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Vector Autoregressive Model of GDP, Money Supply and Exchange Rate in Nigeria

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Abstract **Original Research Article**

The research work on vector autoregressive model on economic indicators of gross domestic product, money supply and exchange rate in Nigeria was developed and adequately model. The study yields a stable vector autoregressive model with stationary process and the estimate of the model where significant. The empirical result yields a stable and sustainable economic model for the three economic variables in the study. The unit root test was achieved at order 1 and the inverse root of the polynomial lies within the unit circle. The iterative step of time series analysis, the computational algorithm of VAR with the model adequacy with respect to the plot of residual of the economic indicators was achieved. The inverse of the characteristics polynomial of the variables lies within the unit circle, the response impulse analysis are within the boundaries of estimation. The study also yields R-square that best describe the fit, with RMSE, MAE and MAPE of the three economic variables. The forecast evaluation analysis indicate an upward fluctuation in a long run, the study is now available for economic practitioners to be used for policy implementation.

Keywords: Multivariate Time Series, Economics Variables, Modeling, Vector Autoregressive.

1.1 INTRODUCTION

The vector autoregressive (VAR) model is a workhouse multivariate time series model that relates current observations of a variable with past observations of itself and past observations of other variables in the system. VAR models differ from univariate autoregressive models because they allow feedback to occur between the variables in the model. For example, we could use a VAR model to show how real GDP is a function of policy rate and how policy rate is, in turn, a function of real GDP.

Multivariate time series (MTS) data are widely available in different fields including medicine, finance, science and engineering. Modeling MTS data effectively is important for many decision making activities. Consider a time series variable $(y_{1t}) \dots . . (y_{nt})$. A multivariate time series is the (n x 1) vector time series $\{y_t\}$where i^{th} row of (y_{1t}) is (y_{nt}), that is for any time t,

$$Y_t = (y_{1t}, y_{2t}, \dots . y_{nt})'$$

Njuguna (1993) estimated a six variable VAR model with the following-money supply, domestic price level, exchange rate index, foreign price index, real output, and the rate of interest in an attempt to explain the inflation movement in Kenya. He observed that the rate of inflation and exchange rate explained each other's. Odusola and Akinlo (2001) examine the link between the naira depreciation, inflation and output in Nigeria, adopting vector autoregressive (VAR) and its exchange rate system does not necessarily lead output expansion, particularly in short term.

2.1 LITERATURE REVIEW

Multivariate time series analysis is used when one wants to model and explain the interactions and co-movements among a group of time series variables (Economic indicators). Multivariate methods are very important in economics and much less so in other applications of forecasting. The multivariate view is central in economics, where single variables are traditionally viewed in the context of relationship to other variables. Debelle *et al.*, (2005), argues that along with change in output growth, exchange rate changes have historically played a key role in the adjustment of external imbalances in industrial countries. Zettelmeyer (2004), and Kearn and Maners (2005) finds that, a surprise monetary policy shock that increase the interest rate has a significant appreciating effect on the exchange rate. Andrew *et al.*, (2001) the advantage of providing an observable commitment to monetary policy, they formalize the argument that because it is more transparent, the exchange rate has a natural advantage as an instrument for monetary policy.

The VAR model has been developed to address the fact that most questions of interest to empirical macro- economists involve several variables and thus must be addressed using multivariate times series (MTS) methods. Forecasts from VAR models are superior to those from univariate time series models, quite flexible because they can be made conditional on the potential future paths of specified variables in the models.

3.1 RESEARCH METHODOLOGY

This research paper focuses on the statistical framework of the empirical model of the study. The data type and source of this study employed the secondary macroeconomic time series data in its analysis sourced from Central Bank of Nigeria Statistical Bulletin (Vol. 21 Dec., 2022).

3.2 Unit Root Test

A number of alternative tests are available for testing whether a series is stationary or not. The Augmented Dickey – fuller (ADF) tests was applied where the null hypothesis states that the series is not stationary and this is either accepted or rejected by examination of the t-ratio of the lagged term x_{E-1} compared with the tabulated values. If the t-ratio is less than the critical value the null hypothesis of a unit root (i.e. the series is not stationary) is accepted. If so the first difference of the series is evaluated and if the null hypothesis is rejected the series is considered stationary and the assumption is that the series is integrated of order one 1(1). The ADF regression test is as follows:

$$\Delta x_t = \lambda_0 + \lambda_1 x_{t-1} + \lambda_2 T + \sum_{i=1}^{n} \Psi_i \Delta x_{t-1} + \varepsilon \ldots\ldots (1)$$

Where,

Δ is the difference operator.

x is the natural logarithm of the series

T is a trend variable

λ and Ψ are the parameters to be estimated and

ε is the error term

3.3 Model Specification

Model specification in the present context involves selection of the VAR order. Lutkepohl (2007) because the number of parameters in these models increases with the square of the number of variables it is also often desirable to impose zero restrictions on the parameter matrices and thereby eliminates some lagged variables from some of the equations of the systems.

3.3.1 Lag Length Selection/Choosing the Lag Order

The most common procedures for VAR order selected are sequential testing procedure and application of model selection criteria. For the purpose of this research study the model selection criteria is applied.

