Factors Influencing Changes in the Nigerian Equity Market at Different Forecast Horizons

***Garba, M.K., Afolayan, R.B., Banjoko, A.W. and Salihu, F.**

Department of Statistics, University of Ilorin, Ilorin, Nigeria

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Abstract

This study investigates the impact of macroeconomic variables on All Share Index (ASI) of the Nigerian Stock Exchange (NSE) and its contribution to equity market fluctuations at different forecast horizons. The study utilizes the Vector Error Correction Model (VECM), Granger Causality test, Impulse Response Function (IRF) and Forecast Error Variance Decomposition (FEVD) in estimating quarterly data from 2000 to 2014 extracted from Statistical Bulletin of the Central Bank of Nigeria (CBN). The results revealed that macroeconomic indicators are inefficient to explain the equity market in the short run while ASI shows responsiveness to the indicators in the long run. It was also discovered that ASI benefits from high exchange rates while inflation rate has an adverse negative effect and particularly serve as a major hindrance to business growth in Nigeria. Findings from this study have implications for policy makers, investors, researchers and stock market regulators on ways to achieve economic development sustainability in the long run via the use of financial indicators as important factors in explaining equity market movement.

Keywords: *All Share Index, Vector Error Correction Model, Impulse Response Function, Forecast Error Variance Decomposition*

1.0 Introduction

Stock market is a sensitive segment of the economy through which a nation's economic status is assessed. It capitalizes the present and future values of growth opportunities while evaluating the growth of all sectors in the economy. Changes in the past values of equity market alone might not be sufficient to explain movement in the market. Macroeconomic variables among other factors give signal for equity market participants to expect higher or lower returns when investing in stock. If external indicators accurately reflect the expectations about the future performance of the market, then they should be employed as leading indicators of future equity market movement.

A number of macroeconomic variables such as inflation, exchange rate, federal fund rate, current account balance, unemployment rate, fiscal balance, money supply, interest rate and interbank call money rate have been documented in literature as some of the microeconomic variables that influence stock markets. Although, there was no consensus on their appropriateness [1–3] Examining historical returns data during periods of high and low inflation can provide some clarity for investors. Numerous previous studies considered the impact of inflation on stock returns. But unfortunately, these studies have produced conflicting results when factors like geographical locations and time periods are taken into account. While some researchers opined that inflation has a negative effects on stock markers [4], others believed it has a positive effect [5]. Similar contradicting results are obtainable using money supply, interest rate, exchange rate and industrial index [6–14].

*** Corresponding Author: Tel: +234(0)8035568461; Email: garbamk@gmail.com**

Naturally, trading on the floor of the Nigerian Stock Exchange (NSE) is expected to be influenced by macroeconomic variables which are outside the realm of capital market. For the purpose of this study, quarterly data were used to carry out necessary analysis needed to investigate the changes in equity market with focus on four of these macroeconomic variables - inflation rate, money supply, exchange rate and prime lending rate - to serve as indicators that determine the equity market movement in Nigeria. This study examines the long-term equilibrium relationships as well as the short-term causalities between the selected macroeconomic variables and the Nigerians Stock Exchange All Share Index (ASI) employing appropriate statistical tools for financial time series data. Effects of unexpected shocks (innovations) to variables in the model were also measured using Impulse Response Functions (IRF) and Forecast Error Variance Decompositions (FEVD) for the forecast horizons.

2.0 Materials and Methods

2.1 Data Description

The data sets used for this work were secondary data extracted from the Statistical Bulletin of Central Bank of Nigeria [15]. The data consist quarterly All Share index (ASI) of the Nigerian Stock Exchange (NSE), Inflation Rate (IR), Broad Money Supply (M2), Exchange Rate (XR) and Prime Lending Rate (PLR) for a period of fifteen years starting from the first quarter of 2000 to the last quarter of 2014. Each of the variables has of sixty observations. The ASI was used as a proxy for equity market, M2 as proxy for Money Supply and PLR as proxy for interest rate. The datasets are accessible at http://www.cenbank.org/documents/Statbulletin.asp

2.2 Methodology

The stationarity conditions of the series were examined using Augmented Dickey-Fuller (ADF) approach which the procedures were described by [16, 17]. The number of integration of k linear variables is the maximum (m) order of integration for the group. If some variables are found to be integrated of order one $I(1)$ and the others are of order two $I(2)$, then $m = 2$. If some are $I(0)$ and the others are $I(1)$, then $m = 1$ and so on. If two or more of the variables have the same order of integration, the test for co-integration was carried out to verify the existence of long-run equilibrium relationship in the multivariate time series data using Johansen's methodology in which the number of co-integrating vectors can be determined by examining the number of independent linear combinations (r) for a k time series variable set that yields a stationary process.

