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Statistical Analysis of the Effect of Environmental Degradation on Mortality Rate: A Vector Autoregressive (VAR) Model Approach

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Abstract

The relationship between air pollution and mortality calls for attention in recent time. Diverse analyses have been conducted globally, including important cities in Africa, United States, Europe, and Asia. In this study, a time-series analysis is proposed to analyze influence of environmental pollution on mortality in Nigeria using the Vector Autoregressive (VAR) Model. Stationarity test shows that the data is stationary and VAR model suitably fits the data. The study reveals that environmental pollution has significant impact on mortality in Nigeria. Some useful recommendations were made.

Keywords: ***Vector Autoregressive Model, Environmental degradation, Mortality***

1.0 Introduction

Health challenges such as respiratory and cardiovascular are triggered or aggravated by exposure to environmental pollution on a daily basis. The harm that environmental pollution causes, varies from nearing death to not too serious illness (Chardon, Host, Pedrono, and Gremy, 2008). It is estimated that a 1% additional death in the USA, continental Europe and the UK may be brought forward by every $10\mu g/m^3$ increase in particulate matter with less than $10\mu m$ in diameter (PM_{10}); it was advanced that the particles lead to more than 8,000 deaths in Great Britain (Ciocco and Thompson, 2015). Environmental pollution is ranked as the 13th cause of worldwide deaths (Logan, 2015).

Environmental pollution is the leading discharge source of environmental pollutants examples are carbon monoxide (CO), nitrogen oxides (NOx), benzene, 1,3-butadiene and primary PM_{10}, which leads to the creation of ozone (O_3) and secondary particles. NOx has adverse effects on human health (Pope III, Thun, Namboodiri, Dockery, Evans, Speizer, and Heath Jr, 2015). Ozone (O_3) is a pollutant which is produced from directly from photochemical reactions between various environmental pollutants, primarily NOx and Volatile Organic Compounds (VOCs) initiated by sunlight. It is a more powerful oxidizing agent than O_2. Exposure to high concentration of O_3 may cause harmful effects on the environment (Pope et al., 2015). These pollutants often increase admissions to hospital and even deaths among vulnerable population.

The link among quality environment and human health, productivity and development is incontrovertible. This position derives from the reasoning that the environment provides the critical basis for development through man's intermediation. While it is an arduous task to accurately devise a globally acceptable and standard technique for placing monetary values on human mortality and morbidity arising from environmental quality changes, the importance of health considerations and benefits in establishing environmental policy justifies at least the productivity approach.

Central to the above environmentally engendered human health challenge in the rich oil region, it is perceived to be deliberate policy gap by successive Nigerian governments. An integrated and collaborative policy environment, a well-crafted, synergistic and pragmatic action embodying plans and programmes by the different levels of government and the private oil conglomerates that will efficaciously tackle the environmental crisis due to air pollution and devastation and the concomitant dehumanizing health status of the people in the Niger Delta region is thus a desideratum.

There is a great need to monitor high levels of pollutant concentrations in collaboration with climatic data, this necessitate for developing adequate time series stochastic methods to understand the intricate mechanism in the development of concentrated environmental pollution. Some statistical techniques such as regression analysis, neural network and others have been suggested to model environmental pollution concentrations (Samet, Marbury, and Spengle, 2014; Doherty, 2015), but there have deficiency of the techniques to model extreme concentration values.

Identifying and putting to use of suitable forecasting techniques for a time series data is important in order not to obtain a misleading result. Some of the common models used is Autoregressive model, moving average model, autoregressive moving average model, to mention but a few. Multivariate time series model are also being used for forecasting. The advantage of multivariate time series model is that it incorporates previous information of the variable, and incorporates interdependence of other variables for improving the performance of forecasting. Vector autoregressive (VAR) model is the commonly used multivariate time series model. The performance of the VAR model is improved by restriction imposed on the parameters. This study is to critically assess the impact of environmental pollution on mortality. The remaining part of this paper is as follows; section 2 contains related studies, section 3 is the methodology, section 4 consists of data and result obtained, while section 5 is the summary and conclusion.

