VECTOR AUTOREGRESSIVE MODELLING OF THE INTERACTION AMONG MACROECONOMIC STABILITY VARIABLES IN NIGERIA (1981-2016)

Abstract

Economic stability is an essential macroeconomic goal for nations all over the world. This informed the desire by macroeconomic managers and investors alike for stable macroeconomic proxy variables. However, the dynamic behaviour of these variables particularly their; evolution, interaction and interdependence obviously cause shocks among themselves. This study therefore, is a multivariate time-series modelling and investigation of the interaction and pattern of causality among exchange rates, inflation rate, interest rates, and implicit price deflator in Nigeria using unrestricted Variance Autoregression (VAR). Quarterly data on the study variables from 1981 to 2016 were sourced from CBN Statistical bulletin and used for the study. Augmented Dickey Fuller Test (constant, and constant & linear trend) results showed that all variables were 1(1) except interest rate 1(0) and implicit price deflator 1(2). The inverse root of AR characteristic polynomial showed that the VAR model was stable. The Trace Statistics and Max Eigen result showed no co-integrating relationship. The Schwarz Information Criterion showed a lag length of 2. The VAR estimates indicated that the exchange rate as well as inflation rates were significantly affected by their first lag, while exchange rate was significantly affected by its first and second lag. The system analysis particularly the Wald statistics showed that both lags of each variable were jointly significant in affecting itself. The impulse response showed that all variables were instantaneously affected by own shocks, however, it ruled out the response in exchange rate to contemporaneous shocks in inflation rate, interest rate and implicit price deflator. The variance decomposition further showed that at least 80% of the impulse response were from own shocks. It was consequently recommended that government should regulates these variables particularly interest rates and exchange rates while implicit price deflator and inflation rate should be stabilise.

Keywords: VAR, Impulse Response, Variance decomposition, Grangers Causality, Economic Stability

I. INTRODUCTION

Nigeria like other developing countries traditionally experienced macroeconomic instability. Conceptually, macroeconomic instability refers to a volatile macroeconomic condition. It is a phenomenon that makes the domestic macroeconomic environment less predictable. This is of concern because unpredictability hampers resource allocation decisions, investment, and growth.

Economic stability refers to absence of excessive fluctuation in key macroeconomic variables. An economy with fairly constant growth rate, low and fairly stable inflation, low and fairly stable interest rate, adequate and stable exchange rate. The World Bank describes a macroeconomic framework as stable "when the inflation rate is low and predictable, real interest rates are appropriate, the real exchange rate is competitive and predictable ... and the balance of payments situation is perceived as viable" (World Bank, 1990).

Economists obviously rely on multiple measures to achieve or guide stability, this paper analyses the maintenance or distortion in stability arising from the interaction among the identified stability variables using VAR approach.

Vector Autoregression (VAR)

Vector autoregression (VAR) is a technique used by macroeconomists to illustrate the joint dynamic behaviour of a collection of variables without requiring strong restrictions as required in the identification of fundamental structural parameters. VAR is an established method of time-series modelling; it has gained so much popularity since its introduction by Sims (1980).

VAR is a natural extension of the univariate autoregressive model; it depicts the dynamic behaviours of multivariate time series. The VAR model has proven to be very useful for financial time series, forecasting and describing the dynamic behaviour of economic time series. It often provides superior forecasts to models from univariate time series (Garba et el., 2017). Forecasts from VAR models are quite flexible because they can be made conditional on the potential future paths of specified variables in the model.

Although some useful applications of the estimates such as impulse-response functions (IRFs) or variance decompositions do require identifying restrictions, estimating the equations of a VAR does not require strong identification assumptions. Restrictions take the form of an assumption about the dynamic relationship between a pair of variables, for example, that exchange rate affect inflation rate only with a lag, or that exchange rate does not affect inflation rate in the long run.

A VAR system contains a set of *m* variables, each of which is expressed as a linear function of *p* lags of itself and of all of the other *m* – 1 variables, including an error term.

VAR is a multivariate autoregressive linear time series model of the form

$$Y_t = \alpha + \sum_{i=1}^{p} \alpha_i Y_{t\text{-}i} + \varepsilon_t \qquad (1)$$

Where; Y_t a set of n time series variables $Y_t = (Y_{t1}, Y_{t2}, \ldots, Y_{nt})$, is a nx1 Vector, α_i are full rank mxm matrix of coefficients, and i = 1, 2, 3,… , p,

$U_t = (U_{t1}, U_{t2}, \ldots, U_{nt})$ is an unobservable i.i.d. zero mean error term.

The reduced form of the unrestricted VAR model is a good approximation for the dynamic process of any vector of time series. This VAR estimation assumed a simple model for the stability variables of Nigerian economy with four endogenous variables: Exchange rate, Inflation rate, Interest rate, and implicit price deflator; the mathematical representation of a reduced form four variable

II. LITERATURE REVIEW

Enders (1995), Lutkepol (2001), Lutkepol (2003) like other proponents of VAR suggest that in the forecasts of economic indicators, VAR models should be used as all variables in the models are endogenous, therefore, not a single variable may be removed when explanations for the behaviour of other variables are offered.

