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**Asymmetric effect of environmental cost of forest rents in the Guinean forest-savanna mosaic: The Nigerian experience**

**Abstract**

Several studies have identified deforestation as a major cause of environmental degradation, but little is known about the asymmetric effect of the environmental cost of forest rents. To fll this gap, our study uses the nonlinear autoregressive distributed lag (NARDL) model and asymmetric causality test to examine the environmental implication of forest rents in the Guinean Forest-Savanna Mosaic of Nigeria over the period 1990:Q1 to 2016:Q4. The empirical results show that forest rents increase CO2 emissions when the shock to forest rents is positive and decreases CO2 emissions when the shock to forest rents is negative. The results further show evidence of asymmetric effects of crop production, fossil fuel energy consumption, and economic growth on CO2 emissions. Moreover, the effects of both positive and negative shocks in economic growth are elastic, suggesting that CO2 emissions respond in a larger magnitude to a 1% positive or negative shock in economic growth. While the positive shock to crop production and economic growth stimulates CO2 emissions, their negative shocks dampen CO2 emissions. In addition, the positive (negative) shocks to fossil energy consumption exert upward (downward) pressure on CO2 emissions. Furthermore, the asymmetric causality test divulges that a positive change in forest rents causes a negative change in CO2 emissions and a negative change in forest rents causes a positive change in CO2 emissions. Based on these findings, the study recommends the need for policymakers to formulate sound policies to protect the forests and transit toward clean energy consumption to minimize energy-related CO2 emissions in the country.

**Keywords:** Keywords Deforestation; Forest rents; Agricultural production; Fossil fuel energy; Guinean Forest-savanna Mosaic; Nigeria

**I. Introduction**

The pertinent issue surrounding the subject of environmental sustainability arises from human activities which has increasingly been narrowed to the sectoral and sub-sectoral aspects of economic activities. Specifically, economic activities from the aspects of land use, forestry and other agricultural activities have been enormously linked with the global greenhouse gas emissions (GHGs) (See Ali et al. 2021). For instance, cutting down forests do not only cease carbon absorptions, but also carbons deposited in the trees are released into the atmosphere as carbon dioxide if the wood is burned or rot after the process of deforestation. As reported by the United States Environmental Protection Agency (USEPA), land use, forestry and agricultural activities (mainly from crop cultivation, livestock, and deforestation) account for about 24% of 2010 global greenhouse gas emissions (Food Agricultural Organization, FAO, 2014).

Importantly, the forest change processes that arise from the removal of density of trees for land use amount to enormous threat to forest ecosystem and climate change challenges associated with most regions of the world. Considering that forest acts as carbon sink because its vegetation and soils retain atmospheric carbon dioxide emissions (CO2) (estimated at 638 Giga tons for 2005), a climatic distortion in forest composition, growth rate, and biodiversity are a trigger for deforestation-induced environmental hazards. Consequently, further utilization of forest or agricultural land area for crop cultivation is reported to account for about 14% of global agricultural carbon emissions (United Nations Framework Convention on Climate Change, 2019). Several benefits are associated with the sustainability of forest area especially in the long term, thus the aspects of political (democracy), social, and economic factors should be geared toward providing environmental protection of the biodiversity vaults (Arshad et al., 2020; Cary & Bekun, 2021).

In the extant literature, there are three categories of studies that directly connect with the concept of the current study. While a category of studies revealed the determinants deforestation, another strand of studies is centered on the determinants of environmental degradation, GHG, and/or climate change, while the third category provide scientific evidence on the relationship between the first two categories i.e the link between deforestation or forest-related factors and environmental degradation such as the GHG or carbon emission. For Cary and Bekun (2021) and related studies, the forces affecting the trend of deforestation include political factor such as democracy, gross domestic product per capita and land use as economic factors, and other socioeconomic factors such as corruption, education, and population. Concerning the drivers of GHG emissions such as the carbon emission, there abound almost inexhaustive strand of studies on this front. The drivers of GHG emissions also span across economic (Stern et al., 1996), energy-related (Ike et al., 2020; Saint Akadiri et al., 2021), socioeconomic (Usman et al., 2020). Moreover, in recent times, the studies of Houghton (2012), Qin et al (2021) and several others have linked GHG-related emissions with both deforestation and forest degradation, thus affirming the evidence of an interlink between GHG emission, deforestation, and the elements of climate change.

Moreover, the global annual increase in emissions from agriculture is estimated at about 8% by 2014, with African continent having the second highest contribution of about 15% behind Asia region (FAO, 2014). Although there exists an arguable projection that the global population is capable of meeting its food need by 2050 without the expected food production decline, which necessarily posing a serious food insecurity. The environmental consequences of both population and food production dynamics are unlikely to be less severe. The reason is that food production is yet expected to increase by 1.5% annually over the period to 2030 as the world population is also expected to increase by 2.3 billion people by 2050. Remarkably, the developing economies is projected to lead the world in terms of imports and crop production, thus causing expansion of arable land mostly in the South American and Sub-Sahara African regions. Based on the aforementioned trends in food production and forestry dynamics, the Intergovernmental Panel on Climate Change (IPCC) reports noted that the challenge associated with climate change is an increased threatening of food security in dryland regions of mainly African states (Mbow et al., 2019). Illustratively, with an average population growth rate of about 2.7% and an increasing agricultural land area to forest area, Nigeria (Africa’s largest populated nation) potentially shares similar climate change ascribed to other parts of African continent. As can easily see in Figure 1 which displays the increasing trend in the ratio of agricultural land area to forest area and the virtual illustration of movement of food production index and carbon emissions (kilo tons) as shown in Figure 2, there is a trilemma between forest resources, food production, and carbon emissions in Nigeria.

