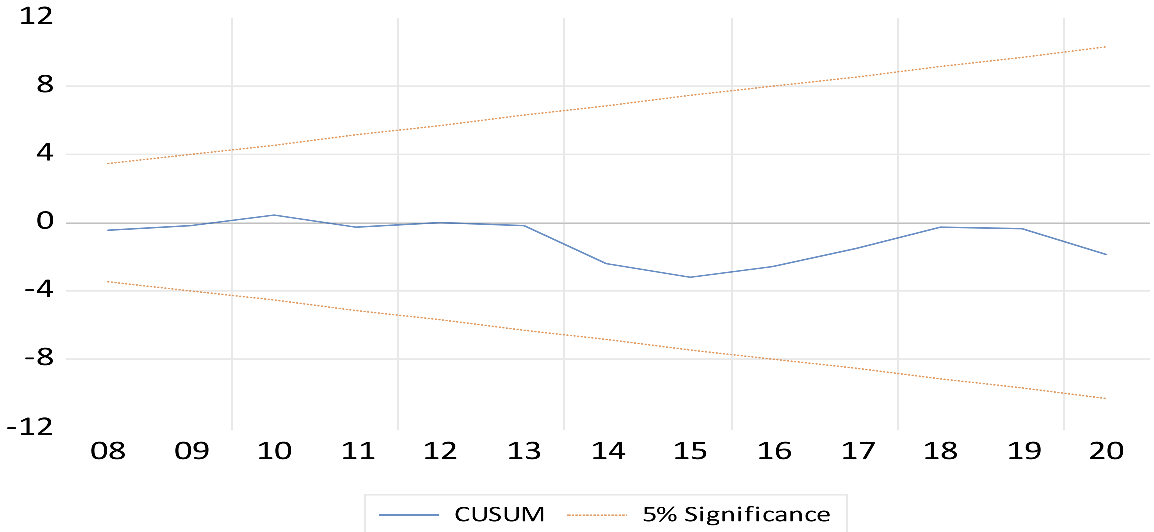

Fig 3: Plot of CUSUM test for the nonlinear ARDL model

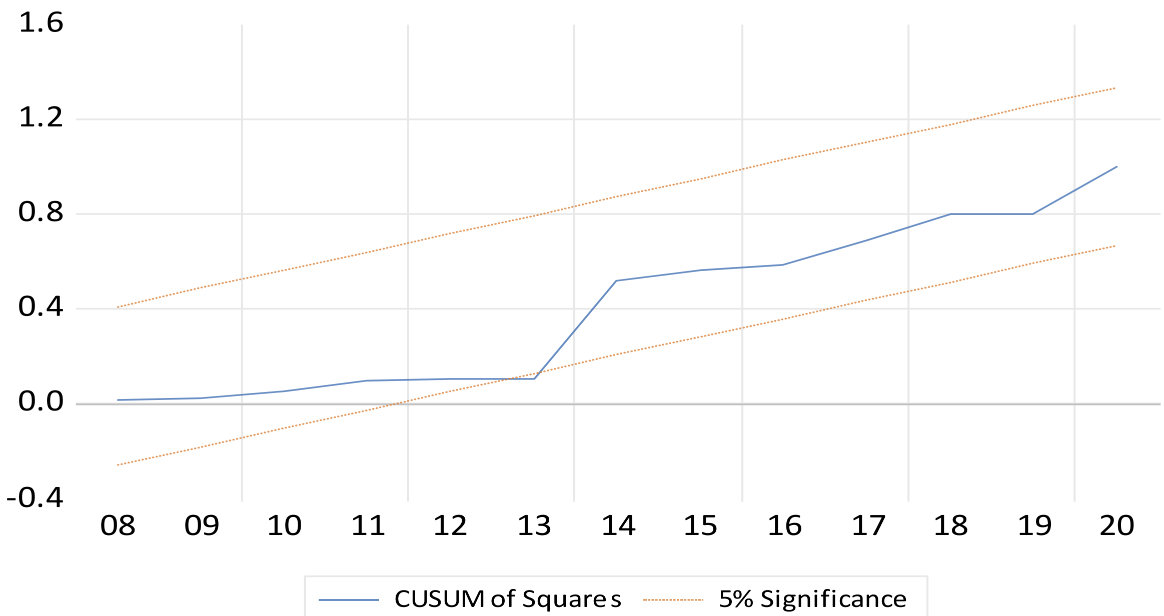

Fig. 4: Plot of COSUMQ test for the nonlinear ARDL model

Shin et al.'s (2014) dynamic multiplier show how carbon emissions adjust asymmetrically to the long-run equilibrium owing to positive and negative shocks in the oil sector (i.e. percentage of oil income in total GDP). This dynamic effect is shown in figure 5. The size of negative and positive shocks is on the vertical axis, while the horizontal axis represents the period. The continuous blue and parrot green lines indicate positive and negative shocks, respectively, and show the effects on carbon emissions caused by 1% positive/ negative shocks on the oil sector (measured as a percentage of the oil income in GDP).

The two lines reveal the asymmetric adjustment to negative and positive shocks at a given forecast, respectively. The adjustment pattern shows asymmetry because positive shocks to the oil sector (i.e. percentage of oil income to GDP) have a greater influence on carbon emissions than a negative shock to the oil sector. This means that an expansion in the oil sector has a greater impact on carbon emissions than a reduction in the oil sector.