(Domac, (2003), used VAR to study the relationship between the exchange rate, inflation, inflation expectations and money supply growth in 53 developing countries using annual data from 1964-1998 to test the level of causality between the aforementioned economic variables. The results from his work showed that 67% of the variances in the rate of inflation in both long run and short run was explained by exchange rate depreciation and expected inflation explained about 10- 20% of movements in the rate of current inflation both in the short run and long run

Garba, Yahya, Babaita, Bankooko, and Amobi (2017) used VAR to model the structural relationships of exchange rates, of Naira to foreign currencies and concluded that Granger causality have been found useful in determining if one time series can be used in forecasting another, because it goes beyond correlation.

III. MATERIALS AND METHODS

3.1. Test for Stationarity

Time series data are often non stationary, however, the assumption of stationarity of the regressors and the regressand are crucial for the adoption of the Least Squares estimators (Etuck, 2012) in (Tuaneh & Essi, 2017). (Tuaneh, & Essi 2017) noted that the Stationarity of a series can strongly influence its behaviour, consequently, the use of non-stationary data can lead to spurious regression. Time series data on all variables included in the model are required to be stationary in order to carry out joint significant test on the lags of the variables. (Gujarati, 2013) explained that the various methods often used to test for stationarity; Augumented Dicky Fuller, the Philip Peron test, and the graphical method (the correlogram). The study however adopted the; Augmented Dickey Fuller Unit Root Test.

Augmented Dickey-Fuller (ADF) unit root test was employed to determine the order of integration of the series (i.e. to investigate the stationary status of each variable). The test is the *t*-statistic on the parameters. The following unit root tests regression equations are used for the first difference of the variables;

$$\Delta EXR_t = \tau_{11} + \tau_{12} \sum_{t-1}^{k} p_i \, \Delta EXR_{t-1} + \mu_{t1} \quad (2)$$

$$\Delta IFR_t = \tau_{21} + \tau_{22} \sum_{t-1}^{k} p_i \, \Delta IFR_{t-1} + \mu_{t2} \quad (3)$$

$$\Delta ITR_t = \tau_{31} + \tau_{32} \sum_{t-1}^{k} p_i \, \Delta ITR_{t-1} + \mu_{t3} \quad (4)$$

$$\Delta IPD_t = \tau_{41} + \tau_{42} \sum_{t-1}^{k} p_i \, \Delta IPD_{t-1} + \mu_{t1} \quad (5)$$

Where: Δ is the difference operator

U_t = random terms, t = time, k = number of lagged differences.

ρ_i= coefficient of the preceding observation, ($_{t-1}$) is the immediate prior observation, k is the number of lags, while τ_{11} - τ_{42} are the parameters to be determined.

The null hypothesis is that the series has a unit root 1(0), if 'τ' is found to be more negative and statistically significant. We compare the *t*-statistic value of the parameter, with the critical value tabulated in (MacKinnon, 1991), We reject the null and conclude that the series do not have a unit root at levels

3.2. Co-integration Test:

After examining the unit root of the study variables, and the order of integration of the series known, it is necessary to determine if there is a long run cointegrating relationship, since only variables that are of the same order of integration may constitute a potential cointegrating relationship.

Regression of one variable time series on one or more variables time series often can give spurious results; to guard against this is to find out if the series are cointegrated. Cointegration means despite being individually non-stationary, a linear combination of two or more time series can be stationary. This means subjecting these time series individually to unit root analysis and finding out if both are I (1) – non-stationary. Cointegration suggests that there is long-run or equilibrium relationship between them. To test whether the linear combination of the series that are non-stationary in levels are cointegrated (i.e. possesses a long-run equilibrium relationship). We employ the Johansen (1991), procedure of testing for a cointegrating relationship in a system of equations. The number of significant cointegrating vectors in nonstationary time series are tested by using the maximum likelihood based λtrace and λmax statistics introduced by Johansen and Juselius (1990). The stationary linear combination is called the cointegrating equation and interpreted as a long run relationship among the variables.

3.3. Models Specification-

Adapting equation (1) in the following VAR model form:

$$\mathbf{U\ (VAR) = (EXR,\ INFL,\ INTR,\ IPD)} \qquad \mathbf{(7)}$$

With the lagged values of the endogenous variables and a constant being the exogenous variables, the VAR, may be written as:

$$EXR_t = \Gamma_{11(i)}EXR_{t-i} + \Gamma_{12(i)}IFR_{t-i} + \Gamma_{13(i)}ITR_{t-i} + \Gamma_{14(i)}IPD_{t-i} + K_1 + \epsilon_{1t} \qquad (8)$$

$$IFR_t = \Gamma_{21(i)}EXR_{t-i} + \Gamma_{22(i)}IFR_{t-i} + \Gamma_{23(i)}ITR_{t-i} + \Gamma_{24(i)}IPD_{t-i} + K_2 + \epsilon_{2t} \qquad (9)$$

$$ITR_t = \Gamma_{31(i)}EXR_{t-i} + \Gamma_{32(i)}IFR_{t-i} + \Gamma_{33(i)}ITR_{t-i} + \Gamma_{34(i)}IPD_{t-i} + K_3 + \epsilon_{3t} \qquad (10)$$

$$IPD_t = \Gamma_{41(i)}EXR_{t-i} + \Gamma_{42(i)}IFR_{t-i} + \Gamma_{43(i)}ITR_{t-i} + \Gamma_{44(i)}IPD_{t-i} + K_4 + \epsilon_{4t} \qquad (11)$$

One key feature of the equation is that no current time variables appear on the right-hand side of any of the equations. This makes it plausible, though not always certain, that the repressors are weakly exogenous.