3.3.2 Model Selection Criteria

The standard model selection criteria which are used in this context chosen the VAR order which minimizes them over a set of possible orders

$$m = 0, 1\ 2 \ldots\ldots Pmax$$

The general form of a set of such criteria is (Lutkepohl, 2007)

$$C(m) = \log\det\left(\textstyle\sum_m^{\wedge}\right) + CT\varphi(m) \ldots\ldots\ldots\ldots (2)$$

Where,

$\sum_m^{\wedge} = T^{-1}\sum_{t=1}^{T} \hat{u}_t \hat{u}_t'$ is the residual covariance matrix estimator for a model of order m.

φ(m) Is a function of the order m which penalizes large VAR orders.

CT is a sequence which may depend on the sample size and identifies the specific criterion. The term $logdet(\hat{\varepsilon}_m)$is a monincreasing function of the order m which $\varphi(m)$ increases with m.

The lag order is chosen which optimally balances these two forces. Gebhard and Jurgen (2007), to estimate the system, the order p ie the maximal lag of the system has to be determined. The multivariate case with k variables, T observations, a constant term and a maximal lag of p, these criteria are as follows:

Final prediction error (FPE)

$$FPE(P) = \left[\frac{T+kp+1}{T-kp-1}\right]^k / \sum \hat{u}\hat{u}(p) / \ \ldots\ldots\ldots\ldots\ldots\ldots (3)$$

Akaike information criterion (AIC)

$$AIC(p) = In\ / \sum \hat{u}\hat{u}(p) / + (k + pk^2)\frac{2}{T} \ldots\ldots\ldots\ldots\ldots (4)$$

Hannan – Quinn criterion (HQ)

$$HQ(p) = In / \sum \hat{u}\hat{u}(p) / + (k + pk^2)\frac{2In(In(T))}{T} \ldots\ldots (5)$$

Shwarz criterion (SC)

$$SC(p) = In / \sum \hat{u}\hat{u}(p) / + (k + pk^2)\frac{In(T)}{T} \ldots\ldots\ldots\ldots (6)$$

$/ \sum \hat{u}\hat{u}(p) /$ is the determinant of the variance covariance matrix of the estimated residuals.

Again it holds that HQ and SC consistently determine the (finite) order of the true maximal lag, that is the order estimated with these criteria converges in probability or almost surely to true VAR order p while the FPE and AIC tend to overestimate it. This is also reflected in the following relations which because of the different punishing terms hold for these criteria.

i. $\hat{p}(SC) \le \hat{p}(HQ) \le \hat{p}(AIC)$
ii. $\hat{p}(SC) \le \hat{p}(AIC) for T \ge 8$

iii. $\hat{p}(HQ) \leq \hat{p}(AIC) for T \geq 16$

Lutkepohl (2007), AIC suggests the largest order, SC chooses the smallest order and HQ is in between. The choice of the best model is based on the model selection criteria, the minimum model selection criteria compared to others.

3.4 Estimation of VAR Model

Estimating unrestricted reduced form VAR models is straight forwards computation. James and Watson (2001) standard practice in VAR analysis is to report results from Granger – causality test, impulse responses and forecast error variance decompositions. These statistics are computed automatically (or nearly so) by many econometrics and statistics packages (R, E-views and SPSS).

A typical VAR analysis proceeds by specifying and estimating a model and then checking its adequacy. If model defects are detected at the later stage, model revisions are made until a satisfactory model has been found. In order to achieve the objectives of this research a multivariate time series analysis with VAR models can in principle be done with fairly straight forward computation algorithm.