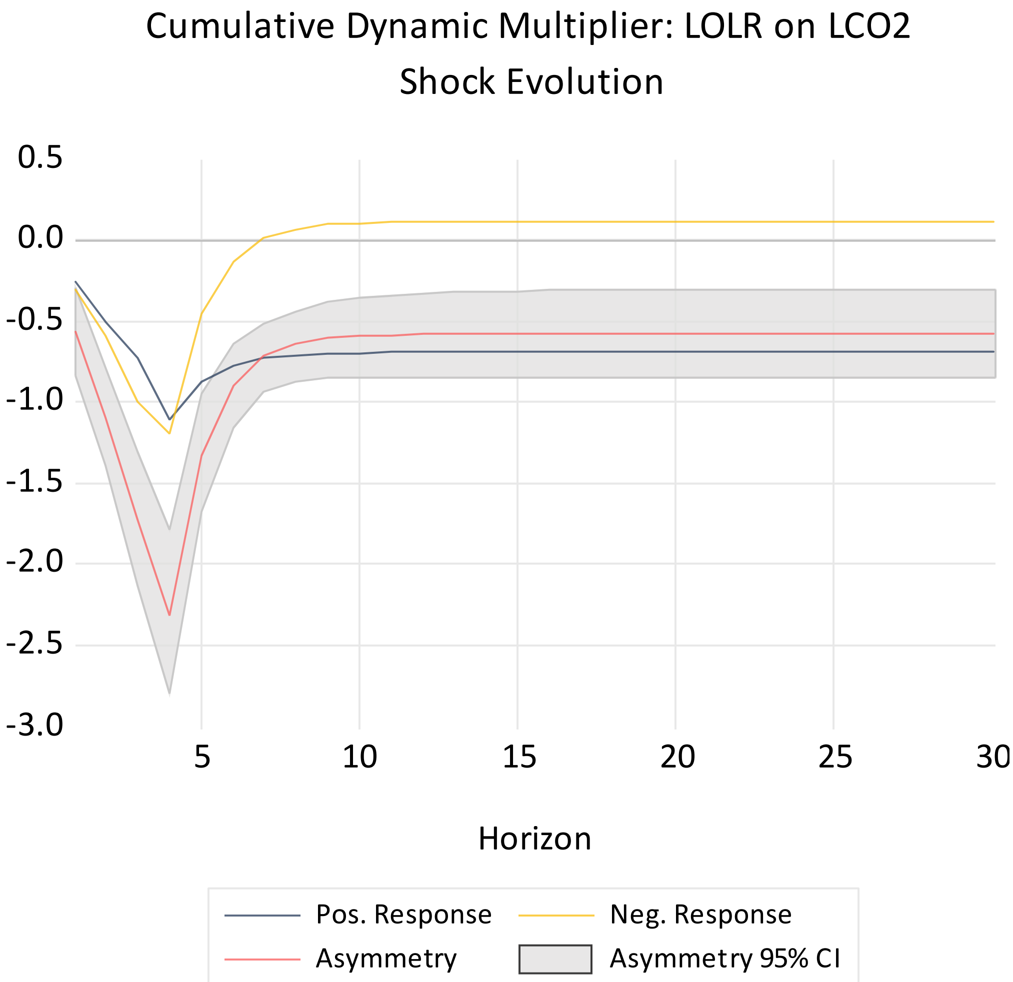

Fig. 5: Dynamic multipliers effects

The study further estimated a multivariate error correction model in which both the negative and positive changes in the oil sector are incorporated[1]. Essentially, we focus on the impulse response functions and the variance decompositions generated from the VECM[2]. The graphs of the impulse response functions at 5% error bounds generated by Monte Carlo simulation for the 5-variable model are plotted in fig. 6. As shown in the figure, a one standard deviation shock applied to the positive change in the oil sector(olr_t^+) produces no strong impact on the carbon emissions in the first four periods but increases between the 5th and 6th periods. It, however, falls sharply from the sixth to the 8th period. It increases sharply from the 8th period to the 10th period. Similarly, a one standard deviation shock applied to the negative change in the oil sector(olr_t^-) has no major impact

[1] To confirm the results for cointegration from the nonlinear bounds test, we employed the Johansen-Juselius's (1990) cointegration test. The results obtained confirm Johansen cointegration and long-run estimates were consistent with those obtained using the bounds test.
[2] It is the consensus in the literature that the individual coefficients from the vector error correction model are difficult to interpret (Sunce and Akanbi 2016).

on carbon emissions till the 2nd period. It declines in the 3rd period and thereafter assumes an upward trend till the 5th period. It, however, falls precipitously from the 6th period to the 8th period only to rise afterward. The non-oil GDP increases carbon emissions slightly from the 1st to the 3rd period. It, however, decreases carbon emissions from the 4th to the 6th period; thenceforth, non-oil GDP increases carbon emissions sharply and reaches a peak in the 7th period. It however drops significantly from the 8th period.

Energy intensity decreases carbon emissions until the 3rd period when it increases carbon emissions till the 5th period. However, energy intensity reduces carbon emissions from the 6th to the 7th period. Thereafter, energy intensity increases carbon emissions sharply only to reduce it in the 10th period. Finally, the oil price has no discernible impact on carbon emissions until the 3rd period, when it rises. However, after the 4th period, oil price precipitates a sharp reduction in carbon emissions until the 7th period. However, it increases carbon emissions till the 9th period before a sharp decline in the 10th period.