However, equations (9) – (12) will be estimated if the variables are stationary at levels, in which case any shock to the stationary variables will be temporary. If the variables are nonstationary and not cointegrated, then they have to be transformed into stationary variables by differencing, if the variables are stationary after first difference and co-integrated then VAR can be transformed to vector error correction model (VECM).

3.4. VAR Lag Length Selection Criteria

The VAR lag length is selected using some model selection criteria. The general approach is to fit VAR models with orders p = 0, 1, 2,.... ,Pmax and choose the value of p which minimizes the model selection criteria (Lutkepohl, 2005). Understanding that choosing too few lags could lead to systematic variation in the residuals whereas, too many lags come with the penalty of fewer degrees of freedom. The optimum or appropriate lag length for the VAR model was concluded based on the VAR lag order selection results in table 1, the researcher consequently concluded that the fit is good at lag 2 according to the Schwarz Information Criteria

Table 1: VAR Lag Order Selection Results

Lag	AIC	SC	HQ

0	39.69855	39.78421	39.73336
1	29.91182	30.77889	30.08589
2	30.00790	30.34015*	30.32121
3	29.54591	30.65958	29.99848
4	29.33480	30.79112	29.92661
5	28.94134*	30.74034	29.67241*
6	29.03831	31.17997	29.90863
7	29.10055	31.58487	30.11012
8	29.23601	32.06300	30.38482

* indicates lag order selected by the criterion

The lag length selection criteria indicated two lags, hence the model above is written as

$$EXR_t = \Gamma 111 EXR_{t-1} + \Gamma 112 EXR_{t-2} + \Gamma 121 IFR_{t-1} + \Gamma 122 IFR_{t-2} + \Gamma 131 INTR_{t-1} + \Gamma 132 INTR_{t-2} + \Gamma 141 IPD_{t-1} + \Gamma\, 142 IPD_{t-2} + K_1 + \varepsilon_{1t} \quad \textbf{(12)}$$

$$IFR_t = \Gamma 211 EXR_{t-1} + \Gamma 212 EXR_{t-2} + \Gamma 221 IFR_{t-1} + \Gamma 222 IFR_{t-2} + \Gamma 231 INTR_{t-1} + \Gamma 232 INTR_{t-2} + \Gamma 241 IPD_{t-1} + \Gamma\, 242 IPD_{t-2} + K_2 + \varepsilon_{2t} \quad \textbf{(13)}$$

$$ITR_t = \Gamma\, 311 EXR_{t-1} + \Gamma 312 EXR_{t-2} + \Gamma\, 321 IFR_{t-1} + \Gamma\, 322 IFR_{t-2} + \Gamma 331 INTR_{t-1} + \Gamma 332 INTR_{t-2} + \Gamma 341 IPD_{t-1} + \Gamma\, 342 IPD_{t-2} + K_3 + \varepsilon_{3t} \quad \textbf{(14)}$$

$$IPD_t = \Gamma 411 EXR_{t-1} + \Gamma 412 EXR_{t-2} + \Gamma 421 IFR_{t-1} + \Gamma 424 IFR_{t-2} + \Gamma 431 INTR_{t-1} + \Gamma 432 INTR_{t-2} + \Gamma 441 IPD_{t-1} + \Gamma 442 IPD_{t-2} + K_4 + \epsilon_{4t} \quad \textbf{(15)}$$

The researcher used Eviews 8 in the statistical data analysis which requires a different model specification, for the purpose of analysis in the Eviews, the model is specified as:

VAR Model Specification (Eviews): LS 1 2 EXR IFR ITR YT @ C

$$EXR = C(1,1)*EXR(-1) + C(1,2)*EXR(-2) + C(1,3)*IFR(-1) + C(1,4)*IFR(-2) + C(1,5)*ITR(-1) + C(1,6)*ITR(-2) + C(1,7)*IPD(-1) + C(1,8)*IPD(-2) + C(1,9)(17) \quad \textbf{(16)}$$

$$IFR = C(2,1)*EXR(-1) + C(2,2)*EXR(-2) + C(2,3)*IFR(-1) + C(2,4)*IFR(-2) + C(2,5)*ITR(-1) + C(2,6)*ITR(-2) + C(2,7)*IPD(-1) + C(2,8)*IPD(-2) + C(2,9) \quad \textbf{(17)}$$

$$ITR = C(3,1)*EXR(-1) + C(3,2)*EXR(-2) + C(3,3)*IFR(-1) + C(3,4)*IFR(-2) + C(3,5)*ITR(-1) + C(3,6)*ITR(-2) + C(3,7)*IPD(-1) + C(3,8)*IPD(-2) + C(3,9) \quad \textbf{(18)}$$

$$IPD = C(4,1)*EXR(-1) + C(4,2)*EXR(-2) + C(4,3)*IFR(-1) + C(4,4)*IFR(-2) + C(4,5)*ITR(-1) + C(4,6)*ITR(-2) + C(4,7)*IPD\,(-1) + C(4,8)*IPD(-2) + C(4,9) \quad \textbf{(19)}$$