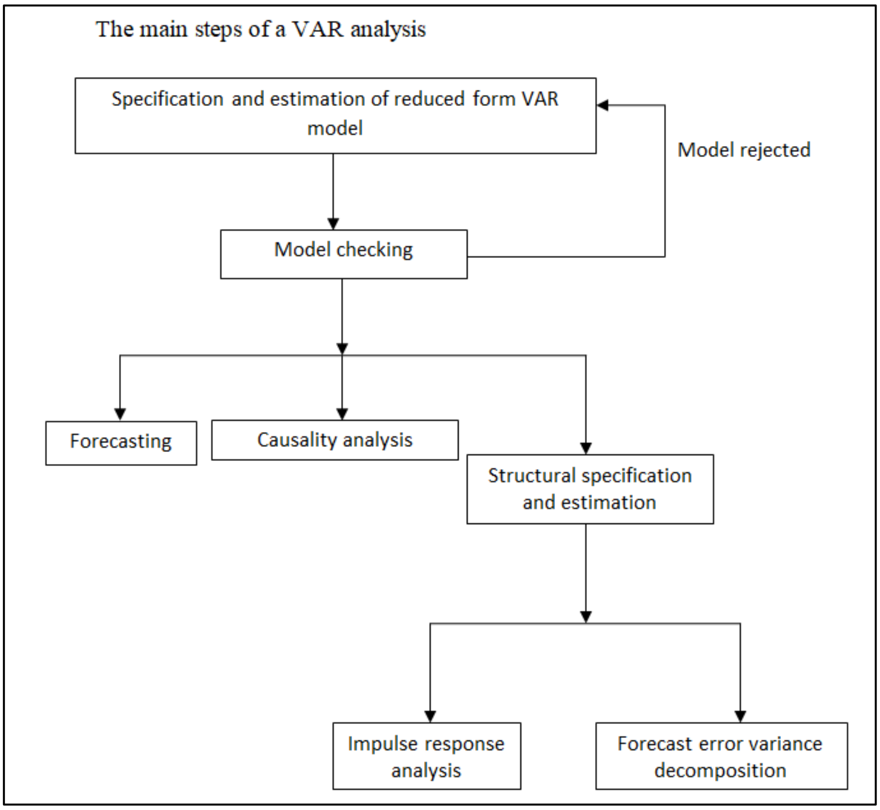

Fig. 1: VAR analysis (figure adapted from Lutkepohl (2007))

Gujarati (2004) VAR methodology superficially resemble simultaneous equation modeling in that it consider several endogenous variables together. But each endogenous variable is explained by its lagged, or past, values and the lagged values of all other endogenous variables in the model, usually, there are no exogenous variables in the model.

3.4.1The Levels VAR Representation

According to Christopher (1980), "if there is true simultaneity among a set of variable, they should all be treated on an equal footing, there should not be any a priori distinction between endogenous and exogenous variables". It is in this spirit that Sims (1980) developed his VAR model.

The stochastic part y_t is a assumed to be generated by a VAR process of order p (VAR (p)) of the form.

$$Y_t = A_{1y_{t-1}} + A_{2y_{t-2}} + \cdots + A_{py_{t-p}} + \mu_t + \varepsilon_t \text{.......... (7)}$$

Where,

$A_i \; \forall i = 1,2, \ldots p$ are (kxk) parameter matrices.

The error process $\mu_t = (\mu_{1t}\mu_{2t}, \ldots \mu_{kt})'$ is a k – dimensional zero mean white noise process with covariance matrix:

$$E(\mu_t, \mu_t') = \varepsilon_\mu$$

In matrix notations the m time series

$y_{it}, i = 1,2, \ldots m$, and $t = 1, \ldots T$

Where,

t is the common length of the time series.

Then a Vector Autoregressive Model is defined as:

$$\begin{pmatrix} Y_{1t} \\ Y_{2t} \\ \vdots \\ Y_{mt} \end{pmatrix} = \begin{pmatrix} \mu_1 \\ \mu_2 \\ \vdots \\ . \\ \mu_m \end{pmatrix} + \begin{pmatrix} A_{11}^{(1)} & A_{12}^{(1)} & A_{1m}^{(1)} \\ A_{21}^{(1)} & A_{22}^{(1)} & A_{2m}^{(1)} \\ \vdots & \vdots & \vdots \\ A_{m1}^{(1)} & A_{m1}^{(1)} & A_{mm}^{(1)} \end{pmatrix} \begin{pmatrix} y_{1,t-1} \\ y_{2,t-1} \\ \vdots \\ y_{m,t-1} \end{pmatrix}$$

$$+ \cdots + \begin{pmatrix} A_{11}^{(p)} & A_{12}^{(p)} & A_{1m}^{(p)} \\ A_{21}^{(1)} & A_{22}^{(1)} & A_{2m}^{(p)} \\ \vdots & \vdots & \vdots \\ A_{m1}^{(p)} & A_{m1}^{(p)} & A_{mm}^{(p)} \end{pmatrix} \begin{pmatrix} y_{1,t-p} \\ y_{2,t-p} \\ \vdots \\ y_{m,t-p} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \vdots \\ \varepsilon_{mt} \end{pmatrix} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (8)$$

Where,

$Y_t = (y_{1t}, y_{2t}, \ldots y_{mt})'$ denote $(nx1)$ vector of time series variables

A_i are (nxn) coefficient matrices

ε_t is an $(nx\,1)$ unobservable zero mean white noise vector process.

3.6 Model Checking

A typical VAR analysis proceeds by specifying and estimating a model and then checking its adequacy if model defects are detected at the later stage, model revisions are made until a satisfactory model has been found. The wide range of procedures is available for checking the adequacy of VARs. A number of procedures considers the estimated residuals and checks whether they are in line with the white noise assumption. Another set of tests checks the stability of the model over time. In addition to these more formal procedures exist and also many informal procedures based e.g. on plots of residuals and autocorrelations for some of these procedures, Lutkpeohl (2004).