2.0 Related studies

Various studies have been carried out in relation to the impact of environmental pollution human health, Isola and Mesagan (2015) carried out a study on the impact of oil production on human condition in Nigeria, the authors looked at environmental degradation, life expectancy, and infant mortality rate were measure human condition. The also authors explored the vector autoregressive (VAR) model and variance decomposition analysis. The findings revealed that oil production of the first period positively impacted environmental degradation, while it was negative in the second period; also that the first period lag has positive relationship but second period lag has a negative relationship with life expectancy. The variance decomposition analysis also showed that oil production worsened environmental degradation and adversely impacted on infant mortality rate, while it positively affected life expectancy.

In the study by Fischbacher-Smith and Adekola (2016), the health risk communication was evaluated in the oil rich Niger Delta region of Nigeria, which suggested that the health of the local population is being affected by risk incidences relating to oil and gas exploration activities, the effects of which are amplified by inadequate communication of health risks to the public.

Okonkwo (2014) highlights the socioeconomic effect of oil leaks in Nigeria. The study showed that socio-economic impacts of spills in Nigeria are glaring, that there are legal frameworks, which are practically ineffective. Oshwofasa, Anuta, and Aiyedogbon (2012) outlined the socio-economic impacts of environmental degradation caused by oil producing industry in Nigeria a case study of the Niger Delta region. The finding revealed that with the enormous resources in the region, instead the people of the region continue to suffer oil degradation through pollution of the environment, gas flaring and oil spillage.

Ejiba, Onya and Adams (2016) pointed out the destructive effect of oil smog in Nigeria. The study carried out by the authors revealed that oil spillage and gas flaring has impacted negatively on the people of the region which has led to destruction of the environment, with significant damage on livelihood, especially on farming and fishing. The situation has increased the weakness of households thereby affecting their health adversely. According to Ejumudo (2011), Nigeria is embroiled and enmeshed in environmental crisis because of the hydra-headed level of pollution, degradation and dislocation that has become common place. With degraded land, polluted sea and perforated environment, the pauperized and marginalized people of the rich yet paradoxically poor and underdeveloped region have become exposed to and afflicted with diseases that are linked to the environment with consequential implications for socio-economic productivity. The author focused on group discussions, interviews and content analyses of relevant academic texts and journals, examined environmental pollution in the region, the catastrophic and dysfunctional effects and the serious health challenges it poses to the Niger Delta people. The findings of the study showed that there is policy gap and gross inaction in respect of the devastated oil region and their poor, malnourished and health endangered people due to the negligence and ingrained poor performance culture of the different levels of the government. The study also revealed that the above abnormality is further aggravated by the somewhat disconnected and largely poor functioning and low performing health care delivery system in Nigeria concluded with some useful remarks and valuable recommendations including a collaborative policy environment, pragmatic action-embodying plans and programmes by the government, private oil sector and the disease-prone oil-bearing communities. Having considered various studies carried out by some authors and methods, this study adopts Vector Autoregressive model to achieve the objective set in this study.

3.0 Materials and Methods

3.1 Vector Autoregressive (VAR)

A Vector Autoregressive $(VAR)$is a multivariate simultaneous equation system in which each variable under study is regressed on a finite number of lags of all variables jointly considered. The method focus on deriving a good statistical representation of the interactions between variables and the data determine the model. VAR model is mainly used for structural analysis and forecasting.

The vector autoregressive (VAR) model was developed in the econometric modeling of time series. Using the vector autoregressive methodology reveal interesting hidden association of variables considered for investigation.

A process y_t is said to be a vector autoregressive process of order p denoted by VAR (p) if it satisfies the equation

$$y_t = v + A_1 y_{t-1} + \cdots + A_p y_{t-p} + u_t, t = 0, \pm 1, \pm 2 \ldots, u_t \sim N(0, \sigma^2) \quad (1)$$

Where $y_t = (y_{1t}, \ldots, y_{kt})'$ is a $(k \times 1)$ random vector, the A_i are fixed $(k \times k)$ coefficient matrices, $V = (V_1, \ldots V_k)'$ is a fixed $(k \times 1)$ vector of intercept terms allowing for the possibility of a non-zero mean, $E(y_t)$. Finally $u_t = (u_1, \ldots u_t)'$ is a k-dimensional white noise or innovation process, that is,

$$E(u_t) = 0$$

$$E(u_t u_t') = \Sigma_u$$

$$E(u_t u_s') = 0 \; for \; t \neq s$$

The covariance matrix Σ_u is assumed to be non-singular, if not otherwise stated.