According to Johansen and Juselius [18], there are two methods (maximum eigen value test and trace test) for determining the number of co-integrating relations. Both methods involve estimation of the matrix Π, which is a $k\ by\ k$ matrix with rank r. If there is no co-integration, a Vector Autoregressive (VAR) model with first-difference is appropriate. As reported previously, models of simultaneous equations are necessary to clearly identify the endogenous and the exogenous variables [19]. The decision regarding such a differentiation among variables was heavily criticized by Sims [20], where it was argued that all variables should be treated as endogenous. This implies that in its general reduced form, each equation has the same set of regressors which leads to the development of the Vector Autoregressive (VAR) models. From the point of view of forecasting, each equation in VAR contains only its own lagged values and the lagged values of the other variables in the system [21]. Meanwhile, Wooldridge [22] explained that whether the current value is included or not depends partly on the purpose of the equation. However, in forecasting, current value is rarely included since the first variable has a contemporaneous impact on the second variable and vice versa.

If variables are co-integrated, the error correction term is included in a VAR model and the model becomes a Vector Error Correction Model (VECM) otherwise known as a restricted VAR. The advantage of a VECM over a VAR on differenced variables is that it gives long-run structural relationship plus information on adjustment, which provides better insight in financial and economic processes. An error correction model is not a model that corrects the error in another model but they are category of multiple time series models that directly estimate the speed at which a response variable returns to equilibrium after a change in a determinant variable.

Consider a VAR model

$$y_t = c + \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + \ldots + \alpha_p y_{t-p} + u_t \tag{1}$$

And a VECM can be estimated as follows:

$$\Delta y_t = \Gamma_1 \Delta y_{t-1} + \Gamma_2 \Delta y_{t-2} + \ldots + \Gamma_p \Delta y_{t-p} + \Pi y_{t-1} + u_t \tag{2}$$

$where\ \Gamma_i = -(I - \alpha_1 - \cdots - \alpha_i),\ I = identity\ matix,\ \Pi = \sum_{i=1}^{p} \alpha_i - I,\ for\ i = 1, 2, \ldots, p-1$

For this study, $\boldsymbol{k = 5}$, $\boldsymbol{p = 1}$ and $\boldsymbol{\Pi = \pi\beta'}$

$$y_t = \begin{pmatrix} ASI_t \\ IR_t \\ M2_t \\ XR_t \\ PLR_t \end{pmatrix}, \Delta y_t = \begin{pmatrix} D(ASI_t) \\ D(IR_t) \\ D(M2_t) \\ D(XR_t) \\ D(PLR_t) \end{pmatrix}, \Delta y_{t-1} = \begin{pmatrix} D(ASI_{t-1}) \\ D(IR_{t-1}) \\ D(M2_{t-1}) \\ D(XR_{t-1}) \\ D(PLR_{t-1}) \end{pmatrix}, u_t = \begin{pmatrix} u_{ASIt} \\ u_{IRt} \\ u_{M2t} \\ u_{XRt} \\ u_{PLRt} \end{pmatrix}, \pi = \begin{pmatrix} C(1) \\ C(8) \\ C(15) \\ C(22) \\ C(29) \end{pmatrix}$$

$$\Gamma_i = \begin{pmatrix} C(2) & C(3) & C(4) & C(5) & C(6) \\ C(9) & C(10) & C(11) & C(12) & C(13) \\ C(16) & C(17) & C(18) & C(19) & C(20) \\ C(23) & C(24) & C(25) & C(26) & C(27) \\ C(30) & C(31) & C(32) & C(33) & C(34) \end{pmatrix} \text{ and } \beta' = \begin{pmatrix} \beta'_{ASI} & \beta'_{IR} & \beta'_{M2} & \beta'_{XR} & \beta'_{PLR} \\ \beta'_{IR} & \beta'_{ASI} & \beta'_{M2} & \beta'_{XR} & \beta'_{PLR} \\ \beta'_{M2} & \beta'_{ASI} & \beta'_{IR} & \beta'_{XR} & \beta'_{PLR} \\ \beta'_{XR} & \beta'_{ASI} & \beta'_{IR} & \beta'_{M2} & \beta'_{PLR} \\ \beta'_{PLR} & \beta'_{ASI} & \beta'_{IR} & \beta'_{M2} & \beta'_{XR} \end{pmatrix}$$

The $\boldsymbol{\Pi}$ matrix contains information regarding the long-run relationships, this can be decomposed as $\boldsymbol{\Pi} = \boldsymbol{\pi\beta'}$ where $\boldsymbol{\pi}$ will include the speed of adjustment to equilibrium coefficients, while $\boldsymbol{\beta'}$ will be the long-run matrix of coefficients. $\boldsymbol{\beta' y_{t-1}}$ is equivalent to error correction term, $\boldsymbol{k}$ is the number of endogenous variables, $\boldsymbol{p}$ is the lag length and $\boldsymbol{t}$ is the time period.