3.7 Forecasting

Forecasting from a VAR (p) is a straight forward extension of forecasting from an Autoregressive (p). The multivariate wold form is (Sims, 1986)

$Y_t = \mu + \varepsilon_t + \Psi_1 \varepsilon_{t-1} + \Psi_2 \varepsilon_{t-2} + \cdots, \ldots\ldots\ldots\ldots\ldots (9)$

$Y_t = \mu + \varepsilon_t + \Psi_1 \varepsilon_{t+h-1} + \cdots + \Psi_{h-1} \varepsilon_{t+1}, \ldots\ldots\ldots (10)$

Noted that

$$E(Y_t) = \mu$$

$$Var(Y_t) = E[(Y_t - \mu)(Y_t - \mu)']$$

$$= E\left[\left(\sum_{k=1}^{\infty} \Psi_k \varepsilon_{t-k}\right)\left(\sum_{k=1}^{\infty} \Psi_k \varepsilon_{t-k}\right)^{/}\right]$$

$$= \sum_{k=1}^{\infty} \Psi_k \sum \Psi_k^{/}$$

The minimum MSE linear forecast of Y_{t+h} based on it is

$Y_{t+h}/t = \mu + \Psi_h \varepsilon_t + \Psi_{h+1} \varepsilon_{t-1} + \cdots, \ldots\ldots\ldots\ldots\ldots (11)$

The forecast error is

$\varepsilon_{t+h/t} = Y_{t+h} - Y_{t+h/t}, \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. \ldots. (12)$

The forecast error MSE is

$MSE\left(\varepsilon_{t+\frac{h}{t}}\right) = E[\varepsilon_{t+h/t} \varepsilon_{t+h/t}'] \ldots\ldots\ldots\ldots\ldots\ldots.. (13)$

$$= \sum + \Psi_1 \sum \Psi_1^{/} + \cdots + \Psi_{h-1} \sum \Psi_{h-1}^{/}$$

$$= \sum_{s=1}^{h-1} \Psi_s \sum \Psi_s^{/}$$

4.1 RESULT

The VAR Model:

===============================

LNEXCHGRATE = C(1,1)*LNEXCHGRATE(-1) + C(1,2)*LNEXCHGRATE(-2) + C(1,3)*LNGDP(-1) + C(1,4)*LNGDP(-2) + C(1,5)*LNMOSUPPLY(-1) + C(1,6)*LNMOSUPPLY(-2) + C(1,7)

LNGDP = C(2,1)*LNEXCHGRATE(-1) + C(2,2)*LNEXCHGRATE(-2) + C(2,3)*LNGDP(-1) + C(2,4)*LNGDP(-2) + C(2,5)*LNMOSUPPLY(-1) + C(2,6)*LNMOSUPPLY(-2) + C(2,7)

LNMOSUPPLY = C(3,1)*LNEXCHGRATE(-1) + C(3,2)*LNEXCHGRATE(-2) + C(3,3)*LNGDP(-1) + C(3,4)*LNGDP(-2) + C(3,5)*LNMOSUPPLY(-1) + C(3,6)*LNMOSUPPLY(-2) + C(3,7)

The VAR Model - Substituted Coefficients:

===============================

LNEXCHGRATE = 0.59548730552*LNEXCHGRATE(-1) + 0.319974470961*LNEXCHGRATE(-2) + 0.367526510723*LNGDP(-1) - 0.231061307713*LNGDP(-2) + 0.0447754212898*LNMOSUPPLY(-1) + 0.0010929443574*LNMOSUPPLY(-2) - 1.69430127915

LNGDP = 0.022183655119*LNEXCHGRATE(-1) + 0.0113273523027*LNEXCHGRATE(-2) + 1.03874506378*LNGDP(-1) - 0.0886905338477*LNGDP(-2) + 0.206989378779*LNMOSUPPLY(-1) - 0.200463035614*LNMOSUPPLY(-2) + 0.326732013178

LNMOSUPPLY = - 0.0403355819021*LNEXCHGRATE(-1) + 0.0279940160138*LNEXCHGRATE(-2) + 0.0748333849365*LNGDP(-1) + 0.0359932391131*LNGDP(-2) + 0.589253114415*LNMOSUPPLY(-1) + 0.388316311799*LNMOSUPPLY(-2) - 0.839336454152

Table 1: Vector Autoregressive Estimates

Date: 12/18/22 Time: 15:55			
Sample (adjusted): 4 164			
Included observations: 161 after adjustments			
Standard errors in ( ) & t-statistics in [ ]			
	LNEXCHGRATE	**LNGDP**	**LNMOSUPPLY**
LNEXCHGRATE(-1)	0.595487	0.022184	-0.040336
	(0.07641)	(0.02737)	(0.02352)
	[7.79326]	[0.81048]	[-1.71465]
LNEXCHGRATE(-2)	0.319974	0.011327	0.027994
	(0.07614)	(0.02727)	(0.02344)
	[4.20255]	[0.41533]	[1.19427]
LNGDP(-1)	0.367527	1.038745	0.074833
	(0.22430)	(0.08035)	(0.06905)
	[1.63855]	[12.9284]	[1.08369]
LNGDP(-2)	-0.231061	-0.088691	0.035993
	(0.24204)	(0.08670)	(0.07452)
	[-0.95464]	[-1.02296]	[0.48303]
LNMOSUPPLY(-1)	0.044775	0.206989	0.589253
	(0.24559)	(0.08797)	(0.07561)
	[0.18232]	[2.35293]	[7.79359]
LNMOSUPPLY(-2)	0.001093	-0.200463	0.388316
	(0.24271)	(0.08694)	(0.07472)
	[0.00450]	[-2.30577]	[5.19687]
C	-1.694301	0.326732	-0.839336
	(0.95829)	(0.34327)	(0.29502)
	[-1.76805]	[0.95183]	[-2.84498]
R-squared	0.918684	0.948366	0.991630
Adj. R-squared	0.915516	0.946354	0.991304
Sum sq. resids	79.71289	10.22819	7.555254
S.E. equation	0.719455	0.257715	0.221495
F-statistic	289.9759	471.4217	3040.975
Log likelihood	-171.8598	-6.570399	17.81337
Akaike AIC	2.221860	0.168576	-0.134328
Schwarz SC	2.355835	0.302550	-0.000353
Mean dependent	5.739450	11.72701	13.65953
S.D. dependent	2.475240	1.112683	2.375261
Determinant resid covariance (dof adj.)		0.001527	
Determinant resid covariance		0.001337	
Log likelihood		-152.6295	
Akaike information criterion		2.156888	
Schwarz criterion		2.558810	
Number of coefficients		21	