Figure 1: The trend of ratio of agricultural land area to forest area in Nigeria.

Figure 2: The trend of crop production and carbon emissions in Nigeria.

Recently, a major argument has emerged in the literature that structural reforms, shift of policies, national and global imbalances, etc. may result into asymmetric relationships between time series variables. In other words, the impact of a positive shock may not often have the same impact with a negative shock in absolute terms. Therefore, making use of symmetric or linear models may lead to misspecification since the relationships economic variables are mostly nonlinear (See Shin et al. (2014; Balcilar et al. 2020; 2021a&c; Usman, 2020; Balcilar and Usman 2021). Given this background, the main objective of our study is to investigate the asymmetric effect of forest rents and crop production inthe Guinean Forest-Savanna Mosaic of Nigeria over the period 1990:Q1 to 2016:Q4. To this extent, our study contributes to the existing literature by examining the environmental effects of deforestation and crop production on CO2 emissions in Nigeria by incorporating asymmetries. In order to offer a robust investigation, we allow approach to incorporate additional variables such as renewable energy utilization and economic growth to avoid omitted variable bias (OVB) and capture the unobserved factors. In doing this, we state that this study is better positioned to further deepen the scholarly discussion of the trilemma of crop production, forestry, and environmental sustainability. Furthermore, we apply the nonlinear autoregressive distributed lag (NARDL) and asymmetric causality.

The remaining parts of the paper have been arranged in a particular order. The literature section (2) provides concrete review of the related extant studies while section 3 presents detailed information about the data and the empirical methods employed. The last two sections, i.e. (4) and (5) respectively capture the presentation and discussion of the results as well as concluding remarks with insightful policy implications based on the results of the study.

**II. Data and Methods of Analysis**

**(a) Data**

In this paper, the variables employ include per capita CO2 emissions which measure environmental sustainability, forest rents, crop production, renewable energy consumption, and per capita GDP. All the variables are obtained from the World Development Indicators. The variables and their measurements as well as their sources are summarized in Table 1 below:

Table 1: Variable, Measurement, and Source.

|  |  |  |
| --- | --- | --- |
| **Variable & Code** | **Measurement** | **Source**  |
| Carbon Dioxide Emissions (CO2) | Per capita CO2 Emissions in metric tons, measured from the consumption and flaring of fossil fuels. | World Development Indicators |
| Forest Rents (FOR) | Round-wood harvest multiplied by the product of average prices and a region-specific rental rate as a percentage of GDP | World Development Indicators |
| Crop Production (CRP) | Crop production index (2004-2006=100) shows index of all crops for each year relative to the base period 2004-2006 excluding fodder crop. | World Development Indicators |
| Renewable Energy (REN) | The share of renewable energy in total final energy consumption. | World Development Indicators |
| Income (GDP)  | Gross Domestic Production (Constant 2010 USD) per capita | World Development Indicators  |

Source: Authors’ computation

**(b) Empirical Models**

We specify the empirical model to achieve the objective this of study. In doing this, let CO2 emissions denote the measure of environmental degradation, FOR and CRP denote forest rents and crop production which determinants of environmental degradation. Hence the empirical model becomes:

 (1)

Where  is the error term, which is perhaps assumed to have a zero mean i.e. white noise process. By way of construction, we expect an increase in forest rents to reflect a decline in the level of anthropogenic emissions while an increase in crop production to trigger the level of anthropogenic emissions. However, from the literature, it is clear that there are other factors that can determine the level of carbon emissions other than the two variables captured. Hence, we argue on the recent environmental policy directives of the Nigeria’s government that variables such as renewable energy consumption (REN) and economic growth (GDP) are likely to influence the level of emissions significantly in Nigeria. Therefore, the empirical model can be expanded to include these variables as shown in equation (2):

  (2)

From equation (2),  denotes the natural logarithm expression of the variables. The estimates of  which represent the long-run effects of forest rents, crop production, renewable energy consumption, and economic growth on CO2 emissions would be considered valid only if there is existence of a cointegration between them.

Equation (2) assumes that the impact of a positive shock is the same as the impact of a negative shock hence nonlinearity is not required. Hence, previous studies build different empirical models via symmetric or linear models which only hold if the relationship is not symmetric or linear. However, it is widely accepted that individuals react differently to a positive shock compared to a negative shock of the same absolute magnitude (See 20214; Hatemi-J., 2012; Shin et al. 2014; Balcilar et al. 2020a&b). This realization has led to the proliferation of the nonlinear and regime-switching models. In the course of this study, we model asymmetries in a nonlinear ARDL framework following the pioneering work of Shin et al. (2014). In doing this, we express the asymmetric long-run regression as:

   (3)

From equation (3), the scalar I(1) variables are represented by  and  where  is decomposed into the positive and negative, so that  and  would be the partial sum processes of positive and negative changes in .