For P = 1, $VAR(1)$ model:

$$y_t = v + A_1 y_{t-1} + u_t \quad (2)$$

3.2 Stationary VAR Processes

A stochastic process is stationary if its first and second moments are time invariant. In other words, a stochastic process $y_t$is stationary if

$$E(y_{t)} = \mu \; for \; all \; t \quad (3)$$

and

$$E(y_t - \mu)((y_{t-h} - \mu)') = \Gamma_y(h) = \Gamma_y(-h)' \; \forall \; t \; and \; h = 0,1,2,.. \quad (4)$$

For a higher order $VAR(p)$ process,

$$y_t - \mu = A_1(y_{t-1} - \mu) + \cdots + A_p\big(y_{t-p} - \mu\big) + U_t \quad (5)$$

The Yule-Walker equations are also obtained by post multiplying with $(y_{t-h} - \mu)'$ and taking expectations. For h= 0, using $\Gamma_y(i) = \Gamma_y(-i)'$.

$$\Gamma_y(0) = A_1\Gamma_y(-1) + \cdots + A_p\Gamma_y(-p) + \Sigma_u$$

$$= A_1\Gamma_y(1)' + \cdots + A_p\Gamma_y(p)' + \Sigma_u \quad (6)$$

and for $h > 0$,

$$\Gamma_y(h) = A_1\Gamma_y(h-1) + \cdots + A_p\Gamma_y(h-p) \quad (7)$$

These equations may be used to compute the $\Gamma_y(h)$recursively for $h \geq p$, if $A_1, \ldots, A_p \; and \; \Gamma_y(h-p), \ldots, \Gamma_y(0)$ are known.

The initial autocovariance matrices for $|h| < p$can be determined using the $VAR(1)$ process,

$$Y_t - \mu = A(Y_{t-1} - \mu) + U_t \quad (8)$$

Where $Y_t \, , A, and \; U_t$ as in (7) and $\mu = (\mu', \ldots, \mu') = E(Y_t)$.

Since the autocovariance depend on the unit of measurement used for the variables of the system, they are sometimes difficult to interpret. Therefore, the autocorrelations $\rho_y(h) = D^{-1}\Gamma_y(h)D^{-1}$ are usually more convenient to work with as they are scale invariant measures of the linear dependencies among the variables of the system. Here D is a diagonal matrix with the standard deviations of the components of $y_t$on the main diagonal. That is, the diagonal elements of D are the square roots of the diagonal elements of $\Gamma_y(0)$. Denoting the covariance between $y_{i,t}$and $y_{j,t-h}$ by $\Sigma_{ij}(h)$ is the ithelements of $\Gamma_y(h)$ the diagonal elements $\gamma_{11}(0), \ldots, \Sigma_{kk}(0) \; of \; \Gamma_y(0)$are the variances of $y_{1t}, \ldots, y_{kt}$. Thus

$$D^{-1} = \begin{pmatrix} \frac{1}{\sqrt{\Sigma_{11}(0)}} & 0 \\ 0 & \frac{1}{\sqrt{\Sigma_{kk}(0)}} \end{pmatrix}$$

and the correlation between $y_{i,t}$and $y_{j,t-h}$is

$$\rho_{ij}(h) = \frac{\Sigma_{ij}(h)}{\sqrt{\Sigma_{ii}(0)}\sqrt{\Sigma_{jj}(0)}} \tag{9}$$

which is just the ithelement of $\rho_y(h)$.

3.3 Vector Autoregressive VAR Models Analysis

The vector autoregressive model will be used to examine several economic time series at a time. The vector autoregression (VAR) will be used to determine the inter-relationship between economic time series and analyzing the dynamic impact of random disturbances on the system of variables. The VAR approach sidesteps the need for structural modeling by treating every endogenous variable in the system as a function of the lagged values of all of the endogenous variables in the system. The VAR process is defined as;

$$y_t = A_1 y_{t-1} + \cdots + A_p y_{t-p} + Bx_t + u_t \tag{10}$$

where $y_t$is a k vector of endogenous variables, $x_t$is a vector of exogenous variables, $A_1, \dots, A_p$and B are matrices of coefficients to be estimated, $u_t$and is a vector of innovations that may be contemporaneously correlated but are uncorrelated with their own lagged values and uncorrelated with all of the right-hand side variables.