The system of equation above can also be presented in Eviews for ease of analysis, explanation and understanding as:

$$EXR = C(1) * EXR(-1) + C(2) * EXR(-2) + C(3) * IFR(-1) + C(4) * IFR(-2) + C(5) * ITR(-1) + C(6) * ITR(-2) + C(7) * IPD(-1) + C(8) * IPD(-2) + C(9) \quad \textbf{(20)}$$

$$IFR = C(10) * EXR(-1) + C(11) * EXR(-2) + C(12) * IFR(-1) + C(13) * IFR(-2) + C(14) * ITR(-1) + C(15) * ITR(-2) + C(16) * IPD(-1) + C(17) * IPD(-2) + C(18) \quad \textbf{(21)}$$

$$\begin{aligned}\text{ITR} = {} & \text{C}(19) * \text{EXR}(-1) + \text{C}(20) * \text{EXR}(-2) + \text{C}(21) * \text{IFR}(-1) + \text{C}(22) * \\ & \text{IFR}(-2) + \text{C}(23) * \text{ITR}(-1) + \text{C}(24) * \text{ITR}(-2) + \text{C}(25) * \text{IPD}(-1) + \text{C}(26) * \\ & \text{IPD}(-2) + \text{C}(27) \qquad \textbf{(22)}\end{aligned}$$

$$\begin{aligned}\text{IPD} = {} & \text{C}(28) * \text{EXR}(-1) + \text{C}(29) * \text{EXR}(-2) + \text{C}(30) * \text{IFR}(-1) + \text{C}(31) * \\ & \text{IFR}(-2) + \text{C}(32) * \text{ITR}(-1) + \text{C}(33) * \text{ITR}(-2) + \text{C}(34) * \text{IPD}(-1) + \text{C}(35) * \\ & \text{IPD}(-2) + \text{C}(36) \qquad \textbf{(23)}\end{aligned}$$

This is an indication that 36 parameters would be estimated. The square of the number of variables multiplied by the number of lags plus the number of variables $[(4^2)2 + 4] = 36$

IV. RESULTS

4.1 Time Plots

The time plots shown in figure 1 to figure 4 are indications that all variables showed fluctuations within the period of the study, no variable followed a steady trend.