  (4)

  (5)

According to Shin et al. (2014), the cumulative positive and negative partial sums of  can be utilized within the framework of the ARDL(*p*, *q*) model proposed by Pesaran et al. (2001) as follows:

  (6)

From Equation(6),  is  vector of dependent variables,  represents the autoregressive parameter,  and  are the asymmetric distributed parameters, and  is the error term which has a constant variance and zero mean. The *p* and *q* denote the lag orders in the model. Therefore, the error correction model as provided by Pesaran et al. (2001) can be modified so that the asymmetric version of the error correction model can be given as:

 

  for  (7)

Where  is the difference operator, . The long-run effect of CO2 emissions is obtained from the estimates of  normalized on  However, normalization can be economically meaningful only if cointegration is established. To test for nonlinear cointegration, Shin et al. (2014) recommend the use of F-test as proposed by Pesaran et al. (2001) and the alternative t-test  proposed by Banerjee et al. (1998). The null hypothesis for asymmetric cointegration is given as: .

Furthermore, for asymmetric relationship to be estimated, there is a need to perform long-run and short-run asymmetry tests. This test helps us to know whether the relationship between the variables is characterized by asymmetries. To do this, we apply the WALD test with the null hypothesis for the long run and for the short run.[[1]](#footnote-1) Afterwards, we estimate the long-run coefficients of the decomposed variables into their positive and negative changes as: and . Similarly, the short-term adjustment parameters are captured by  and for all .

According to Shin et al. (2014), the asymmetric dynamic multipliers linked with a unit change in  or  on can be computed. This would help provide useful information concerning asymmetric patterns. Therefore, the short- and long-term asymmetry paths are computed through the cumulative dynamic multiplier effects of the  and on CO2 emissions, represented by 

 and  with  (8)

where by construction, when   and  where  and are the decomposed positive (increase) and negative (decrease) asymmetric long-run coefficients.

Furthermore, it is straightforward to also estimate the causal relationship between the variables. As noted by Hatemi-J (2012), the impact of a positive shocks is usually not the same with that of the negative shock of the same magnitude in absolute terms. Therefore, to capture the asymmetries in the causal relations, we apply an asymmetric causality developed by Hatemi-J (2012). The test is focused on two integrated variables, i.e. and:

 and  (9)

where   and  are the initially values,  and  correspond to error terms which are independent and identically distributed random variables while  and . Both  and  represent the positive shocks while  and  represent the negative shocks. Within the framework of the directional asymmetric causality proposed by Hatemi-J (2012), we capture the asymmetric effects of both positive and negative shocks of the variables by applying the cumulative sums of the shocks:

  and  (10)

Specifically, equation (10) is used in investigating the asymmetric causal relationship between the variables within the framework of a vector autoregressive model of order *p*, VAR(*p*) as shown by Hatemi-J (2012).

**III. Empirical Results and Discussion**

**4.1 Preliminary Analysis**



Fig. 1: Time series plots of log of CO2, positive and negative sums of CRP, FOR, Log of GDP, and REN

Figure 1 displays the time series plots of the variables employed in this study. This is very important in time series analysis because the presence of drifts, trends, seasonality, or structural breaks can distort the estimate of the econometric model. As shown in the Figure, it is clear that apart from the log of CO2 emission seems to be characterized by fluctuations attributing to changes in policies to reduce the emissions of greenhouse gases of which CO2 emission constitutes a greater percentage. The decomposition of the sums of positive and negative changes in all the variable indicate that the positive changes trend upwards while the negative changes trend downwards with no evidence of noticeable structural breaks.

Table 2 provides the descriptive statistics of the variables which have been decomposed into their positive and negative changes. From the Table, it is clear that the mean scores of the variables are all small with the mean of the positive change in renewable energy having the lowest score (in absolute term) while the negative change in forest rent (in absolute term) have the largest. The standard deviation scores show that the variables are less volatile. Also, the skewness of the variables are mostly not far away from zero, although variables such as log of CO2, positive changes in forest rent and negative change in crop production index are having a negative score while the rests of the variables are having a positive score. The kurtosis of the variables are all positive but far away from three. Consequently, the Jarque-Bera statistics are large with probabilities showing rejection of the null hypothesis of normal distribution at 5% in all the variables except positive changes in forest rest and crop production.

Table 3 reports the results of the unit root tests. Based on the three different standard tests conducted i.e. ADF test, PP test and DF-GLS test, we find that all the variables are not stationary in their levels. This, therefore, leads us to take the first differences of the variables and conduct the tests. The results of the unit root tests at first differences show evidence of stationarity. Therefore, we conclude that the variables used for the estimations are all integrated of order one, I(1). To check the appropriate model for this study, we apply a symmetry test using a WALD test for both long run and the associated short run. The results of the symmetry tests as reported in Table 4 suggest that the null hypothesis of symmetric relationship is rejected for all the variables in the long run and short run, except for the short run effect of GDP. Therefore, if linear model is imposed on the relationship, it will lead to misspecification. This test justifies the choice of the nonlinear ARDL and asymmetric causality approaches employed in this study. As robustness, we apply the BDS nonlinearity test proposed by Brock *et al.* (1987). The results as shown in Table 5, therefore, confirm the earlier results that to circumvent misspecification leading to spurious regression, nonlinear and asymmetric models are appropriate.