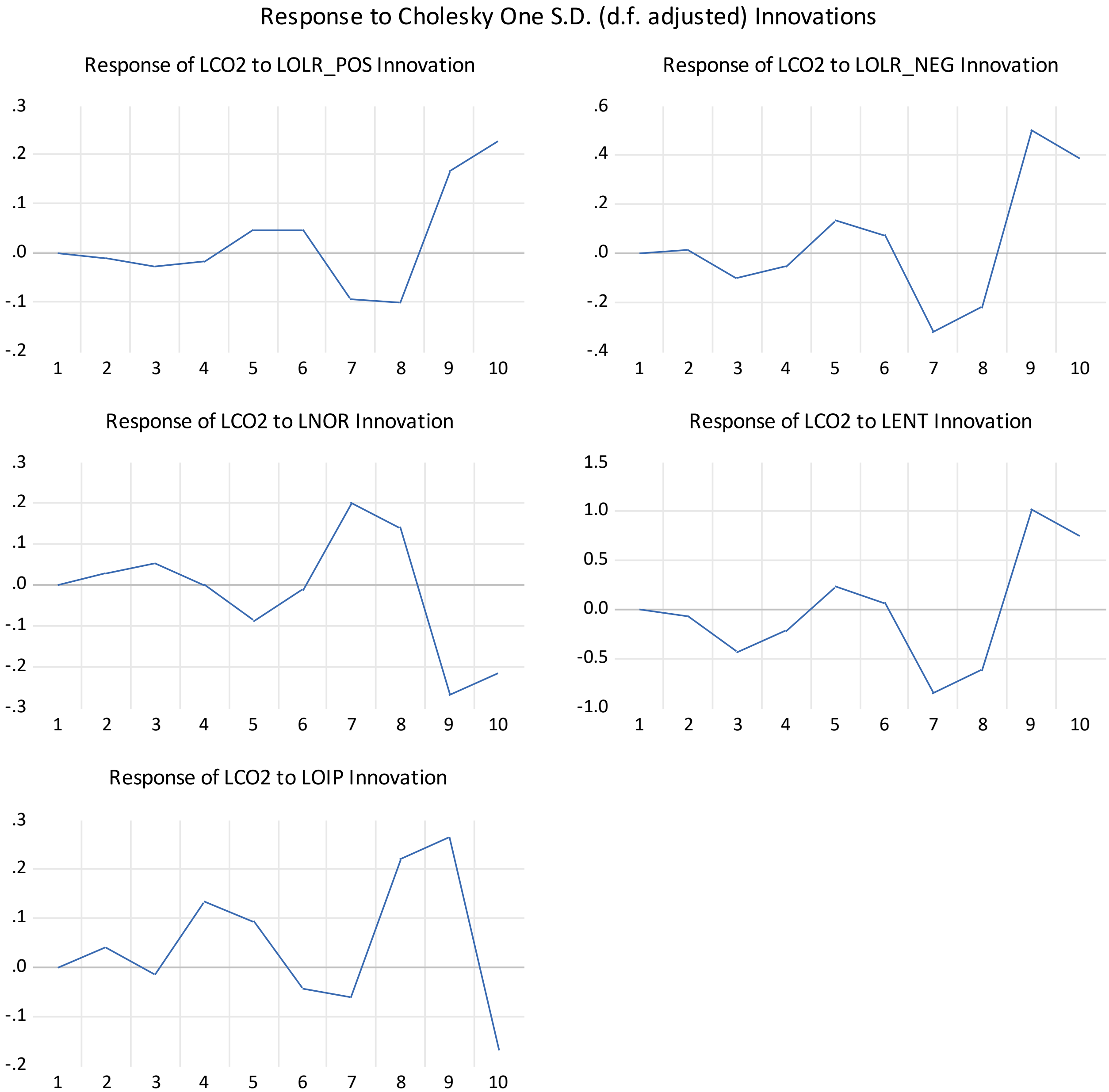

Fig. 6: Impulse Response functions

The outcomes of the VDs are reported in Table 8. It shows that an increasing oil sector has a considerable high impact in the very short run. However, the proportion of variance explained by the increased oil sector drops from approximately 15 per cent in the 2nd period to approximately 4 per cent in the 10th period. In contrast, the decreased oil sector has a marginal impact on carbon emissions in the very short run. The proportion of variance explained by decreased oil sector increases steadily from approximately 4 per cent in the 3rd period to approximately 14 per cent in the 10th period. It accounts for approximately 6.5 per cent of the variation in carbon emissions over the 10-period horizons. The proportion of variation in carbon emissions explained by non-oil GDP is 13 and 18 per cent in the 1st and 2nd periods, respectively. However, it drops precipitously from 18 per cent in the second period to approximately 5 per cent in the 10th period. Energy intensity has a relatively low impact in the 1st and 2nd periods. The proportion of variance explained by energy intensity rises phenomenally