Table 2: VAR Residual Normality Tests

Orthogonalization: Cholesky (Lutkepohl)				
Null Hypothesis: Residuals are multivariate normal				
Date: 12/18/22 Time: 16:33				
Sample: 1 164				
Included observations: 161				
Component	Skewness	Chi-sq	df	Prob.*
1	1.281361	44.05729	1	0.0000
2	0.931410	23.27860	1	0.0000
3	2.198670	129.7163	1	0.0000
Joint		197.0522	3	0.0000
Component	Kurtosis	Chi-sq	df	Prob.
1	11.34592	467.2653	1	0.0000
2	25.69700	3455.823	1	0.0000
3	25.66918	3447.357	1	0.0000
Joint		7370.445	3	0.0000
Component	Jarque-Bera	df	Prob.	
1	511.3226	2	0.0000	
2	3479.101	2	0.0000	
3	3577.073	2	0.0000	
Joint	7567.497	6	0.0000	
*Approximate p-values do not account for coefficient estimation				

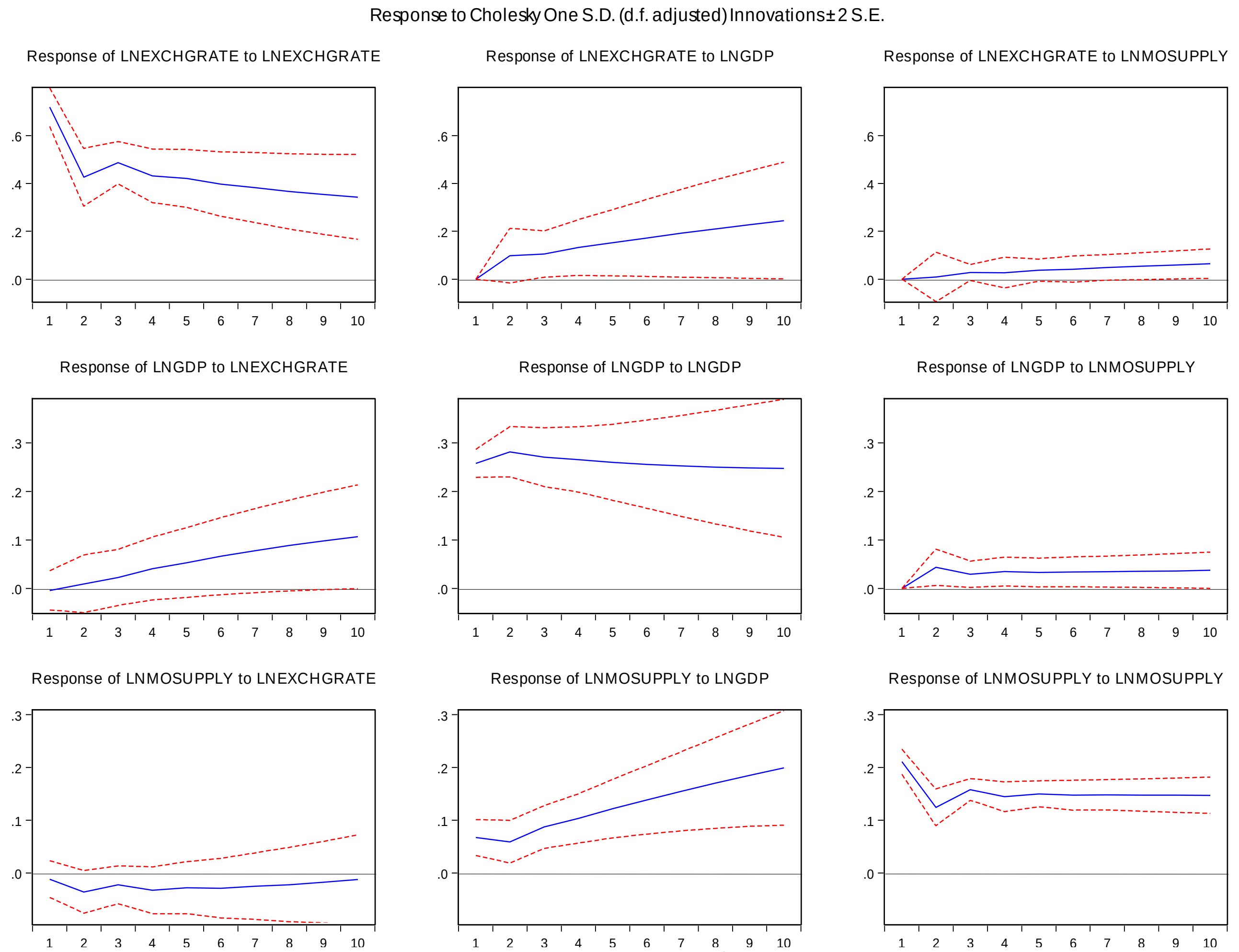

Fig. 2: The Impulse Response Analysis Graph of the Economic Variables

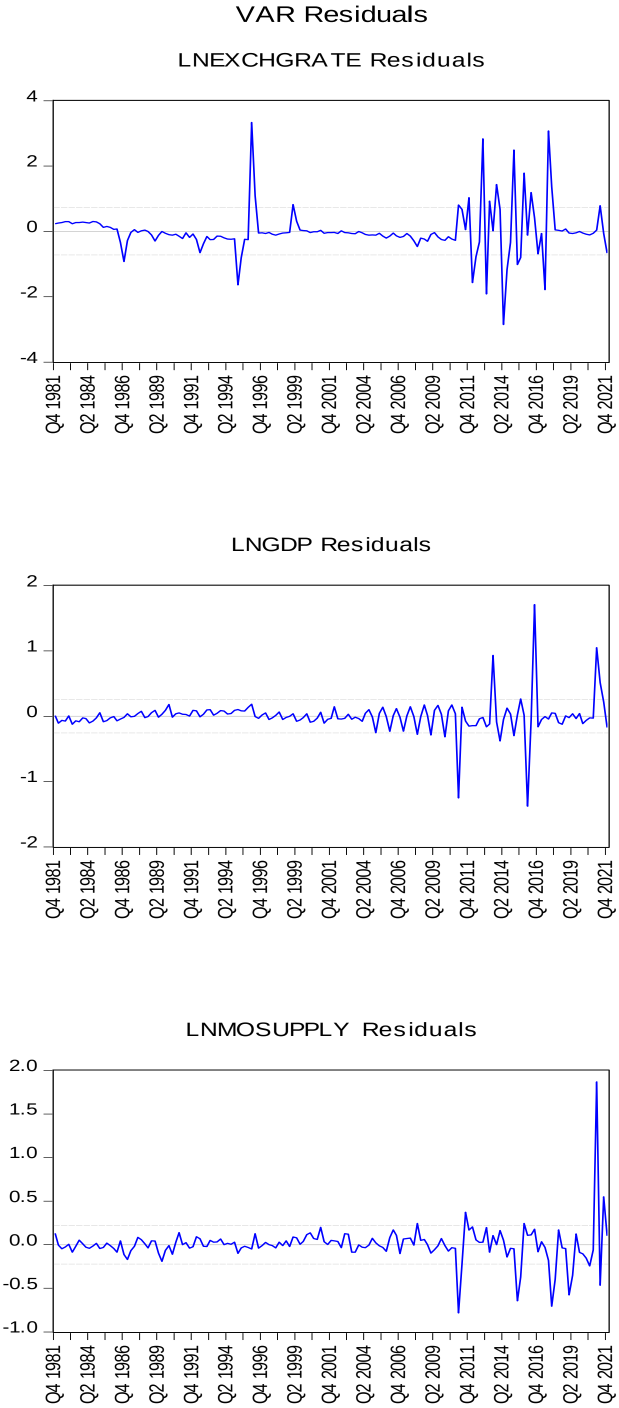

Fig. 3: The Plot of VAR Residual of the Economic Variables

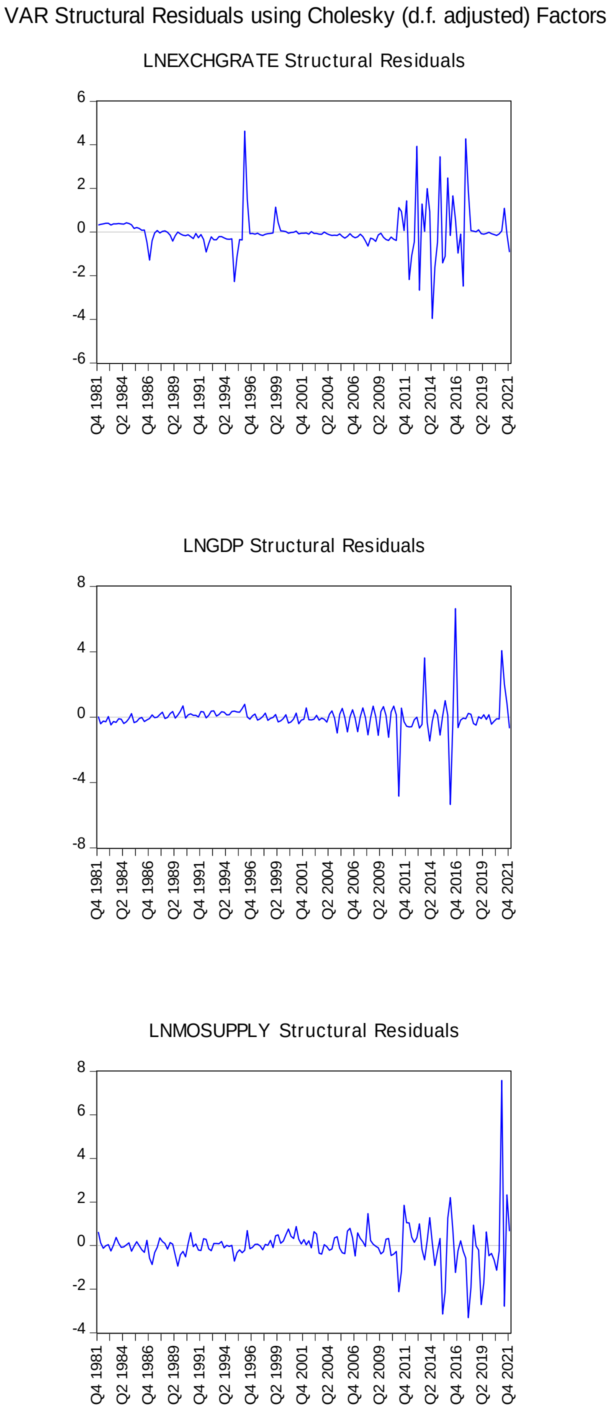

Fig. 4: The Plot of VAR Structural Residual Via Cholesky Factor

CONCLUSION