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | LNCO2 | FOR\_POS | FOR\_NEG | CRP\_POS | CRP\_NEG | LNGDP\_POS | LNGDP\_NEG | REN\_POS | REN\_NEG |
|  Mean | -0.598126 |  1.138040 | -1.490960 |  0.770284 | -0.131803 |  0.307135 | -0.166492 |  0.100167 | -0.120994 |
|  Median | -0.439834 |  1.241546 | -1.340017 |  0.696059 | -0.019332 |  0.284942 | -0.191183 |  0.078389 | -0.139908 |
|  Maximum | -0.204327 |  2.201953 |  0.000000 |  1.434181 |  0.000000 |  0.708174 | -0.013048 |  0.187424 | -0.002103 |
|  Minimum | -1.259854 |  0.015131 | -2.798313 |  0.048242 | -0.471685 |  0.000000 | -0.268078 |  0.000000 | -0.202488 |
|  Std. Dev. |  0.326258 |  0.536346 |  1.043155 |  0.386710 |  0.178874 |  0.264701 |  0.051622 |  0.060972 |  0.060203 |
|  Skewness | -0.591757 | -0.247910 |  0.131938 |  0.262723 | -0.910278 |  0.234730 |  1.629753 |  0.006515 |  0.248033 |
|  Kurtosis |  1.788747 |  2.389836 |  1.445204 |  1.964358 |  2.050079 |  1.447810 |  4.871996 |  1.753266 |  1.803613 |
|  Jarque-Bera |  12.78578 |  2.755860 |  11.08797 |  6.012717 |  18.79978 |  11.72401 |  62.99064 |  6.930553 |  7.478512 |
|  Probability |  0.001673 |  0.252100 |  0.003911 |  0.049472 |  0.000083 |  0.002846 |  0.000000 |  0.031264 |  0.023772 |
|  Sum | -63.99950 |  121.7703 | -159.5327 |  82.42042 | -14.10288 |  32.86346 | -17.81462 |  10.71792 | -12.94631 |
|  Sum Sq. Dev. |  11.28308 |  30.49275 |  115.3463 |  15.85169 |  3.391548 |  7.427057 |  0.282470 |  0.394063 |  0.384192 |
|  Observations |  107 |  107 |  107 |  107 |  107 |  107 |  107 |  107 |  107 |

Table 2: Descriptive Statistics

Source: Authors’ computations from E-Views 10

**Table 3: Unit root tests**

|  |  |  |  |
| --- | --- | --- | --- |
|  | **ADF Test** | **PP Test** | **DF-GLS** |
| **Variable** | **Test Statistic** | **Test Statistic** | **Test Statistic** |
|  | -1.082 | -1.553 | -2.467 |
|  | -1.863 | -2.573 | -2.484 |
|  | -0.699 | -0.986 | -2.087 |
|  | -1.132 |  -0.296 | -1.315 |
|  | -2.860 | -2.660 | -1.856 |
|  |  |  |  |
|  | -5.451\*\*\* | -5.591\*\*\* | -4.232\*\*\* |
|  | -5.680\*\*\* | -5.680\*\*\* | -4.572\*\*\* |
|  | -5.577\*\*\* | -5.577\*\*\* | -4.399\*\*\* |
|  | -3.397\*\*\* | -3.283\*\* | -1.732 |
|  | -6.888\*\*\* |  -6.633\*\*\* | -4.907\*\*\* |

**Note**: The table reports the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Dickkey-Fuller GLS unit root tests. The model include both a constant and a linear time trend. The null hypothesis for the ADF, PP and DF-GLS tests is simply stating that the series is nonstationary. Superscripts \*\*, and \*\*\* denote significance at 1% and 5% level respectively

**Table 4: Long- and Short-run Symmetry Tests**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Exogenous** |  | **Long-run Asymmetry (WLR)** |  | **Short-run Asymmetry (WSR)** |
| **Variable** |  | **F-Statistic** |  | **p-value** |  | **F-Statistic** |  | **p-value** |
|  |  | 12.37\*\*\* |  | 0.001 |  | 3.687\* |  | 0.061 |
|  |   | 8.372\*\* |  | 0.006 |  | 3.516\* |  | 0.067 |
|  |  | 8.423\*\* |  | 0.006 |  | 8.448\*\* |  | 0.005 |
|  |  | 5.204\*\* |  | 0.024 |  | 2.229 |  | 0.142 |

Notes: Superscripts\*\*\* and \*\* denote 1% and 10% significance level. WLR and WSR indicate the Wald test for the long- and short-run with their respective p-values.

**Table 5: BDS Non-linearity Tests**

|  |  |  |  |
| --- | --- | --- | --- |
| **Variable** | **BDS Statistic** | **Standard Error** | **p-value** |
|  | 0.1887\*\*\* | 0.0056 | 0.0000 |
|  | 0.1935\*\*\* | 0.0043 | 0.0000 |
|  | 0.1978\*\*\* | 0.0051 | 0.0000 |
|  | 0.1610\*\*\* | 0.0063 | 0.0000 |
|  | 0.1984\*\*\* | 0.0048 | 0.0000 |

Notes: Superscripts \*\*\* denotes significance level at 1%. The maximum correlation dimension for the test 2.

**4.2 Estimates of Nonlinear Bounds Testing/ARDL Model**

Having established that the nonlinear model would provide the best fitting for the relationship, we apply the Nonlinear ARDL model proposed by Shin et al. (2014). Before then, we conduct the nonlinear bounds testing cointegration following Pesaran et al. (2001). The results as presented in Table 6, suggest that the null hypothesis of no cointegration cannot be held since the F-test estimated i.e. 5.79 is far greater than critical value of 3.77 at 1% level of significance. Therefore, we conclude that a long run relationship exists between the dependent variables and all the explanatory variables in this study.