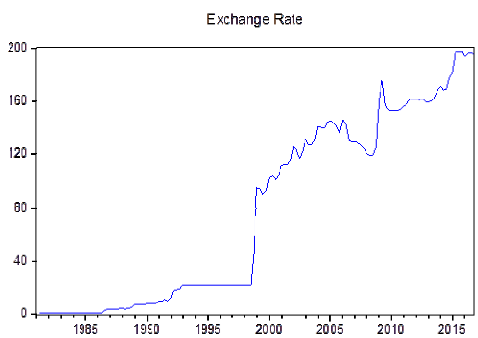

Figure 1: Time plot of Exchange Rate

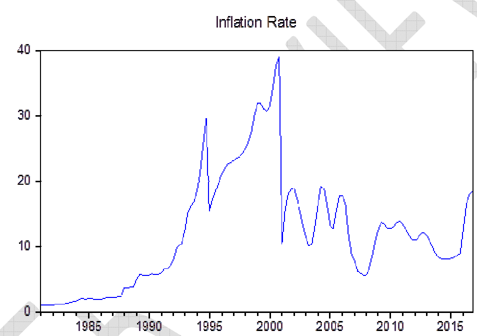

Figure 2: Time plot of Inflation Rate

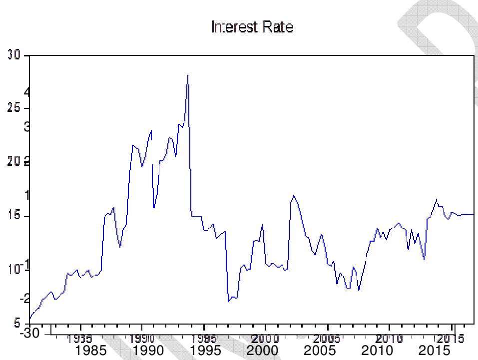

Figure 3: Time plot of Interest Rate

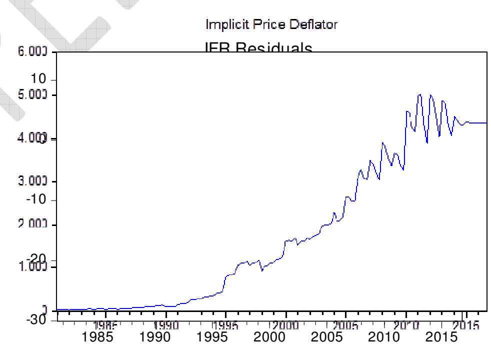

Figure 4: Time plot of Implicit Price

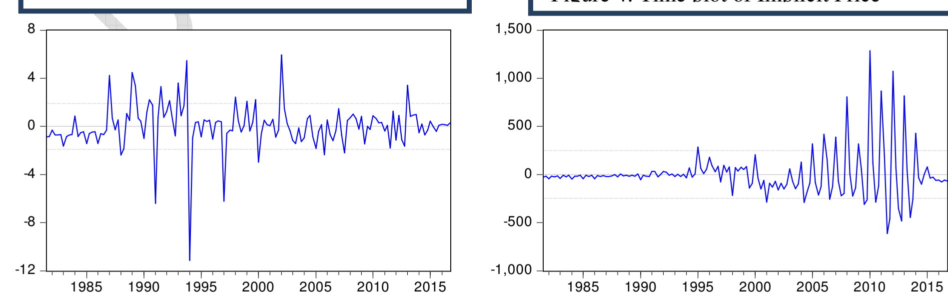

Figure 5: Residual Plots at levels on all Variables

4.2. Diagnostic Test Results

4.2.1. Unit Root Test Result

Since the study variables involved time series data, the Johansen technique cannot be applied unless it is established that the variables concerned are stationary. Data on each series were tested for stationarity so as to avoid the problem of spurious regression (Tuaneh and Essi, 2017). For this study, the Augmented Dickey-Fuller (ADF) test was used to test the null hypothesis of a unit root. The null hypothesis of a unit root is rejected in favour of the stationary alternative in each case if the test statistic is more negative than the critical value. A rejection of the null hypothesis means that the series do not have a unit root.

Table 2 presents results of the unit root tests, p-values are in brackets. The results showed that at levels, all variables had unit root (p-values > 0.05), however, all variables do not have unit root at levels (t-values more negative than the test statistics at 99% confidence, more so p-values are less than 0.05 level of significance at both intercept, and Constant & trend, consequently the null hypothesis of unit roots were rejected. Conclusively, Exchange rate, Inflation Rate, Interest Rate and Implicit price deflator were stationary at order 1(1).

Table 2: Augmented Dickey-Fuller Unit Root Test Result

Variables	Levels		1st Difference		Order of Integration
	Constant	Constant, Linear Trend	Constant	Constant, Linear Trend	
Exchange Rate (EXR_t)	0.0538(0.96)	-2.3907(0.38)	-6.6041 (0.000)	-6.6435 (0.000)	1(1)
Inflation Rate (IFR_t)	-2.2331(0.19)	-2.2931(0.43)	-9.6703 (0.000)	-9.6426 (0.000)	1(1)
Interest Rate (ITR_t)	-3.0371(0.03)	-2.9982(0.13)	-9.9293 (0.000)	-9.9090 (0.000)	1(1)
Implicit Price Deflator (IPD_t)	0.0942(0.96)	-2.2261(0.47)	-4.8860 (0.000)	-4.9357 (0.000)	1(1)

Test critical values:	*%level*	*Constant*	*Constant, Linear Trend*
	1% level	*-3.4768*	*-4.0239*
	5% level	*-2.8818*	*-3.4417*
	10%level	*-2.5776*	*-3.1454*

4.2.2. Co-integration Test Result

The long run combination of stationary processes can be non stationarity. Cointegration exists if two variables have a long run or equilibrium, relationship between them. This study employs the Johansen maximum likelihood approach to test for co-integration. Though trace statistic is said to be more robust to both skewness and excess kurtosis in residuals than the maximum-eigen value test, the Johansen maximum likelihood approach is said to be more preferable to the other methods due to its properties (Wassell and Saunders, 2000) the researcher consequently used both maximum-eigen test and the trace statistics .

Table 3 showed the result of the λ_{trace} and λ_{max} statistics respectively. Max-eigenvalue test and Trace test indicates no co-integration at the 0.05 level

Table 3: Johansen Co-integration Test Result

Hypothesized		Trace	0.05		Max-Eigen	0.05	
No. of CE(s)	Eigenvalue	Statistic	Critical Value	*P***	Statistic	Critical Value	*P.***
None	0.1225	38.0860	47.8561	*0.2983*	18.0379	27.5843	*0.4920*
At most 1	0.0912	20.0481	29.7970	*0.4196*	13.2054	21.131	*0.4335*
At most 2	0.0480	6.8427	15.4947	*0.5960*	6.7938	14.264	*0.5138*
At most 3	0.0003	0.0489	3.8414	*0.8249*	0.0489	3.8414	*0.8249*

Max-eigenvalue test and Trace test indicates no co-integration at the 0.05 level

4.3. VAR Analysis Result of the Contemporaneous Coefficients

$$\mathrm{EXR}_t = \mathbf{1.25}\mathrm{EXR}_{t-1} - \mathbf{0.29}\mathrm{EXR}_{t-2} + \mathbf{0.26}\mathrm{IFR}_{t-1} - \mathbf{0.15}\mathrm{IFR}_{t-2} - \mathbf{0.10}\mathrm{ITR}_{t-1} - \mathbf{0.07}\mathrm{ITR}_{t-2} - \mathbf{0.001}\mathrm{IPD}_{t-1} + \mathbf{0.002}\mathrm{IPD}_{t-2} + \mathbf{0.35}$$

$$\mathrm{IFR}_t = \mathbf{0.03}\mathrm{EXR}_{t-1} - \mathbf{0.03}\mathrm{EXR}_{t-2} + \mathbf{0.90}\mathrm{IFR}_{t-1} + \mathbf{0.02}\mathrm{IFR}_{t-2} + \mathbf{0.06}\mathrm{ITR}_{t-1} + \mathbf{0.12}\mathrm{ITR}_{t-2} - \mathbf{0.00007}\mathrm{IPD}_{t-1} + \mathbf{0.0003}\mathrm{IPD}_{t-2} + \mathbf{0.09}$$

