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Indirect Effect of Gas Production on Climate Change in Nigeria

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Abstract: *This study was to ascertain if gas flaring mediate upon gas production and climate change. This became necessary owing to the problems of climate change that has become very visible owing to crude oil drilling production in Nigeria and the south-south region of the country in particular. These climate changes ranges from high rainfall variability, temperature change, degradation of forest and forest resources as well as the aquatic habitat. This climate change was also observed in high volume of rainfall and the resultant flooding in the Niger delta region of Nigeria. These occurrences have caused several loss of lives and properties, hence the need for this study to ascertain if gas flaring mediates upon gas production and climate change in Nigeria. The mediation analysis was employed in this study using gas production as dependent variable, rainfall data as a proxy for climate change. Our findings have shown that gas flaring has a significant relationship with some, but not all of the variables involved. This leads to the conclusion a partial mediation exist between gas production and climate change. And this relationship is partially mediated by gas flaring.*
Keyword: *climate change, gas flaring, gas production, rainfall, Niger delta*

I. Introduction

Climate Change is a serious and one of the most important issues globally. The earth's climate change is mainly due to greenhouse gases triggered by human activities. Carbon di-oxide (CO_2), the principal greenhouse gas (GHG) is emitted by various means. Industrialization and technology have negatively impacted the environment by emitting the GHGs and discharging other pollutants. Crude oil production, fuel combustion accounts for the high amount of CO_2 emission. Most devastating is the burning of gas by flaring that leads to the emission of carbon dioxide, the main greenhouse gas. These gases released during gas flaring make up about 80% of global warming to date [1]

Onyenechere [2] argues that climate change has been one of the major environmental issues of discuss in recent times, noting that serious environmental problems are likely to arise in Nigeria in association with the probable global warming which may result from emissions of greenhouse gases into the atmosphere,

NRC [4] defines Climate change as a significant and lasting change in the statistical distribution of weather patterns over periods ranging from decades to millions of years; noting that it may be a change in average weather conditions, or in the distribution of weather around the average conditions.

Similarly Onyenechere [2] defined Climate change as a change in collective patterns of expression in various elements of weather, arguing that climate change is a permanent departure of climatic patterns from mean values of observed climate indices

Odjugo[6] argues that climate change has caused a shift in the normal timing and length of wet and dry seasons, shift in the seasonal variability of weather and climate; and increase in the seasonal fluctuation of the water bodies. Rainfall variability refers to variations in the mean state and other rainfall statistics on all spatial and temporal scales beyond that of individual precipitation events

Azuwike & Enwereuzor [7] noted that rain is a renewable resource, highly variable in space and time and subject to depletion or enhancement due to both natural and anthropogenic causes. According to the authors, rainfall (pattern) as a climatic factor is known to be changing worldwide and there has been growing concern as to the direction and effects of the changes on settlement and infrastructures

In identifying the relationship between two variables, typically referred to as the independent and dependent variables, theory suggests that a third variable may improve understanding of the nature of the relationship between the two primary variables. When the third variable is considered a mediator, it is hypothesized to be linked in a causal chain between the independent and dependent variables. In other words, the independent variable causes the mediator and the mediator causes the dependent variable. The search for intermediate causal variables is called mediation analysis. Mediation analyses are common in social science research, as they elaborate upon other relationships.

Fairchild & MacKinnon (2009) noted that a mediation model is one that seeks to identify and explain the mechanism or process that underlies an observed relationship between an independent variable and a dependent variable via the inclusion of a third explanatory variable, known as a mediator variable. Rather than hypothesizing a direct causal relationship between the independent variable and the dependent variable, a mediational model hypothesizes that the independent variable influences the mediator variable, which in turn influences the dependent variable. Thus, the mediator variable serves to clarify the nature of the relationship between the independent and dependent variables.

James et al. (2006) noted that researchers often test whether there is complete or partial mediation by testing whether the c′ coefficient is statistically significant, which is a test of whether the association between the independent and dependent variable is completely accounted for by the mediator. If the c′ coefficient is statistically significant and there is significant mediation, then there is evidence for partial mediation. Because psychological behaviors have a variety of causes, it is often unrealistic to expect that a single mediator would be explained completely by an independent variable to dependent variable relation (Judd & Kenny 1981a).