For the purpose of this study, the relationship between environmental pollution and mortality will be examined using VAR model. The parameter of a vector autoregressive model (VAR) can be estimated using least square method and Maximum likelihood method and the two methods are asymptotically equivalent.

The Least Square Method follows that;

Suppose the sample $\{y_t\}_{t=1}^{n}$ is available that such

$$y_t = \phi_0 + \phi_2 y_{t-1} + \cdots + \phi_p y_{t-p} + U_t \tag{11}$$

Then $VAR(p)$ model can be written as

$$y_t' = y_t'\beta + U_t' \tag{12}$$

Where $y_t = \left(1, y_{t-1}', \dots, y_{t-p}'\right)'$ is $(kp+1)$ dimensional vectors and $\beta' = \left(\phi_0, \phi_{2,} \dots, \phi_p\right) \, is \; k \times (kp \times 1)$ matrix.

The least square estimate of β is

$$\hat{\beta} = \left[\sum_{t=p+1}^{p} Z_t Z_t'\right]^{-1} \left[\sum_{t=p+1}^{p} Z_t^p Z_t\right] \tag{13}$$

the least square residual is

$$\widehat{U}_t = y_t - \sum_{i=1}^{p} \hat{\phi}_i \, y_{t-1}, t = p+1, \dots, n \tag{14}$$

and the least square estimate of Σ_u is

$$\hat{\Sigma}_u = \frac{1}{n-(k+1)(p-1)} \sum_{t=p+1}^{n} \widehat{U}_t \widehat{U}_t' \tag{15}$$

For a stationary $VAR(p)$ model with independent error termsU_t, it can be shown that the least estimate $\hat{\phi}$ is consistent.

If $\hat{b} = vec\ (\hat{\beta})$, then $\hat{b}$ is asymptotically normal with mean $vec(\hat{\beta})$ and covariance matrix $cov(\hat{\beta}) = \hat{\Sigma}_u \otimes (\sum_{t=p+1}^{n} y_t Z_t')$ where $\otimes$ denote the knoncher product.

The coefficients of the model are the same as those of least squares estimate in (13). However, the estimates of Σ_u is

$$\hat{\Sigma}_u = \frac{1}{n-p} \sum_{t=p+1}^{n} \hat{U}_t \hat{U}_t' \qquad (16)$$

4.0 Empirical Analysis and Results

The result of various analysis carried out in this study are presented in this section.

4.1 The Data

The data set was obtained from the publications of World Health Organization, The United Nations International Children's Emergency Fund (UNICEF), and National Bureau of Statistics. The data include Particle Matter (PM), the PM is measure of environmental pollution, and infant Mortality rate obtained from UNICEF. The data covers from the year 2000 to 2016. The Mortality rate represents deaths of infants under 1 year old per 1000 live births. It excludes fetal deaths. Particle pollution or PM is a complex mixture of extremely small particles and liquid droplets. Particle pollution is made up of a number of components, including acids (such as nitrates and sulfates), organic chemicals, metals, and soil or dust particles. Fine particulate matter is particulate matter that is 2.5 microns in diameter and less. It is also known as PM2.5 or inhale-able particles because it penetrates the respiratory system further than larger particles. PM2.5 material is primarily formed from chemical reactions in the atmosphere and through fuel combustion (e.g., motor vehicles, power generation, industrial facilities, residential fire places, wood stoves and agricultural burning).

PM – Particle Matter

Mortality – Mortality Rate

The models (VAR (2)) to be fitted to the data are

Model: $PM_t = \alpha_1 MOR_{t-1} + \alpha_2 MOR_{t-2} + \beta PM_{t-1} + e_t$

4.2 Descriptive Analysis

The descriptive analysis was used to summarized the characteristics of the variables consider in this study with a view of showing the important features of each of the PM and infant Mortality.