Table 7 reports the results of the long-run and short-run coefficients of CO2 emissions function. In the long run, a positive change in forest rents has a negative and significant effect on CO2 emissions but a negative change of the same magnitude reduces CO2 emissions significant. The further find that a positive change in crop production causes CO2 emissions to rise by 0.0262% while a negative change of the same magnitude dampen CO2 emissions by 0.0342%. The effects of both the positive and negative changes in renewable energy consumption exert downward pressure on CO2 emissions. In other words, as renewable energy consumption increases, CO2 emissions are bound to reduce with the reduction caused by a positive change having a stronger effect. Moreover, the results show that a 1% rise of positive change in per capita GDP stimulates CO2 emissions by 2.7626% while a negative change of the same size or magnitude reduces per capita GDP by 8.5490%. This implies that the effect of a negative change in GDP is stronger on CO2 emissions than the positive change of GDP in the long run.

The short run analysis reveals that a 1% increase in a positive change to forest rent has a negative impact of 0.1584% on CO2 emission while a 1% increase in a negative change to forest rent would increase CO2 emission. However, the way a positive shock to forest rent causes CO2 emission to rise is stronger than the way its negative shock of the same magnitude reduces CO2 emission. In the case of crop production, a 1% positive shock in crop production triggers CO2 emission to rise by 0.0157% but a negative shock of the same magnitude reduces it by 0.0037%. Although the impact of a negative shock is smaller and statistically insignificant. For renewable energy consumption, we find that both the positive and negative shocks have a declining effect on CO2 emission with evidence that the positive shock having a stronger impact. Specifically, a 1% increase in positive change to renewable energy reduces CO2 emission by 0.1503% but when renewable energy reduces by 1%, CO2 emission would reduce by only 0.0748%. Furthermore, the impact of a 1% positive shock in per capita GDP causes CO2 emission to rise by 2.5587% while a negative shock in per capita GDP of the same size causes CO2 emission to reduce by 6.9586%.

Furthermore, we check for the best-fitting of the Nonlinear ARDL model specification through series of diagnostic tests. As provided in the bottom of the Table 7, the result of the Brusch-Godfrey Lagrange Multiplier test for serial correlation indicates that the model has no serial correlation issue. The result of the ARCH test for conditional heteroscedasticity show absence of conditional heteroscedasticity while the result of the RAMSEY RESET test confirms that the models are correctly specified. Also, the Jarque-Bera statistic indicates that residuals of the models are normally distributed. Additionally, the plots of the cumulative sum (CUSUM) and the cumulative sum of squares (CUSUM squares) in Figure 2 provides suggest that the coefficients of the long run and short run of the nonlinear ARDL models are stable. This is because the plots of both the CUSUM and CUSUM of square fall within the critical bounds.

Table 6: Nonlinear Bounds testing cointegration

|  |  |  |
| --- | --- | --- |
| **Model Estimated** | ***F*-Statistic** | **K** |
|  |  5.791755\*\*\* | 8 |
| **Critical Value** | **Lower I(0)** | **Upper I(1)** |
| 1% Level of Significance | 2.62 | 3.77 |

 Notes: \*\*\* implies that the null hypothesis of no cointegration is rejected at 1% level of significance and the critical value is determined where $k=8$ independent variables with unrestricted intercept and no trend. The maximum lag order is 6 and the optimal lag order is selected by the Akaike Information Criterion (AIC).

**Table 7: NARDL long- and short-run coefficients**

|  |
| --- |
| **Dependent Variable:**  |
| **Variable** | **Coefficient** | **Std. Error** | ***p*-value** |
|  | –0.2877\* | 0.1580 | 0.0753 |
|  |  0.4449\*\*\* | 0.1232 | 0.0008 |
|  |  0.0262\*\* | 0.0109 | 0.0201 |
|  | –0.0342\*\* | 0.0137 | 0.0163 |
|  | –0.1057\*\* | 0.0436 | 0.0193 |
|  | –0.0877 | 0.0713 | 0.2254 |
|  |  2.7626\*\* | 1.0679 | 0.0130 |
|  | –8.5490\* | 4.4576 | 0.0615 |
|  |  |  |  |
|  |  0.5035\*\*\* |  0.0902 | 0.0000 |
|  | –0.1584\*\*\* |  0.0508 | 0.0032 |
|  |  0.1219\*\*\* | 0.0211 | 0.0000 |
|  |  0.0157\*\* |  0.0064 | 0.0179 |
|  | –0.0037 | 0.0051 | 0.4676 |
|  | –0.1503\*\*\* | 0.0191 | 0.0000 |
|  | –0.0748\*\*\* | 0.0238 | 0.0029 |
|  |  2.5587\*\* |  0.9677 | 0.0112 |
|  | –6.9586\*\*\* | 2.0053 | 0.0012 |
| Constant | –0.2354\*\* | 0.0935 | 0.0154 |
|  |  |  |  |
| **Model diagnostics** | **Statistic** | ***p*-value** |  |
| $$ χ^{2}-SERIAL$$ | 0.5237 | 0.4715 |  |
| $$ χ^{2}-ARCH$$ | 0.1116 | 0.7390 |  |
| $$ χ^{2}-RESET$$ | 0.8972 | 0.3745 |  |
| $$ χ^{2}-NORMAL$$ | 1.8143 | 0.4037 |  |

Note: Superscripts \*\*\*, \*\*, and \* show level of significant at 1%, 5%, and 10%. The maximum lag order selected is 6.