In a relationship analysis, an independent variable may not show any significant effect on a dependent variable, but the effect may be found significant indirectly through a third variable. A mediator serves as a third variable that alters the relationship between an independent variable and a dependent variable. Inclusion of a mediator in research allows researchers to more-precisely consider the explanations of the relationship between independent and dependent variables

One reason for testing mediation is trying to understand the mechanism through which the causal variable affects the outcome. Mediation and moderation analyses are a key part of what has been called process analysis, but mediation

This study therefore seeks to ascertain if gas flaring is a mediator between gas production and climate change. The study further tests the significance of the indirect effect if any, that exists between gas production production and climate change

II. Literature Review

Baron & Kenny (1986) explained the meaning of statistical mediation and propose a simple method that, apparently, allows identifying mediator variables using the sequential adjustment from several linear regression models. During these twenty five years, few works have been more cited than Baron and Kenny's and perhaps, so decisively influenced the way applied researchers understand and analyze mediation in health and social sciences.

Many studies investigating mediation according to MacKinnon, Fairchild & Fritz (2007) use a randomized experimental design, where participants are randomized to levels of one or more factors in order to demonstrate a pattern of results consistent with one theory and inconsistent with another theory Differences in means between groups are then attributed to the experimental manipulation of the mediator. The results of the randomized study along with the predictions of different theories are used to provide evidence for a mediation hypothesis and suggest further studies to localize and validate the mediating process.

Statistical approaches to estimating and testing the mediation effects have been discussed extensively in the psychological literature (e.g., Baron and Kenny, 1986; Bollen and Stine, 1990; Shrout and Bolger, 2002; MacKinnon et al., 2002, 2007). Overall, there are two main ways to test the mediation effects. The first one, perhaps also the most influential and widely used one, is the approach outlined by Baron and Kenny (1986). This single sample method (MacKinnon et al., 2002) is based on a large-sample normal approximation test provided by Sobel (1982, 1986) which has low statistical power in many situations (e.g., MacKinnon et al., 2002). The second one may be called the resampling method which is based on the bootstrap resampling procedure (Bollen and Stine, 1990; Efron, 1979, 1987). This method is shown to perform better than the first one in small sample size studies (MacKinnon, Lockwood, and Williams, 2004).

According to Small (2013) researchers are often interested in mediation analysis to understand how a treatment works, in particular how much of a treatment's effect is mediated by an intermediated variable and how much the treatment directly affects the outcome not through the mediator. The standard regression approach to mediation analysis assumes sequential ignorability of the mediator, which is that the mediator is effectively randomly assigned given baseline covariates and the randomized treatment. The author argued that since the experiment does not randomize the mediator, sequential ignorability is often not plausible.

MacKinnon et al. (2002) reviewed and compared 14 methods to test the mediation effects through a Monte Carlo study and found that testing $H0 : ab = 0$ was the best way to evaluate the mediation effects. MacKinnon, Lockwood, and Williams (2004) also compared the bootstrap resampling method with the single sample method and found that the bootstrap method obtained more accurate confidence limits (See also Shrout and Bolger, 2002). They further suggested that confidence limits if the mediation effects provided much more information than the estimates themselves.

Pardo & Román (2013) argues that the great popularity of Baron and Kenny's (1986) proposed strategy could lead one to think that it is the best way of demonstrating mediation (or, at least, a good way of doing it). But the massive use of a method doesn't guarantee it is a safe strategy. In fact, Baron and Kenny's proposed method contains important limitations.

Judd and Kenny (1981) and Frazier et al., (2004) noted that earlier approaches to mediation analysis largely relied on a form of structural equation modeling. Unfortunately, these earlier methods were not derived from a formal framework for causal inference and did not permit sensitivity analyses with respect to key identification assumptions. Furthermore, earlier methods were difficult to correctly extend to nonlinear models such as those with binary outcome variables. The tools in the mediation package enable users to conduct sensitivity analyses and cover several common statistical models that handle binary dependent variables. In this article, we discuss the foundations of these methods and how to use the mediation package.