from 8 per cent in the 2nd period to 68 per cent from the 3rd to the 10th period except in the 5th and 6th periods when the magnitude stands at 58 and 55 per cent, respectively. It accounts for approximately 52.61 per cent of the variation in carbon emissions over the 10-period horizon. The proportion of variance explained by oil price is relatively low except in the 2nd, 5th, and 6th periods when the magnitude stands at approximately 8 per cent. Oil price, on average, accounts for approximately 5.58 per cent of the variation in carbon emissions[3].

Table 8: Decomposition of Variance Error of gin from VECM

Period	SE	Explained by Innovation					
		olr^{+}	*olr*$^{-}$	*nor*	*ent*	*oip*	*co2*
1	0.14683	14.418	0.005	13.446	0.123	2.443	69.654
2	0.24067	14.774	0.211	17.942	8.131	8.003	50.938
3	0.55548	6.046	3.569	7.759	67.139	1.527	13.959
4	0.65084	6.444	3.263	6.979	61.778	7.263	14.274
5	0.73651	5.121	5.699	5.474	57.658	8.781	17.266
6	0.75572	4.867	6.261	5.482	55.449	8.413	19.529
7	1.22882	3.761	9.443	6.173	69.708	3.375	7.541
8	1.44419	4.507	9.272	6.562	68.851	5.150	5.657
9	1.88431	3.096	12.616	4.901	68.958	5.764	4.666
10	2.09594	3.608	13.625	4.650	68.308	5.078	4.730