 

Fig. 2: CUSUM and CUSUM Squares at 5% level of significance

Furthermore, we examine the dynamic cumulative multiplier effects of all the variables. In other words, the dynamic multiplier effects of positive and negative shocks in forest rents, crop production, renewable energy, and per capita GDP are evaluated. As presented in Figures 3 to 6, the thick black line represent a positive change in a variable in question, a dotted black line denotes a negative change in a variable in question, while a dotted red line corresponds to asymmetry plot. The confidence interval lines are given by light dotted red lines with 95% level of significance and 15 horizons. The difference between the positive and the negative shocks is represented by . The dynamic effect of a negative change outweighs the positive change hence the cumulative effect is positive. In the case of crop production, we find that its cumulative effect is positive because the positive change in crop production outweighs its negative change. Furthermore, the dynamic effect of both the positive and the negative changes in renewable energy exert a negative effect on CO2 emission. However, the effect of the positive change is stronger, suggesting that the cumulative effect is invariably negative. Also, the plot of the dynamic multiplier effect of per capita GDP reveals that its positive change stimulates CO2 emission but the negative change of per capita GDP reduces CO2 emission; although the effect of a negative change is stronger, making the cumulative effect of the dynamic multiplier effect to be negative.



Fig. 3: Dynamic multiple adjustments of forest rents



Fig. 4: Dynamic multiple adjustments of crop production



Fi0g. 5: Dynamic multiple adjustments of renewable energy



Fig. 6: Dynamic multiple adjustments of per capita GDP

 **4.3 Asymmetric Causality Analysis**

Theoretically, if cointegration is established, there must be evidence of either a way-one directional causality or a two-way directional causality. In this study, we depart from applying the traditional symmetric causality test to asymmetric causality test proposed by Hatemi-J (2012). The results of this test is presented in Table 8. From the results a neutral effect is observed in most cases. For example, a neutral effect is established between positive (negative) shock in forest rents and CO2 emission. We also observe that a positive shock in forest rents causes a negative shock in CO2 emission and negative shock in forest rents is found to cause a positive shock in CO2 emission. Furthermore, we find that a negative shock in crop production causes a positive shock in CO2 emission.

In a similar vein, an asymmetric directional causality is found between a positive shock in CO2 emission and a negative shock in renewable energy shock. We also find that a positive shock in crop production causes a negative shock in per capita GDP while a negative shock in crop production predicts a positive shock in per capita GDP. In the case of per capita GDP and forest rent, we find evidence that a positive per capita GDP causes a positive shock in forest rents. Moreover, a positive shock in renewable energy is found to cause a negative shock in per capita GDP while a negative shock in renewable energy causes a negative shock in per capita GDP. Also, we find a negative shock in renewable energy to Granger cause a positive shock in per capita GDP.