In extensive sets of simulations, MacKinnon et al. (2002) and MacKinnon et al (2004) examined the performance of these methods (among others) to assess their Type I error rates and power. They recommended the use of the distribution of the product approach or bootstrapping over the Sobel test or causal steps approach, on the grounds that the former have higher power while maintaining reasonable control over the Type I error rate. Even though it is the most commonly used method, the causal steps strategy cannot be recommended except in large samples.

Oyeka & Nwankwo (2014) proposed and developed the use of the non-cummulative dummy variables of 1's and 0's to represent levels of parent independent variables in dummy variable multiple regression models. The regression coefficients obtained using their proposed methods were easier to interpret and clearly understood than the use of the cumulatively coded ordinal dummy variables of 1's and 0's that could be used for the same purpose. Their method also enables the simultaneous estimation of the total, absolute or overall effect of a parent independent variable as well as its direct effect through its representative dummies and its indirect effect on a given independent variable through the mediation of other parent independent variables in the model was demonstrated. According to the authors, an advantage of using dummy variables to represent independent variables in a multiple regression model is that it enables separate estimation of the partial effect of each level or category of a parent independent variable on a dependent variable which clearly provides additional information. It also enables the simultaneous estimation of not only the direct effects as we have already seen, but also the total or absolute effect and the indirect effect of a parent independent variable on a dependent variable through the mediation of other parent independent variables in the regression model. They found that the indirect effect of a given parent independent variable on a dependent variable is the difference between its total or absolute effect and its direct effect through its representative dummy variables. The total or absolute effect itself is the simple regression coefficient or regression effect of the parent independent variable using directly its assigned numerical codes on the dependent variable. Thus the indirect effect of the parent independent variable A on a dependent variable Y through the mediation of other parent independent variables in the model is estimated as its total or absolute effect less its direct effect

Milovanović (2013) showed the procedure for researching hidden influence of predictor variables in regression models and depicting suppressor and mediator variables. The author also showed that detection of suppressor and mediator variables could provide refined information about the research problem. The author applied the procedure to relation between Atlantic atmospheric centers and air temperature and precipitation amount in Serbia is chosen

Suradi & Ali et al (2009) investigated how the third variable can be determined whether it functions as a full mediator or a partial mediator in a relationship analysis between independent variable and dependent variable. A mediator serves as a third variable that alters the relationship between an independent variable and a dependent variable. Inclusion of a mediator in research allows researchers to more-precisely consider the explanations of the relationship between independent and dependent variables. The mediation analyses are carried out in investigating the role of customer overall satisfaction as a mediator in a study on the influence of quality broadband services on customer loyalty. Results show that overall satisfaction is a partial mediator in the relationship analysis between customer services, registration services, promotion and billing, and loyalty while overall satisfaction is a full mediator in the relationship between service quality and loyalty. Thus, in achieving, maintaining and enhancing customer loyalty in broadband services, telecommunication companies should put extra effort in getting customer satisfaction, especially in the services they provide. Loyal customers are also subjected to satisfaction they received in the customer and registration services and in promotion and billing introduced by the companies

Igweze, Amagoh & Ashinze (2014) noted that exploration and production of crude oil in the Niger delta are associated with high environmental impact, which may have its own contribution to the climate change recorded over the years in the region. Their analysis of rainfall variations in the Niger Delta region shows that Akure in Ondo state recorded the least average rainfall across the study area and over the years while the highest average rainfall was recorded in Calabar in Cross Rivers State.

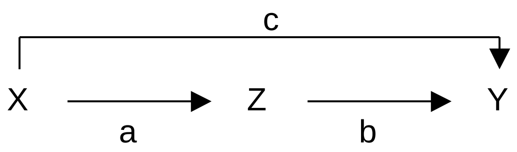
III. Research Method

This study employs the mediation analysis in determining if gas flaring is a mediating factor between gas production and climate change. Quantity of gas produced is used as the independent variable (X); rainfall data for selected towns in the Niger-delta area where known for crude oil and gas production, were used as a proxy for climate change (Y). The selected towns were in line with the work of Igweze, Amagoh & Ashinze

(2014). The towns include: Warri in Delta State, Port Harcourt in Rivers State, Benin in Edo state, Ikom and Calabar in Cross River State, Uyo in Akwa Ibom State and Owerri in Imo state. The volume of gas flared (Z) is the variable to be tested for mediation.