Granger Causality test was carried out to provide short-run causal relationship of the determinant variables using a standard Wald test, with a null hypothesis that the coefficients of the $\boldsymbol{p}$ lagged values of a determinant variable are zero. Rejection of the null hypothesis implies the presence of Granger causality between the response variable and the determinant variable. The Wald test statistics is asymptotically chi-square distributed with $\boldsymbol{p}$ degrees of freedom. IRF and FEVD were estimated to check the causal impact of unexpected shocks in the model. It is possible to obsess the effect of a non-recurring shock in one variable, to all variables over time. Considering a Vector Moving Average (VMA) Model:

$$y_t = \mathrm{B}(\psi)^{-1}c + \mathrm{B}(\psi)^{-1}u_t \tag{3}$$

where $\mathrm{B}(\psi) = I - \psi_1 B - \psi_2 B^2 - \cdots - \psi_p B^p$ and $\psi_0 = 1$

Equation (3) can be written as:

$$y_t = \bar{Y} + \psi_0 u_t + \psi_1 u_{t-1} + \psi_2 u_{t-2} + \psi_3 u_{t-3} + \cdots$$

$$= \bar{Y} + \sum_{k=0}^{\infty} \psi_k \, u_{t-k} \tag{4}$$

where $\boldsymbol{\psi_k}$ are the weights of past stocks often referred to as the IRF of y_t [23]. The VMA model is usually employed to trace the impulse response. The effects of the various shocks of the explanatory variables on the dependent variables (that is the impulse responses) can be determined by differentiating (3) with respect to each of the shocks in u_t [23].

The forecast error $\boldsymbol{u_{t+h}}$ at period $\boldsymbol{h}$ is defined as the difference between the actual forecast $\boldsymbol{\hat{y}_{t+h}}$ and its conditional expectation $\boldsymbol{y_{t+h}}$, consisting of optimal estimates, which can be expressed as a linear combination of weights.

$$u_{t+h} = y_{t+h} - \hat{y}_{t+h}$$
$$= \psi_0 u_{t+h} + \psi_1 u_{t+h-1} + \psi_2 u_{t+h-2} + \cdots + \psi_{h-1} u_{t+1} \tag{5}$$

Where:
$$y_{t+h} = \bar{Y} + \psi_0 u_{t+h} + \psi_1 u_{t+h-1} + \psi_2 u_{t+h-2} + \cdots \tag{6}$$
$$\hat{y}_{t+h} = \bar{Y} + \psi_1 u_{t+h-1} + \psi_2 u_{t+h-2} + \cdots \tag{7}$$

1-period forecast error: $y_{t+1} - \hat{y}_{t+1} = \psi_0 u_{t+1}$
2-period forecast error: $y_{t+2} - \hat{y}_{t+2} = \psi_0 u_{t+2} + \psi_1 u_{t+1}$
h-period forecast error: $y_{t+h} - \hat{y}_{t+h} == \psi_0 u_{t+h} + \psi_1 u_{t+h-1} + \cdots + \psi_{h-1} u_{t+1}$ (8)

FEVD measure the contribution of each type of shock to the forecast error variance. Considering $\boldsymbol{y_t}$, its one step ahead forecast error variance at time $\boldsymbol{t-1}$ is expressed as

$$Var(\hat{u}_{t+1}) = Var(u_{t+1}) = \sigma_u^2 \tag{9}$$

and in terms of expectations, the forecast error variance is:

$$\begin{aligned} Var(u_{t+h}) &= E(u_{t+h})^2 \\ &= E(y_{t+h} - \hat{y}_{t+h})^2 \\ &= (\psi_0^2 + \psi_1^2 + \psi_2^2 + \cdots + \psi_{h-1}^2)\sigma_u^2 \\ &= \left(1 + \sum_{i=1}^{h-1} \psi_i^2\right)\sigma_u^2 \end{aligned} \quad (10)$$

The optimum values for the $\boldsymbol{\psi}$ weights are found by minimizing the Forecast Error Variance (FEV) otherwise known as mean square forecast error, which is based on the conditional expectation of $\boldsymbol{y_t}$.

2.3 Statistical Analysis

Statistical analysis was performed using EViews econometric package. Variables included in the model were selected based on availability over the study period and were treated as time series data.

3.0 Results

3.1 Trend Analysis and Johansen Cointegration Test

The time series plots give the trend of each variable over the study period (Fig. 1). The plots indicated that all the variables are not stationary as they do not move at a constant rate over time. There is presence of seasonality, trend and increasing or decreasing variance over the study period.