The study of economic growth provides you with both a theoretical and empirical understanding of how these factors (economic indicators) combine to provide the right recipe for a country's long-run growth. The research paper models the economic indicators of gross domestic product, money supply and exchange rate of quarterly data from 1981 to 2021 in Nigeria. The study yields a stable vector autoregressive model with stationary process and the estimate of the model where significant. The empirical result yields a sustainable economic model for the three economic variables in the study. The unit root test was achieved at order 1 and the inverse root of the polynomial lies within the unit circle. The iterative step of time series analysis, the computational algorithm of VAR with the model adequacy with respect to the plot of residual of the economic indicators was achieved. The inverse of the characteristics polynomial of the variables lies within the unit circle, the response impulse analysis are within the boundaries of estimation. The study also yields R-square that best describe the fit, with RMSE, MAE and MAPE of the three economic variables. The forecast evaluation analysis was obtained.

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APPENDIX

Table 3: Forecast Evaluation

Date: 12/18/22 Time: 16:46					
Sample: 1 164					
Included observations: 164					
Variable	Inc. obs.	RMSE	MAE	MAPE	Theil
LNEXCHGRATE	164	3.098602	2.168544	25.05175	0.206446
LNGDP	164	1.967157	1.183580	7.582335	0.079003
LNMOSUPPLY	164	2.893481	1.572653	8.072393	0.098106
RMSE: Root Mean Square Error					
MAE: Mean Absolute Error					
MAPE: Mean Absolute Percentage Error					
Theil: Theil inequality coefficient					

Table 4: Roots of Characteristic Polynomial

Endogenous variables: LNEXCHGRATE	
LNGDP LNMOSUPPLY	
Exogenous variables: C	
Lag specification: 1 2	
Root	Modulus
0.027395	0.027395
0.955758	0.955758
0.907742	0.907742
-0.429898	0.429898
-0.293536	0.293536
0.057607	0.057607
Warning: At least one root outside the unit circle.	
VAR does not satisfy the stability condition.	