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| **Table 8: Asymmetric Causality Test** |
| Hypothesis | Fisher statistic | P-value | Decision |
| $FOR^{+}$*≠>* $lnCO\_{2}^{+}$ | 0.195 | 0.907 | Fail to Reject |
| $FOR^{+}$*≠>* $lnCO\_{2}^{-}$ | 6.375\*\* | 0.041 | Reject |
| $FOR^{-}$*≠>* $lnCO\_{2}^{-}$ | 1.056 | 0.590 | Fail to Reject |
| $FOR^{-}$*≠>* $lnCO\_{2}^{+}$ | 4.857\*\*\* | 0.088 | Reject |
| $lnCO\_{2}^{+}$ *≠>* $FOR^{+}$ | 0.252 | 0.882 | Fail to Reject |
| $lnCO\_{2}^{+}$ *≠>* $FOR^{-}$ | 0.141 | 0.932 | Fail to Reject |
| $lnCO\_{2}^{-}$ *≠>* $FOR^{-}$ | 0.269 | 0.874 | Fail to Reject |
| $lnCO\_{2}^{-}$ *≠>* $FOR^{+}$ | 0.005 | 0.998 | Fail to Reject |
| $CRP^{+}$ *≠>* $lnCO\_{2}^{+}$ | 2.577 | 0.276 | Fail to Reject |
| $CRP^{-}$*≠>* $lnCO\_{2}^{+}$ | 7.429\*\* | 0.024 | Reject |
| $CRP^{-}$ *≠>* $lnCO\_{2}^{-}$ | 1.238 | 0.538 | Fail to Reject |
| $CRP^{+}$*≠>* $lnCO\_{2}^{-}$ | 0.113 | 0.945 | Fail to Reject |
| $lnCO\_{2}^{+}$ *≠>* $CRP^{+}$ | 4.077 | 0.130 | Fail to Reject |
| $lnCO\_{2}^{+}$ *≠>* $CRP^{-}$ | 0.200 | 0.905 | Fail to Reject |
| $lnCO\_{2}^{-}$ *≠>* $CRP^{-}$ | 1.219 | 0.544 | Fail to Reject |
| $lnCO\_{2}^{-}$ *≠>* $CRP^{+}$ | 0.275 | 0.872 | Fail to Reject |
| $REN^{+}$ *≠>* $lnCO\_{2}^{+}$ | 0.464 | 0.793 | Fail to Reject |
| $REN^{+}$ *≠>* $lnCO\_{2}^{-}$ | 1.271 | 0.530 | Fail to Reject |
| $REN^{-}$ *≠>* $lnCO\_{2}^{-}$ | 0.414 | 0.813 | Fail to Reject |
| $REN^{-}$ *≠>* $lnCO\_{2}^{+}$ | 0.116 | 0.944 | Fail to Reject |
| $lnCO\_{2}^{+}$ *≠>* $REN^{+}$ | 0.159 | 0.924 | Fail to Reject |
| $lnCO\_{2}^{+}$ *≠>* $REN^{-}$ | 8.235\*\* | 0.016 | Reject |
| $lnCO\_{2}^{-}$ *≠>* $REN^{-}$ | 3.580 | 0.167 | Fail to Reject |
| $lnCO\_{2}^{-}$ *≠>* $REN^{+}$ | 1.524 | 0.467 | Fail to Reject |
| $lnGDP^{+}$*≠>* $lnCO\_{2}^{+}$ | 0.495 | 0.781 | Fail to Reject |
| $lnGDP^{+}$*≠>* $lnCO\_{2}^{-}$ | 0.233 | 0.890 | Fail to Reject |
| $lnGDP^{-}$*≠>* $lnCO\_{2}^{-}$ | 2.503 | 0.286 | Fail to Reject |
| $lnGDP^{-}$*≠>* $lnCO\_{2}^{+}$ | 0.149 | 0.928 | Fail to Reject |
| $lnCO\_{2}^{+}$ *≠>* $lnGDP^{+}$ | 0.786 | 0.675 | Fail to Reject |
| $lnCO\_{2}^{+}$ *≠>* $lnGDP^{-}$ | 0.584 | 0.747 | Fail to Reject |
| $lnCO\_{2}^{-}$ *≠>* $lnGDP^{-}$ | 0.670 | 0.715 | Fail to Reject |
| $lnCO\_{2}^{-}$ *≠>* $lnGDP^{+}$ | 0.272 | 0.873 | Fail to Reject |
| $CRP^{+}$ *≠>* $FOR^{+}$ | 4.546 | 0.103 | Fail to Reject |
| $CRP^{+}$ *≠>* $FOR^{-}$ | 0.295 | 0.863 | Fail to Reject |
| $CRP^{-}$ *≠>* $FOR^{-}$ | 3.973 | 0.137 | Fail to Reject |
| $CRP^{-}$ *≠>* $FOR^{+}$ | 0.159 | 0.924 | Fail to Reject |
| $FOR^{+}$ *≠>* $CRP^{+}$ | 0.618 | 0.734 | Fail to Reject |
| $FOR^{+}$ *≠>* $CRP^{-}$ | 1.801 | 0.406 | Fail to Reject |
| $FOR^{-}$ *≠>* $CRP^{-}$ | 1.797 | 0.407 | Fail to Reject |
| $FOR^{-}$ *≠>* $CRP^{+}$ | 0.272 | 0.873 | Fail to Reject |
| $CRP^{+}$ *≠>* $lnGDP^{+}$ | 0.164 | 0.921 | Fail to Reject |
| $CRP^{+}$ *≠>* $lnGDP^{-}$ | 4.800\*\*\* | 0.091 | Reject |
| $CRP^{-}$ *≠>* $lnGDP^{-}$ | 0.577 | 0.749 | Fail to Reject |
| $CRP^{-}$ *≠>* $lnGDP^{+}$ | 7.058\*\* | 0.029 | Reject |
| $lnGDP^{+}$*≠>* $CRP^{+}$ | 0.107 | 0.948 | Fail to Reject |
| $lnGDP^{+}$*≠>* $CRP^{-}$ | 4.292 | 0.117 | Fail to Reject |
| $lnGDP^{-}$*≠>* $CRP^{-}$ | 0.221 | 0.895 | Fail to Reject |
| $lnGDP^{-}$*≠>* $CRP^{+}$ | 0.803 | 0.669 | Fail to Reject |
| $CRP^{+}$*≠>* $REN^{+}$ | 0.107 | 0.948 | Fail to Reject |
| $CRP^{+}$*≠>* $REN^{-}$ | 0.107 | 0.948 | Fail to Reject |
| $CRP^{-}$*≠>* $REN^{-}$ | 0.107 | 0.948 | Fail to Reject |
| $CRP^{-}$*≠>* $REN^{+}$ | 0.107 | 0.948 | Fail to Reject |
| $REN^{+}$*≠>* $CRP^{+}$ | 0.107 | 0.948 | Fail to Reject |
| $REN^{+}$*≠>* $CRP^{-}$ | 0.107 | 0.948 | Fail to Reject |
| $REN^{-}$*≠>* $CRP^{-}$ | 0.107 | 0.948 | Fail to Reject |
| $REN^{-}$*≠>* $CRP^{+}$ | 0.107 | 0.948 | Fail to Reject |
| $FOR^{+}$ *≠>* $lnGDP^{+}$ | 0.934 | 0.627 | Fail to Reject |
| $FOR^{+}$ *≠>* $lnGDP^{-}$ | 2.032 | 0.362 | Fail to Reject |
| $FOR^{-}$ *≠>* $lnGDP^{-}$ | 1.601 | 0.449 | Fail to Reject |
| $FOR^{-}$ *≠>* $lnGDP^{+}$ | 1.848 | 0.397 | Fail to Reject |
| $lnGDP^{+}$*≠>* $FOR^{+}$ | 47.083\* | 0.000 | Reject |
| $lnGDP^{+}$*≠>* $FOR^{-}$ | 4.222 | 0.121 | Fail to Reject |
| $lnGDP^{-}$*≠>* $FOR^{-}$ | 0.038 | 0.981 | Fail to Reject |
| $lnGDP^{-}$*≠>* $FOR^{+}$ | 1.199 | 0.549 | Fail to Reject |
| $FOR^{+}$ *≠>* $REN^{+}$ | 3.134 | 0.209 | Fail to Reject |
| $FOR^{+}$ *≠>* $REN^{-}$ | 0.218 | 0.897 | Fail to Reject |
| $FOR^{-}$ *≠>* $REN^{-}$ | 0.068 | 0.966 | Fail to Reject |
| $FOR^{-}$ *≠>* $REN^{+}$ | 1.056 | 0.590 | Fail to Reject |
| $REN^{+}$*≠>* $FOR^{+}$ | 0.586 | 0.746 | Fail to Reject |
| $REN^{+}$*≠>* $FOR^{-}$ | 2.219 | 0.330 | Fail to Reject |
| $REN^{-}$*≠>* $FOR^{-}$ | 0.325 | 0.850 | Fail to Reject |
| $REN^{-}$*≠>* $FOR^{+}$ | 1.719 | 0.423 | Fail to Reject |
| $lnGDP^{+}$*≠>* $REN^{+}$ | 0.736 | 0.692 | Fail to Reject |
| $lnGDP^{+}$*≠>* $REN^{-}$ | 3.252 | 0.197 | Fail to Reject |
| $lnGDP^{-}$*≠>* $REN^{-}$ | 3.553 | 0.169 | Fail to Reject |
| $lnGDP^{-}$*≠>* $REN^{+}$ | 1.508 | 0.471 | Fail to Reject |
| $REN^{+}$*≠>* $lnGDP^{+}$ | 0.894 | 0.639 | Fail to Reject |
| $REN^{+}$*≠>* $lnGDP^{-}$ | 10.528\*\* | 0.005 | Reject |
| $REN^{-}$*≠>* $lnGDP^{-}$ | 7.327\*\* | 0.026 | Reject |
| $REN^{-}$*≠>* $lnGDP^{+}$ | 8.160\*\* |  0.017 |  Reject |
| **Note:** The symbol ‘’ ≠> ‘’ indicates no causality. Hatemi-J Criterion (HJC) used for lag selection. The asterisks “ \*\*\*, \*\*, \* ” denote significance at the 0.10, 0.05 and 0.01 significance levels, respectively.  |