$$\mathrm{ITR}_t = \mathbf{0.02}\mathrm{EXR}_{t-1} - \mathbf{0.02}\mathrm{EXR}_{t-2} + \mathbf{0.005}\mathrm{IFR}_{t-1} - \mathbf{0.03}\mathrm{IFRt} - 2 + \mathbf{0.80}\mathrm{ITR}_{t-1} + \mathbf{0.91}\mathrm{ITR}_{t-1} - \mathbf{0.0002}\mathrm{IPD}_{t-1} - \mathbf{0.0002}\mathrm{IPD}_{t-2} + 11.51$$

$$\mathrm{IPD}_t = -\mathbf{1.09}\mathrm{EXR}_{t-1} + \mathbf{3.60}\mathrm{EXR}_{t-2} + \mathbf{0.50}\mathrm{IFR}_{t-1} - \mathbf{1.17}\mathrm{IFR}_{t-2} - \mathbf{2.12}\mathrm{ITR}_{t-1} + 3.\mathbf{99}\mathrm{ITR}_{t-2} + \mathbf{0.82}\mathrm{IPD}_{t-1} + \mathbf{0.06}\mathrm{IPD}_{t-2} + \mathbf{39.94}$$

The estimated model (substituted coefficients) above is a representation of the detail VAR estimation output. The estimates of the coefficients of multiple determinations (R^2) of the models were respectively 0.992, 0.883, 0.808, and 0.979 respectively indicating that the dependent variables were largely explained by the independent variables. The Durbin Watson statistics were 1.82, 2.03, 2.03, and 2,12 respectively, hence there was no reason to suspect serial autocorrelation. The VAR estimates indicate that exchange rate, inflation rates, interest rates, and implicit price deflator were positively and significantly affected by their own first lags. Only exchange rate was significantly affected by its own second lag. The system analysis particularly the Wald statistics showed that both lags of each variable were jointly significant in affecting itself.

The VAR result above satisfy the stability condition as no root lies outside the unit root circle as shown in graph of the inverse roots of a characteristic polynomial in figure 6 below. More so, the table 4 showed that the modulus less than one but greater than zero

Table 4: Roots of Characteristic Polynomial (Endogenous variables: EXR IFR ITR IPD, Exogenous variables: C)

Root	Modulus
0.997994	0.997994
0.919457 - 0.043599i	0.920490
0.919457 + 0.043599i	0.920490
0.836571	0.836571
0.357837	0.357837
-0.091403	0.091403
-0.074191 - 0.049922i	0.089423
-0.074191 + 0.049922i	0.089423

No root lies outside the unit circle.

VAR satisfies the stability condition.

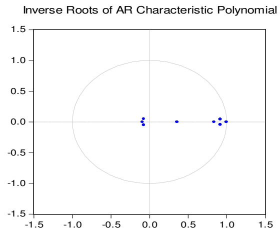

Figure 6: Inverse roots of a Characteristic Polynomial

4.4. Granger Causality

The granger causality test conducted and the summary result presented in table 5 below showed that only the combine lags (lag 1 and lag 2) of exchange rates granger caused implicit price deflator (PV = 0.022 < 0,05). Inflation rates (lag 1 and lag 2) taken together do not granger cause exchange rates, interest rates and implicit price deflator taken diagonally from top to bottom. Similarly, the lags of interest rates jointly do not granger cause exchange rates, inflation rates and implicit price deflator. The probability values in the last column of table 3 indicate that the lags of all the independent variables taken together do not granger cause the dependent variables.

Most notably, the combine lags of each variable significantly affected itself. Exchange rates (lag 1and lag 2) significantly caused current exchange rate (chi-sq = 1755.4, *P = 0.000*). Inflation rates (lag 1and lag 2) significantly caused current Inflation rates (chi-sq = 862.1, *P = 0.000*). Interest rates (lag 1and lag 2) significantly caused current Interest rates (chi-sq = 546.3, *P = 0.000*). Implicit Price Deflator (lag 1and lag 2) significantly caused current Implicit Price Deflator. (chi-sq = 583.2, *P = 0.000*)

Table 5: Granger Causality (Block Exogeneity Wald and System Wald) Test Result (Test Statistics is Chi-square and P-values in Bracket)

Dependent Variables	Independent Variables EXR	IFR	ITR	IPD	All
Exchange Rate (EXR_t)	**1755.4(0.00)***	4.524(0.10)	0.142(0.93)	3.019 (0.22)	6.903(0.32)
Inflation Rate (IFR_t)	1.044(0.59)	**862.1(0,00)***	1.621(0.44)	0.277(0.87)	2.537(0.86)
Interest Rate (ITR_t)	0.760(0.68)	2.095(0.35)	**546.3(0.00)***	0.123(0.94)	2.883(0.82)
Implicit Price deflator (IPD_t)	**7.566(0.02)***	0.081(0.95)	0.222(0.89)	**583.2(0.00)***	8.733(0.18)