The results of the causality test based on the VEC model are reported in Table 9. As the results showed, neither nor negative changes in oil price Granger-cause carbon emissions. Energy intensity and oil price have predictive power on carbon emissions. Carbon emissions, decreased oil sector, non-oil GDP and energy intensity Granger-cause increased oil sector. However, oil price does not Granger-cause increased oil sector. Carbon emissions, increased oil sector, non-oil GDP and energy intensity and oil price do not severally or jointly Granger-cause decreased oil sector. Carbon emissions, increased oil sector, decreased oil sector and oil price do not Granger-cause non-oil GDP. However, energy intensity Granger-cause carbon emissions.

The causality tests show that carbon emissions, decreased and increased oil sector, non-oil GDP and oil price do not severally or jointly Granger-cause energy intensity. Likewise, carbon emissions, decreased and increased oil sector, non-oil GDP and energy intensity do not severally or jointly Granger-cause oil price. In sum, the causality results show unidirectional causality running from carbon emissions to the increased oil sector and not otherwise. There is unidirectional causality from the decreased oil sector to the increased oil sector.

[3] To ascertain if the estimated VDs outcomes are sensitive to the ordering of the model's variables, we rearranged the sequence by placing carbon emissions first and positive change in the oil sector last. The only difference in the results obtained is that the proportion of the variation explained by own shock increases marginally over the 10-period horizon.

Table 9: Block Exogeneity Wald Test

	co2	*olr*$^{+}$	*olr*$^{-}$	*nor*	*ent*	*oip*	joint
co2	-------	3.263	2.451	6.473**	3.112	8.978**	20.298**
olr^{+}	9.923***	-----	8.629**	11.271***	7.820**	2.711	28.237***
olr^{-}	2.028	5.373	----	5.558	1.458	2.350	8.895
nor	3.803	5.317	2.317	-----	6.769**	3.245	20.298**
ent	0.607	1.817	0.557	1.691	----	3.368	6.263
oip	0.138	1.569	0.901	2.703	0.614	-----	7.928

Note: *, ** and *** denote significance levels for 10%, 5% and 1% , respectively

5. Conclusion

The oil sector is the main driver of the gross domestic product in Nigeria. The sector generates over 80 per cent of the country's total revenues. Due to the economy's dependency on the oil sector, increasing greenhouse gas emissions arising from growth have often been neglected. Indeed, to date, no known study has examined empirically the relationship between the oil sector and carbon emissions in Nigeria. Therefore, this study investigates the impact of the oil sector on carbon emissions in the Nigerian context taking into cognizance the possibility of asymmetry in the relationship. To achieve the aforementioned objective, our study utilizes Nigeria's annual data over the period 1980-2020. The paper employs linear and nonlinear ARDL models and VECM in which IRFs and VDs are generated to assess the dynamics of the relationship. Also, the Granger causality test is conducted to determine the direction of causality among the variables.

The results from linear and nonlinear ARDL show that the variables are cointegrated. The results from nonlinear ARDL confirm asymmetry in the short and long run. This shows that carbon emissions respond differently to changes in the oil sector (measured as oil income share of GDP). The effect of increasing and decreasing oil sector's income share of the national income is found to be negative and elastic in both the long- run and short- run. However, compared to negative change in the oil income share, positive change in oil income share of GDP produces a much more significant and stronger impact on carbon emissions in Nigeria. The results show that non-oil GDP increases carbon emissions both in the short and long run. Energy intensity has no significant effect on carbon emissions in both the short and long run. Oil price reduces carbon emissions only in the short run. The outcomes of the IRFs and VDs generally support the results of the nonlinear ARDL. The causality test shows a unidirectional causality from carbon emissions to the increased oil sector and not otherwise.

This study has led to some policy suggestions. First, increasing oil sector income coupled with strict enforcement of all environmental regulations designed to control carbon emissions will reduce carbon emissions in Nigeria. Second, an increase in oil prices, especially in the short run, will help reduce carbon emissions. Third, the government must focus on environmental regulations to reduce carbon emissions generated from the non-oil sector. Finally, nonlinearity and asymmetry need to be considered when analyzing the oil sector-carbon emissions nexus in Nigeria.

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