Table 1: Summary Statistics for Particle Matter

Count	16
Average	22.1875
Standard deviation	14.0248
Coeff. of variation	63.2105%
Minimum	1.0
Maximum	45.0
Range	44.0
Stnd. Skewness	**0.310086**
Stnd. Kurtosis	**-0.985929**

Table 1 shows summary statistics for Particle Matter (PM). It includes measures of central tendency, measures of variability, and measures of shape. The Standardized skewness and standardized kurtosis are of particular interest, which can be used to determine whether the sample comes from a normal distribution. Values of these statistics outside the range of -2 to +2 indicate significant departures from normality, which would tend to invalidate any statistical test regarding the standard deviation. In this case, the standardized skewness value is within the range expected for data from a normal distribution. The standardized kurtosis value is within the range expected for data from a normal distribution. Figure 1 shows the histogram.

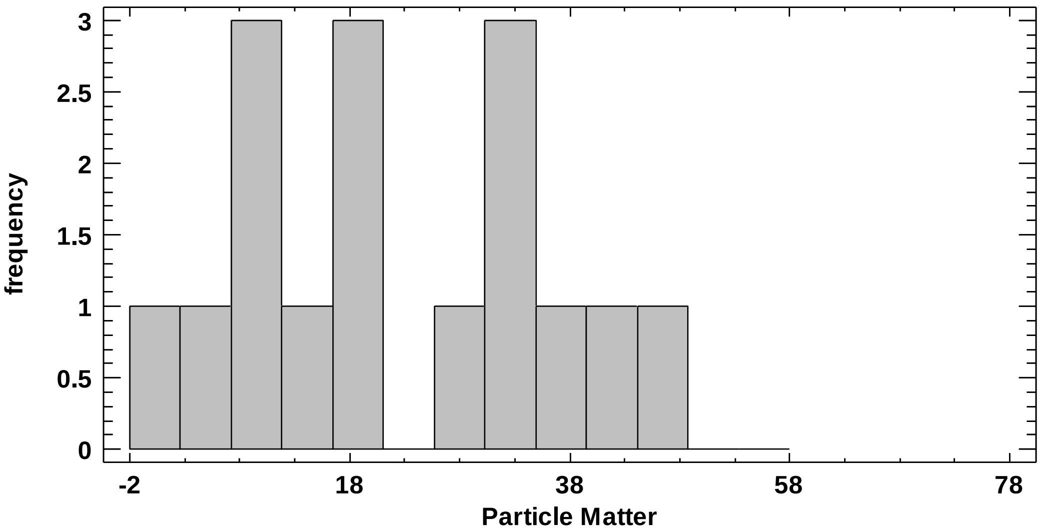

Figure 1: Histogram of Particle Matter

Table 2: Summary Statistics for Mortality rate

Count	16
Average	7.325
Standard deviation	1.46674
Coeff. of variation	20.0238%
Minimum	5.4
Maximum	10.7
Range	5.3
Stnd. Skewness	**1.19573**
Stnd. Kurtosis	**0.235753**

Table 2 shows summary statistics for Mortality rate. It includes measures of central tendency, measures of variability, and measures of shape. The standardized skewness and standardized kurtosis, is used to determine whether the sample comes from a normal distribution. Values of these statistics outside the range of -2 to +2 indicate significant departures from normality, which would tend to invalidate any statistical test regarding the standard deviation. In this case, the standardized skewness value is within the range expected for data from a normal distribution. The standardized kurtosis value is within the range expected for data from a normal distribution.

Confidence Intervals for Mortality rate

95.0% confidence interval for mean: 7.325 +/- 0.781574 [**6.54343, 8.10657**]

95.0% confidence interval for standard deviation: [**1.08349, 2.27006**]

The standard interpretation of these intervals is that, in repeated sampling, these intervals will contain the true mean or standard deviation of the population from which the data come 95.0% of the time. In practical terms, we can state with 95.0% confidence that the true mean Mortality rate is somewhere between 6.54343 and 8.10657, while the true standard deviation is somewhere between 1.08349 and 2.27006.