4.6. Impulse Response

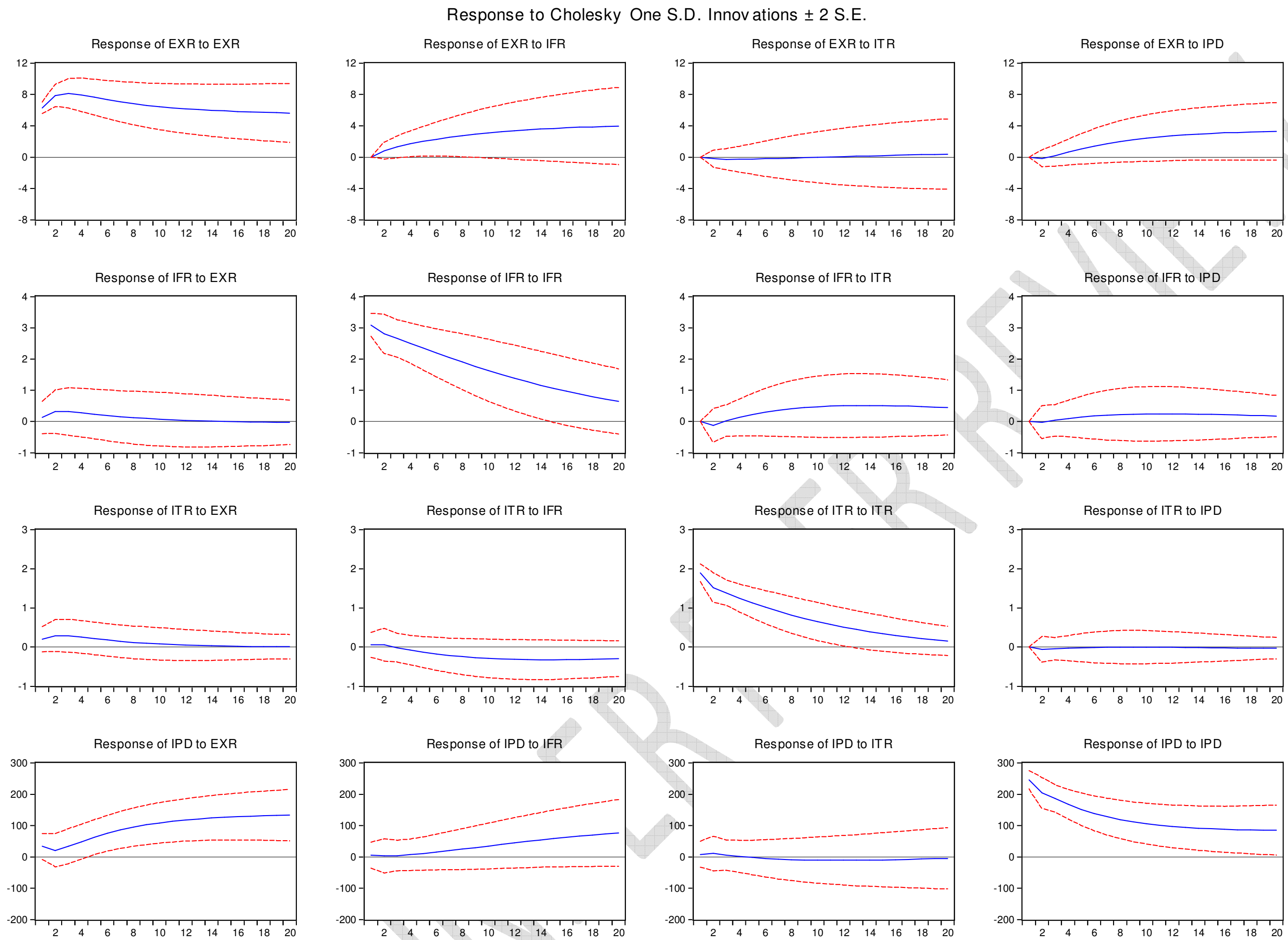
Response to Cholesky One S.D. Innovations ± 2 S.E.
Response of EXR to EXR
Response of EXR to IFR
Response of EXR to ITR
Response of EXR to IPD
Response of IFR to EXR
Response of IFR to IFR
Response of IFR to ITR
Response of IFR to IPD
Response of ITR to EXR
Response of ITR to IFR
Response of ITR to ITR
Response of ITR to IPD
Response of IPD to EXR
Response of IPD to IFR
Response of IPD to ITR
Response of IPD to IPD

Figure 7: Impulse Response graphs

The zero values right from the start at lag zero for the immediate or contemporaneous response is to shocks are impose by the Cholesky decomposition by the particular ordering. The first column of figure 7 represent response of exchange rates to shocks to all other variables, the second column represent variations in inflation rates to shocks to all other variables, the third column represent changes in interest rates to shocks to all other variables, while the forth column represent response of interest rates to shocks to all other variables.

4.6.1. Impulse Response of Exchange Rates

The first row of figure 7 above shows the response of exchange rates to shocks to exchange rates, inflation rates, interest rates and implicit price deflator. The zero values right from the start at lag zero ruled out to have an immediate effect. Consequently, exchange rate had an immediate and positive response to shocks in exchange rates, it however did not have an immediate nor positive response to shocks in inflation rates, interest rates and implicit price deflator, the response to interest rates is not immediate nor subsequently.

4.6.2. Impulse Response of Inflation Rates

The second row of figure 7 above shows the response of inflation rates to shocks to in all studied variables. Inflation rates had an immediate and positive response to shocks in inflation rates, it however did not have an immediate response to shocks in exchange rates, interest rates and implicit price deflator, the response to exchange rates and implicit price deflator were not immediate nor subsequently.