**IV. Conclusion and Recommendations**

The rising level of CO2 emission in the recent times has triggered the need to investigate the factors behind it. Given the increased deforestation and agricultural activities, this study examines the environmental cost of forest rents and crop production in Nigeria on the basis of nonlinear models. The results provide evidence of an asymmetric influence of forest rents and crop production on CO2 emission in Nigeria between 1990:Q1 to 2016:Q4. The empirical results in long run and short run provide that the positive change in forest rent causes CO2 emission to diminish but its negative change of the same size promotes CO2 emission emissions to rise. The results further show that the CO2 emission increasing effect of crop production following its positive change is less than the CO2 emission decreasing effect of crop production following its negative change. However, in the short run, the effect of a positive shock is stronger. In addition, our study reveals that the positive and negative changes in renewable energy have a dampen effect on CO2 emission with a positive shock having a stronger effect. For case of per capita GDP, the positive shock stimulates CO2 emission while the negative shock of per capita GDP reduces CO2 emission both in the long run and short run with evidence that the negative shock having a stronger effect.

The results of the asymmetric causality reveal that a positive shock in forest rents causes a negative shock in CO2 emission while a negative shock in forest rents causes a positive shock in CO2 emission. Also, a negative shock in crop product predicts a positive shock in CO2 emission. Furthermore, a positive shock in CO2 emission predicts renewable energy while a positive shock in crop product leads to a negative shock in per capita GDP. Our results also show that a negative shock in crop production is found to cause a positive shock in per capita GDP while a positive shock in per capita GDP predicts a positive shock in forest rents. Also, a positive shock in renewable energy causes a negative change in per capita GDP but a negative shock in renewable energy leads to a negative shock in per capita GDP. Finally, a negative shock in renewable energy is said to detect a positive shock in per capita GDP,

The important policy implications emanating from the findings of this study are as follows: First deforestation could lead to more fossil fuel emissions. Therefore, there is a need to preserve ecosystem by directing environmental policies towards strengthening forest rents and reduce forest burning and falling down of trees. Generally, deforestation reduces rain and stimulates higher temperature. The protection of Guinean Forest-Savanna Mosaic would help to reduce CO2 emissions and other significant effects of climate change in Nigeria. Also, even though food security is a necessary condition for economic growth and development, the cultivation of crop may distort land from absorbing heat and light, leading to radioactive forcing. To avoid this, a modern and mechanized practice of crop production is necessary. Therefore, Nigeria’s government should direct policies towards encouraging agricultural mechanization. In other words, government should intervene by helping farmers in transiting to the path of clean energy. This will mitigate the waste from plastic mulch, stubble burning, soil tillage, deforestation, pesticides, which are all major channels of environmental degradation. Furthermore, the government of Nigeria needs to boost the consumption of renewable energy to reduce consumption of fossil fuels. To this extent, the National Energy Policy (NEP) should encourage full utilization of clean energy by making availability of clean energy supply and affordability. In addition, since increase in per capita GDP endangers the environment, Nigeria’s government should move towards achieving green growth. This again has to do with transiting towards clean energy since energy use is important in the path of stimulating growth.

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1. As robustness checking, we use the linearity test proposed by Brock *et al.* (1987). This test detects nonlinearity in the relationship between the variables. [↑](#footnote-ref-1)