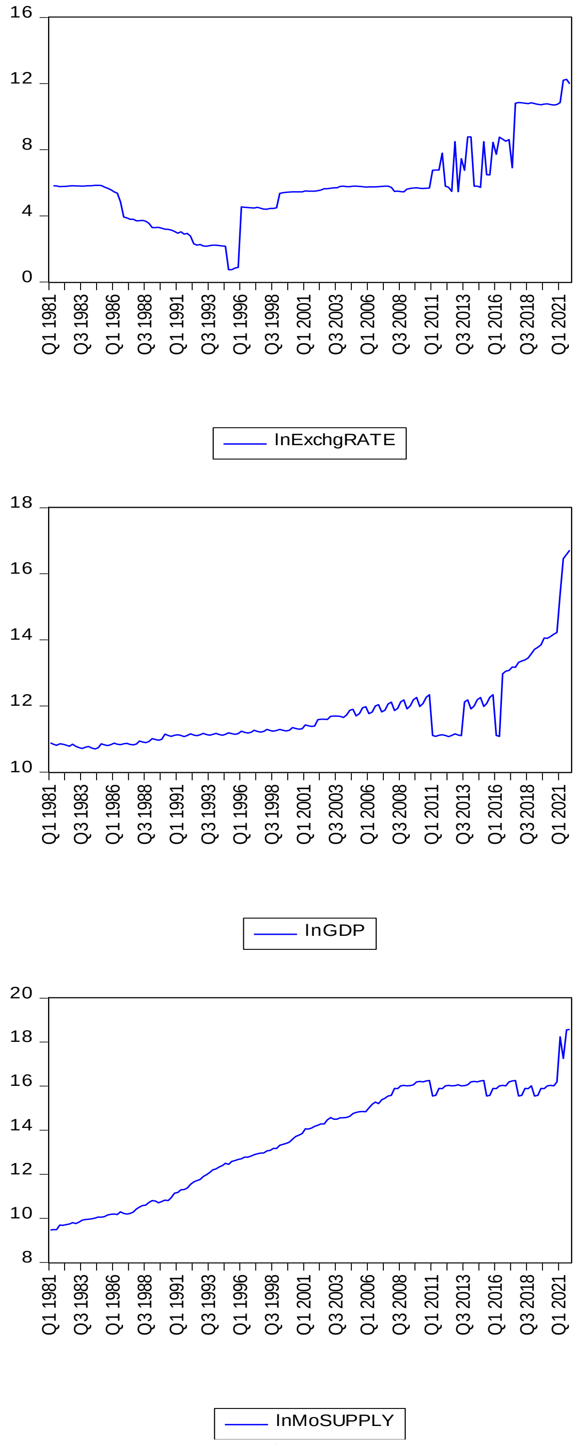

Fig. 5: The Original Plot of the three Economic Variables

Table 5: UNIT ROOT TEST EXCHANGE RATE

Null Hypothesis: D(LNEXCHGRATE) has a unit root			
Exogenous: Constant			
Lag Length: 0 (Automatic - based on SIC, maxlag=13)			
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-18.29574	0.0000
Test critical values:	1% level	-3.470934	
	5% level	-2.879267	
	10% level	-2.576301	
*MacKinnon (1996) one-sided p-values.			

Table 6: UNIT ROOT TEST GDP

Null Hypothesis: D(LNGDP) has a unit root			
Exogenous: Constant			
Lag Length: 1 (Automatic - based on SIC, maxlag=13)			
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-11.82625	0.0000
Test critical values:	1% level	-3.471192	
	5% level	-2.879380	
	10% level	-2.576361	
*MacKinnon (1996) one-sided p-values.			

Table 7: UNIT ROOT TEST MONEY SUPPLY

Null Hypothesis: D(LNMOSUPPLY) has a unit root			
Exogenous: Constant			
Lag Length: 0 (Automatic - based on SIC, maxlag=13)			
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-17.91180	0.0000
Test critical values:	1% level	-3.470934	
	5% level	-2.879267	
	10% level	-2.576301	
*MacKinnon (1996) one-sided p-values.			

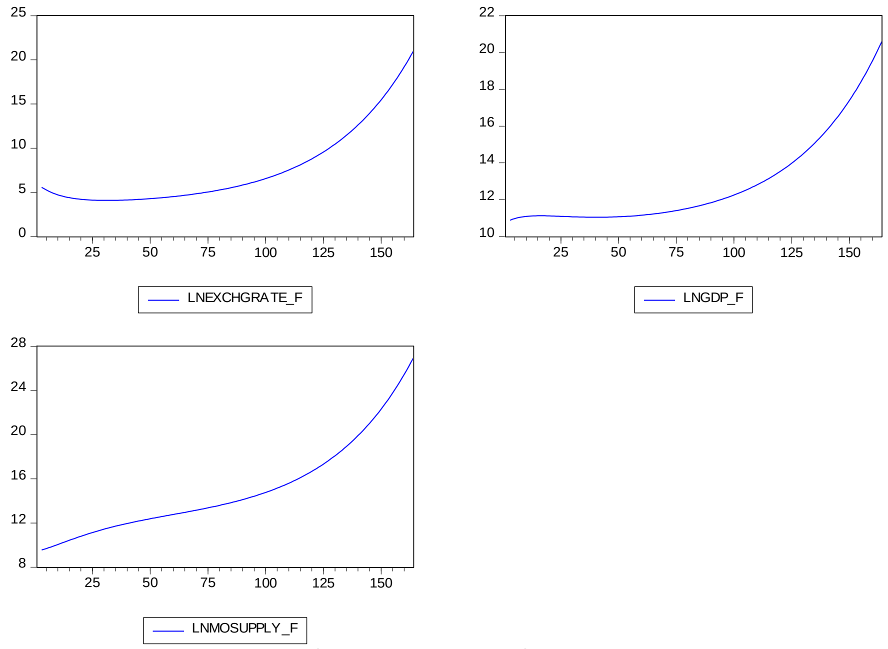

Fig. 6: The Plot of the Forecast Values of the Economic Variable

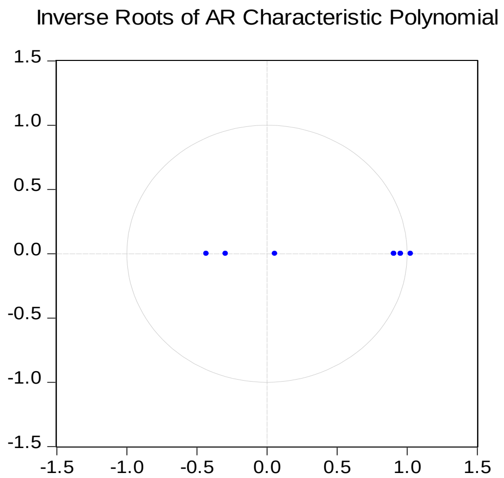

Fig. 7: AR Characteristic Polynomial of the endogenous graph of the all the economic variables