This method of mediation involves firstly, ascertaining if gas flaring during gas production is a mediating variable for climate change and gas production. If this is ascertained, the indirect effect is then tested. The data used for this study was obtained form 2003 and 2013 Annual Statistical Bulletin of the Nigerian National Petroleum Corporation (NNPC). The five point moving average was used to update the rainfall data from 2008 to 2013.

Hence, Let gas production be denoted by X , climate change by Y and gas flaring Z, then the diagram below shows the mediation path of X and Y



Thus, the mediational effect in which X leads to Y through Z is called the indir*ect* effect. The indirect effect represents the portion of the relationship between X and Y that is mediated by Z.

Testing For Mediation

Baron and Kenny's (1986) four step approach is employed in testing the mediation effects of crude oil production on climate change:

Step 1. Conduct a regression analysis with gass production (X) predicting climate change (Y) (path c),

$$Y = C_0 + CX + e \qquad (1)$$

Step 2. Conduct a regression analysis with X predicting Z to test for path a,

$$Z = a_0 + a_1 X + e \qquad (2)$$

Step 3. Conduct a regression analysis with Z predicting Y to test the significance of path b,

$$Y = b_0 + \boldsymbol{b_1} Z + e \qquad (3)$$

Step 4. Conduct a regression analysis with X and Z predicting Y,

$$Y = \alpha + C'X + bZ + e \qquad (4)$$

Here, mediation is supported if the partial direct effect for path c is non significantly different from zero and path b is significantly greater than zero. If c is non significantly different from zero, results are consistent with a *full* mediational model. If path b is significant after controlling for the direct effect of X (path c), but path c is still significant, the model is consistent with *partial* mediation.

Estimating Indirect effect

Judd & Kenny (1981) Process Analysis outlined a procedure for calculating indirect effect by computing the difference between two regression coefficients. Equations (1) and (2) are required to do this.
The indirect effect is obtained by subtracting coefficient for X in equation (4) from the coefficient in X in equation (1):

$$b_{indirect} = c - c' \qquad (5)$$

According to Sobel (1982), an equivalent way to estimate the indirect effect, is multiply the coefficient of X in equation (2) and the coefficient of Z in equation (4) as follows:

$$b_{indirect} = ab.$$

Test of Significance of the Indirect Effect

A test of significance of the indirect effect can be constructed using a ratio of the indirect coefficient to its standard error. The three tests of indirect effect to be compared in this work are:

$$Z_{indirect} = \frac{b_{indirect}}{S_{(b_{indirect})}} \qquad (6)$$

$$Z_{indirect} = \frac{b_{indirect}}{\sqrt{b^2 S_a^2 + a^2 S_b^2}} \qquad (7)$$

The standard error is given by Baron & Kenny (1986) as

$$s_b = \sqrt{b^2 s_a^2 + a^2 s_b^2 + s_a^2 s_b^2} \qquad (9)$$

Where: b^2 represents the unstandardized coefficient for path b
a^2 represents the square of the unstandardized coefficient for path a;
s_a^2 represents the square of the standard error for the coefficient for path *a*,
s_b^2 is the square of the standard error for path b. Notice that

IV. Result And Discussion Of Findings

Test for Mediation

The SPSS version 20 was used to obtain the required regression result as shown in subsequent tables. (table 1-4)

Table 1: Coefficients for $Y = C_0 + C_1X$ (path C)

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2172.576	1467.999		1.480	.152
	Gasprod(X)	2.384E-006	.000	.437	2.330	.029

a. Dependent Variable: average rainfall (Y)

From table 1, the regression model for path c is given as Y=2172.576+0.000002384X
Path c is significantly different from zero, although the intercept model may not be good for the relationship between gas production and climate change since the p-value is greater than 0.05

Table 2: Coefficients for $Z = a_0 + aX$ (path a)