Both intervals assume that the population from which the sample comes can be represented by a normal distribution. While the confidence interval for the mean is quite robust and not very sensitive to violations of this assumption, the confidence interval for the standard deviation is quite sensitive. Figure 2 shows the histogram of mortality rate

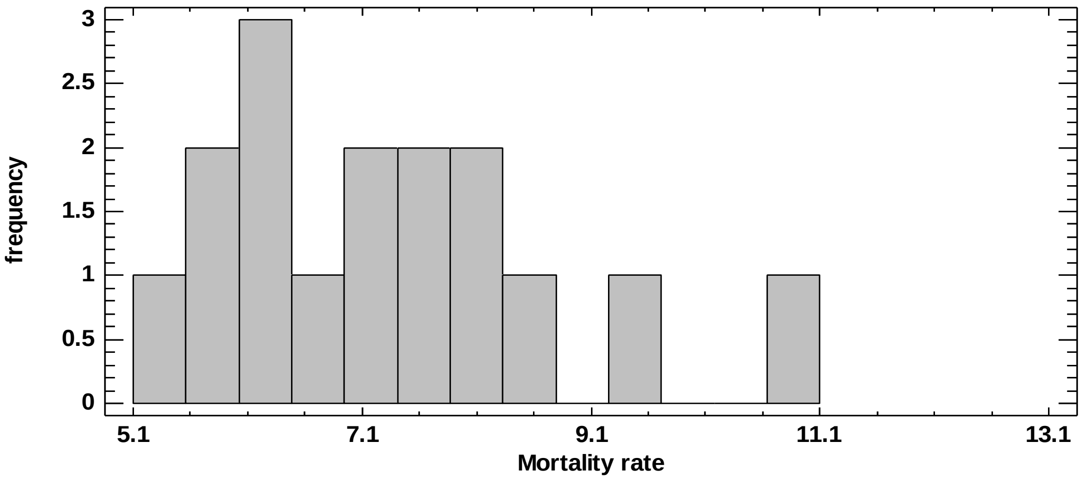

Figure 2: Histogram of Mortality rate

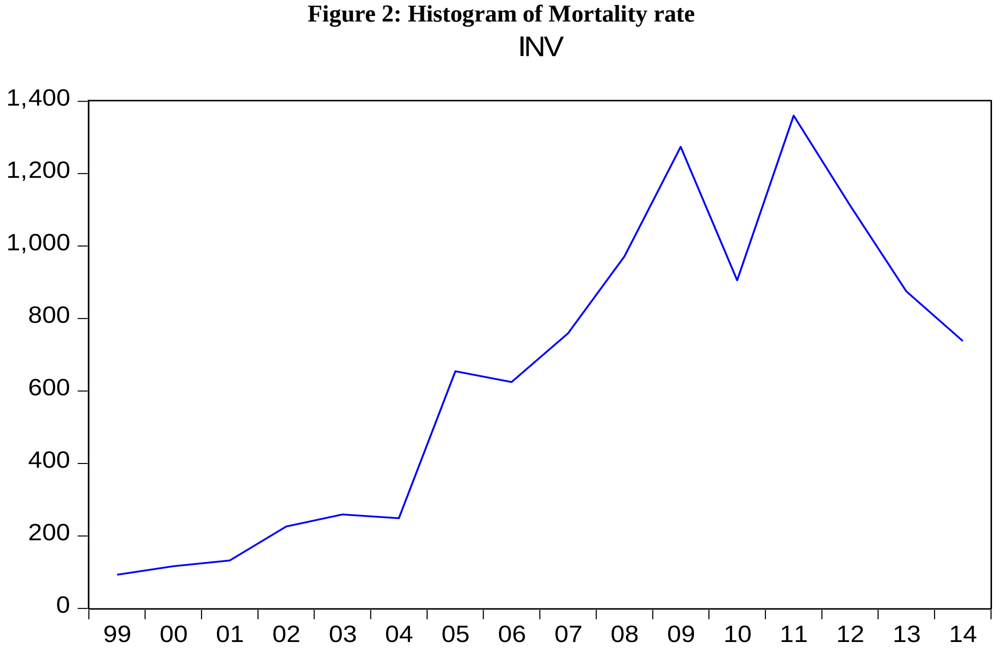

Figure 3: Time plot of Particle Matters, 2000-2015

The time plot for the PM shows a short-term movement of the value in the series in different direction over the period considered. This movement is characterized by a sinusoidal increase in the values of the PM over the period of time. This movement is referred to as secular variation or secular movement. By fitting a straight line freely by hand on the plotted points on the time plot for PM stretching over the period, this plotted point forms a line and this line is the trend of the time plot for PM.