4.6.3. Impulse Response of Interest Rates

Row 3 of figure 7 shows the response of interest rates to shocks to all variables of the study. Interest rates had an immediate and positive response to shocks in interest rates, it however did not have an immediate response to shocks in exchange rates, inflation rates and implicit price deflator, the response to exchange rates, inflation rates, and implicit price deflator were not immediate nor subsequently.

4.6.3. Impulse Response of Implicit Price Deflator

Row 4 of figure 7 shows the response of implicit price deflator to shocks to all variables of the study. implicit price deflator had an immediate and positive response to shocks in itself and exchange rates, it however did not have an immediate response to shocks in exchange rates, inflation rates and interest rate, the response to inflation rates was not immediate nor subsequently.

4.7. Variance Decomposition

4.7.1 Variance Decomposition of Exchange Rates

The first section of table 6 shows that in the short run, the response of exchange rate due to own shock is 98.5%. The table also showed that a shock in inflation rates, interest rate and implicit price deflator can respectively cause 1.3%, 0.06%, and 0.03% fluctuations in exchange rates. In the long run however, the response of exchange rate due to own shock is

88.53%. The fluctuations in exchange rates due to impulse in inflation rates, interest rate and implicit price deflator are 7.82%, 0.06%, and 3.57% respectively.

4.7.2 Variance Decomposition of Inflation Rates

The responses of inflation rates in the short run due to own shock as indicated in the second section of table 6 shows is 97.25%. The shock in exchange rates, interest rate and implicit price deflator can respectively cause 0.88%, 0.06%, and 0.008% fluctuations in inflation rates. In the long run however, the response of inflation rate due to own shock is 97.15%. The fluctuations in inflation rates due to impulse in exchange rates, interest rate and implicit price deflator are 0.79%, 1.57%, and 0.47% respectively.

4.7.3 Variance Decomposition of Interest Rates

The responses of interest rates in the short run due to own shock as indicated in the third section of table 6 shows is 99.03%. The shock in exchange rates, inflation rates and implicit price deflator can respectively cause 2.59%, 0.08%, and 0.06% fluctuations in interest rates. In the long run however, the response of interest rate due to own shock is 95.05%. The fluctuations in interest rates due to impulse in exchange rates, inflation rates, and implicit price deflator are 0.79%, 1.57%, and 0.47% respectively.

4.7.4 Variance Decomposition of Implicit Price Deflator

The fluctuations in implicit price deflator in the short run due to own shock as shown in the third section of table 6 shows is 97.903%. The shocks in exchange rates, inflation rates and interest rates can respectively cause 2.59%, 0.08%, and 0.06% fluctuations in implicit price deflator. However, in the long run, the response of implicit price deflator due to own shock is 82.07%. The fluctuations in implicit price deflator due to impulse in exchange rates, inflation rates, and interest rates are 0.79%, 1.57%, and 0.47% respectively.

Table 6: Variance Decomposition Result

Period	S.E.	EXR	IFR	ITR	IPD
Variance Decomposition of EXR:					
3	13.04274	98.51092	1.381123	0.069878	0.038083
		(1.66923)	(1.46291)	(0.68870)	(0.70566)
10	24.34593	88.53746	7.827635	0.060508	3.574401
		(9.25032)	(6.67171)	(3.30919)	(4.86566)
Variance Decomposition of IFR:					
3	4.969223	0.886573	99.03950	0.065738	0.008185
		(2.72610)	(3.04236)	(0.95249)	(0.76755)
10	7.506602	0.794994	97.15740	1.570381	0.477221
		(4.53409)	(6.94553)	(4.40059)	(2.78445)
Variance Decomposition of ITR:					
3	2.837308	2.595769	0.084582	97.25390	0.065752
		(4.13352)	(1.66767)	(4.84294)	(0.80308)
103	3.859087	2.689754	2.203673	95.05995	0.046620
		(5.09400)	(4.40458)	(7.21623)	(2.84721)
Variance Decomposition of IPD:					
3	373.7500	1.913927	0.037748	0.145731	97.90259
		(3.23674)	(1.35559)	(1.69396)	(3.91306)
10	564.6483	16.69690	1.095751	0.179325	82.02803
		(12.2860)	(3.95528)	(4.12169)	(12.2815)

V. CONCLUSION

During the period considered, the combined lags of exchange rates, inflation rates, interest rates, and implicit price significantly caused own shocks, however, fluctuations due to other study variables were minimal as shown by the impulse response and variance decomposition analyses. Worthy of note is that; the study it ruled out the response of exchange rate to contemporaneous shocks in inflation rate, interest rate and implicit price deflator, it also rule out the fluctuation of inflation rate to contemporaneous impulse in exchange rate, interest rate and implicit price deflator and finally ruled out the response of interest rate to contemporaneous shocks in inflation rate, exchange rate and implicit price deflator. The test of significance particularly the granger causality test indicated significant influence of a particular variable by its combine lags. More so, the causality between exchange rates and implicit price deflator was significant and uni-direction from exchange rates to implicit price.

Since own shocks have been found to be major and significant determinants of impulse, it is recommends that economic modelling should include lags of the dependent variable as independents, particularly for multivariate models. It is also recommended that government regulates this variables particularly interest rates and exchange rates while implicit price deflator and inflation rate should stabilise

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