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	5030818.416	28937439.145		.174	.864
	Gasprod	.295	.020	.950	14.621	.000

a. Dependent Variable: gasflaredZ

Table 2 shows that path a is significantly different from zero as gas flaring has proven to have a significant relationship with gas production.. However , the intercept model proved not to be a good fiit for the relationship between gas production and gas flaring. The regression model for path a is: Z=50308184.41+0.295X

Table 3:Coefficients for $Y = \alpha + C'X + bZ$

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2366.082	979.298		2.416	.024
	Gasprod(X)	1.373E-005	.000	2.516	6.272	.000
	Gasflared(Z))	-3.846E-005	.000	-2.188	-5.454	.000

a. Dependent Variable: averain (Y)

Table 3 gives the model for climate change on gas flaring and gas production. The model is given as: Y=2366.082 + 0.00001373X-0.00003846Z

Both gas production and gas flared are seen to have significant effect on climate change. However, the intercept term is still found not to be significant, suggesting that a non intercept model will give a better fit for the relationship.

The result from table 1-3 indicates the presence of partial mediation between gas production and rainfall variation. Partial mediation implies that the mediating variable accounts for some of the relationship between the independent variable and dependent variable. Hence a test is required to check the significance or otherwise of the indirect effect.

Thus the indirect effect is calculated from equation (7) as:

C - C' = 0.000002384-0.00001374=-0.000036076

The test of indirect effect is calculated from equation (8) as;

$$\boldsymbol{t_{indirect}} = \frac{\mathbf{-0.000036076}}{\boldsymbol{s_{b_{indirect}}}}$$

The standard error, $\boldsymbol{S_{b_{indirect}}}$ is computed from (9) as

=0.00000028504

Thus $\boldsymbol{t_{indirect}} = \frac{\mathbf{0.000036076}}{0.00000028504}$ = 126.56, this value is significant at 5% significant level.

The significance of the indirect effect justifies the significance of the indirect effect and further proves the existence of partial mediation between gas production and climate change mediated by gas flaring.

V. Conclusion

This study was to ascertain if gas flaring mediate upon gas production and climate change. This became necessary owing to the problems of climate change that has become very visible owing to crude oil drilling production in Nigeria and the south-south region of the country in particular. These climate changes ranges from high rainfall variability, temperature change, degradation of forest and forest resources as well as the aquatic habitat. This climate change was also observed in high volume of rainfall and the resultant flooding in the Niger delta region of Nigeria. These occurrences have caused several loss of lives and properties, hence the need for this study to ascertain if gas flaring mediates upon gas production and climate change in Nigeria.

Our findings have shown that gas flaring has a significant relationship with some, but not all effects. This leads to the conclusion that a partial mediation exist between gas production and climate change. And this relationship is partially mediated by gas flaring.

It is therefore recommended that reduction of gas flaring will help reduce the high incidence of climate change in Nigeria especially in the south which is the base of crude oil production. Again converting the gases to cooking gass and other useful gas will help reduce the volume of gass flared and subsequently help curd the incidence of climate change.

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Appendix

year	gas flared(Z)	Average rainfall (Y)	Gas production (X)
1989	18704	2268.44	32084
1990	22410	2205.51	33680
1991	24660	2434.16	33680
1992	24575	2680.99	35100
1993	25770	2462.49	35450
1994	26910	2537.49	37150
1995	26966	2150.25	37039
1996	26580	2499.44	43636
1997	24234	2256.46	42732
1998	23632	2169.7	52453
1999	22362	2409.84	48129
2000	24256	2169.63	51766
2001	26759	2121.93	2082283189
2002	24836	2391.33	2093628859
2003	23943	2464.64	2182432084
2004	886540198	2442.25	2415649041
2005	811315777	2318.73	2287547344
2006	803661823	2347.77	1837278307
2007	759688726	4271.16	2392838898
2008	819398854	8064.06	2400402880
2009	509351905	15635.18	2580165626
2010	581568354	30781.92	2325137449
2011	619032858	64512.44	8064.055
2012	588666724	125081.46	15635.1825
2013	409311430	246255.32	30781.915