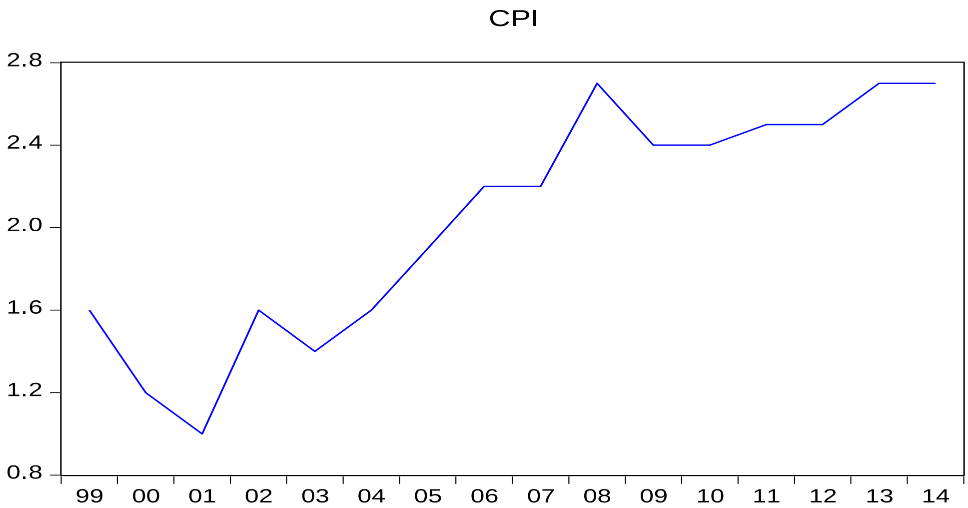

Figure 4: Time plot of Mortality Rate, 2000-2016

The time plot for Mortality Rate shows a short-term movement in the series in different direction over the period considered. By fitting a straight line freely by hand on the plotted points on the time plot for Mortality Rate stretching over the period, this plotted point forms a line and this line is the trend of the time plot for Mortality Rate.

4.3 Unit Root Test

In testing for stationarity or the presence of unit roots in the data, The (ADF) formulae were employed. The results of the test are as presented below:

Table 3: Augmented Dickey-Fuller Unit Root Test

Series	ADFR Test Statistic	5% Critical Values	10% Critical values	Order	Remarks
PM	-1.783871	-3.0124	-2.6461	I(1)	Stationary
Mortality Rate	-4.680257	-3.0207	-2.6504	I(1)	Stationary

The unit root test in Table 3 displays that investment by PM and Mortality Rate are integrated of order one. They are integrated of the same order; 1(1). In Table 3, it was found that ADF Test with trend and intercept indicated that time series are integrated of the same order. The linear combination of series integrated of the same order are said to be cointegrated. The level of their integrations indicates the number of time series have to be differenced before their stationarity is induced. Considering the ADF test statistics at 5% and 10% critical values, it is detected that test statistics are larger (in absolute term) than the critical values. Therefore, the series at that level are said to be stationary.

VECTOR AUTOREGRESSIVE ESTIMATION

Table 4: Vector Autoregressive Model for PM, 2000-2016

Sample (adjusted): 2001 2016	
Included observations: 14 after adjustments	
Standard errors in ( ) & t-statistics in [ ]	
	PM
PM(-1)	0.386948
	(0.28946)
	[1.33679]
PM(-2)	0.187539
	(0.26089)
	[0.71886]
MORTALITY RATE	165.3001
	(76.4386)
	[2.16252]
R-squared	0.742619
Adj. R-squared	0.695822
Sum sq. resids	522979.6
S.E. equation	218.0450
F-statistic	15.86908
Log likelihood	-93.56282
Akaike AIC	13.79469
Schwarz SC	13.93163
Mean dependent	724.4918
S.D. dependent	395.3505

The model obtained is given as:

$$\mathrm{PM_t} = 0.386948MOR_{\mathrm{t}-1} + 0.187539MOR_{\mathrm{t}-2} + 165.3001PM_{\mathrm{t}-1}$$

This is the vector autoregressive model for PM, is explained and determined by the Mortality Rate in its first and second lag by observing the values of t-statistics in the parenthesis above. That is, Mortality Rate determines the PM in its first lag.

The value of R^2 (0.7426) shows that (74%) variation in the PM is explained by the MORTALITY RATE and the value of adjusted R^2 squared (0.6958) shows it is good fit.

Table 5: Vector Autoregressive Model for Mortality Rate, 2000-2016

Vector Autoregression Estimates
Sample (adjusted): 2001-2015
Included observations: 14 after Adjustments
Standard errors in ( ) & t-statistics in [ ]

	MORTALITY RATE
MORTALITY RATE(-1)	0.742884
	(0.29598)
	[2.50991]
MORTALITY RATE(-2)	0.298360
	(0.27174)
	[1.09795]
PM	3.27E-05
	(0.00033)
	[0.10042]
R-squared	0.774921
Adj. R-squared	0.733998
Sum sq. resids	0.861729
S.E. equation	0.279891
F-statistic	18.93591
Log likelihood	-0.350041
Akaike AIC	0.478577
Schwarz SC	0.615518
Mean dependent	2.128571
S.D. dependent	0.542684

The model obtained is given as:

$$\mathrm{MOR_t} = 0.742884PM_{\mathrm{t-1}} + 0.298360PM_{\mathrm{t-2}} - 0.0000327MOR_{\mathrm{t-1}}$$

This is the vector autoregressive model for Mortality Rate, is explained and determined by PM in its first lag and Mortality Rate in the first lag and second lag.

The value of R^2 (0.7749) shows that (77%) variation in the Mortality Rate is explained by the PM and the value of adjusted R^2 squared (0.7339) shows it is good fit.

Table 6: Forecast for Actual and Predicted Values for 2016 and 2017

	PREDICTED				**ACTUAL**			
	PM		MORTALITY RATE		PM		MORTALITY RATE	
Year	2017	2016	2017	2016	2017	2016	2017	2016
Value	896.069	799.427	2.8	3.5	738.197	734.233	2.7	2.7

5.0 Summary and Conclusion

The study examined the effect of environmental pollution on mortality rate in Nigeria. In the study, the data sets were tested for stationarity using the Augmented Dickey-Fuller test. The test showed that PM (used as proxy for environmental pollution) and Mortality Rate was all stationary and fit for modeling. The study employed Vector Autoregression (VAR) model. The findings reveal that there is a long run relationship between environmental pollution and mortality in Nigeria and that the impact of environmental pollution on mortality in Nigeria is negative from the VAR result.

The model was applied to 2000-2015; to make prediction was made for the year 2016. The results showed that the there is significant difference between the predicted PM for 2016 and the actual PM for 2016. The predicted Mortality Rate for 2016 appears to be higher than the actual Mortality Rate for 2016. The predicted PM for 2017 using 2000-2015 data appears to higher than the actual PM for 2017 using 2000-2016 data. Similarly, the predicted Mortality Rate for 2017 using 2000-2015 data appears to higher than the predicted Mortality Rate for 2017 using 2000-2016 data. The predicted PM for 2016 appears to higher than the actual PM for 2016. The predicted Mortality Rate for 2016 appears to be higher than the actual Mortality Rate for 2016. The predicted PM for 2016 appears to higher than the actual PM for 2016. The predicted Mortality Rate for 2016 appears to be higher than the actual Mortality Rate for 2016. The predicted PM for 2017 using 2000-2015 data appears to higher than the actual PM for 2017 using 2000-2016 data. Similarly, the predicted Mortality Rate for 2017 using 2000-2015 data appears to higher than the predicted Mortality Rate for 2017 using 2000-2016 data.

The results obtained from this study using VAR time-series model shows promising applicability of the model for forecasting, the results obtained was higher than actually obtained in the year predicted for. Further study may consider venturing into identifying forecast error in using VAR for predictions. However, the model is recommended for prediction. Also, following results obtained in this study, government and policy makers should make collaborative environment policy that would drastically reduce environmental pollution in the oil producing states and communities, hence reducing mortality rate. Finally, the findings of the study corroborate previous literatures on the subject.

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