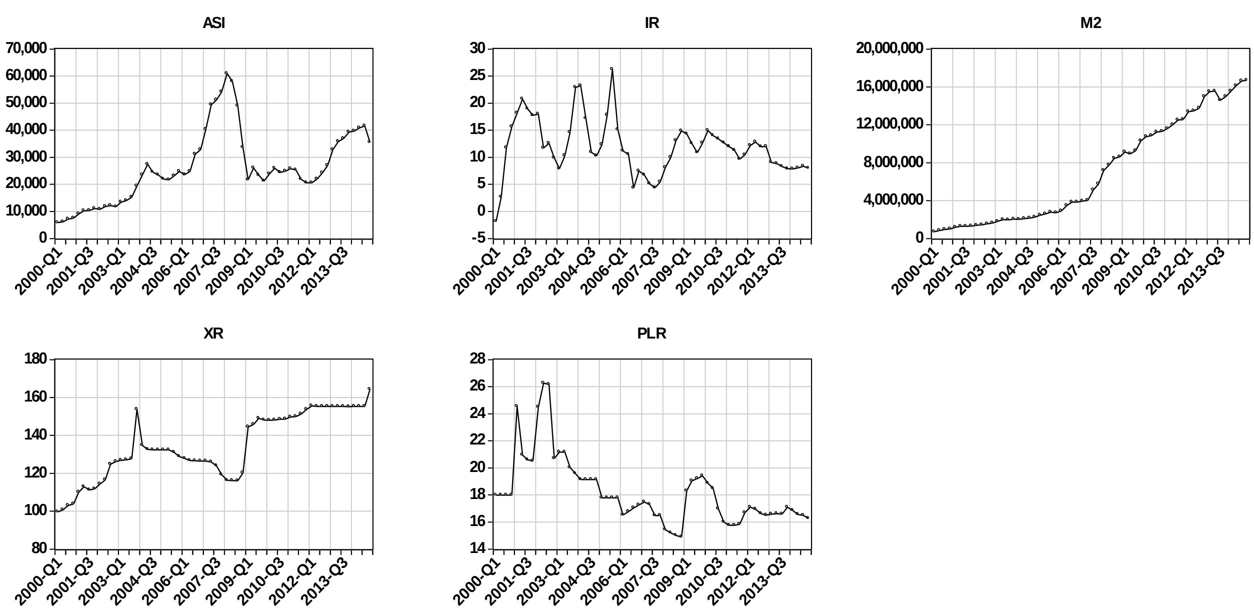

Fig. 1: Time series plots of ASI, IR, M2, XR and PLR

The summary of augmented Dickey-Fuller test is presented in Table 1. The estimated results indicated that all variables were not stationary at 5% level of significance but became stationary after first differenced, showing that the five variables have integration of order 1 denoted as $I(1)$. There is one cointegrating equation based on the estimated result of the trace test and maximum eigenvalue as shown in Table 2. This indicated the presence of long run equilibrium relationship between the five variables.

Table1: Summary of Augmented Dickey-Fuller Test

Variables	Models	Intercept	Trend and Intercept	No Trend and Intercept
ASI	Level	0.1124	0.2499	0.3886
D(ASI)	FD	0.0027*	0.0141*	0.0001*
IR	Level	0.2419	0.1732	0.38
D(IR)	FD	0.0001*	0.0001*	0.0001*
M2	Level	0.9995	0.5629	0.9992
D(M2)	FD	0.0001*	0.0001*	0.0001*
XR	Level	0.5355	0.2723	0.9479
D(XR)	FD	0.0001*	0.0001*	0.0001*
PLR	Level	0.6255	0.6699	0.287
D(PLR)	FD	0.0001*	0.0001*	0.0001*

*Where FD stands for first-difference and * denotes rejection of null hypothesis at 0.05 level*

Table 2: Cointegration Rank Test

Null Hypothesis:	Eigenvalue	Trace			Maximum Eigenvalue		
Number of Cointegrating Equation(s)		Trace Statistic	Critical Value	P-value	Max-Eigen Statistic	Critical Value	P-value
None *	0.4690	81.9474	69.8189	0.0040*	36.7126	33.8769	0.0223*
At most 1	0.2964	45.2348	47.8561	0.0864	20.3868	27.5843	0.3150
At most 2	0.2393	24.8480	29.7971	0.1670	15.8657	21.1316	0.2328
At most 3	0.1340	8.9824	15.4947	0.3670	8.3444	14.2646	0.3448
At most 4	0.0109	0.6380	3.8415	0.4244	0.6380	3.8415	0.4244

*Where * denotes rejection of the hypothesis at the 0.05 level of significance*

3.2 Least Square Regression Estimates of VECM and VEC Granger Causality

The Vector Error Correction Models of the variables considered for this study are as given as equations 11 to 15

$$D(ASI) = C(1) * (ASI_{t-1} + 5657.8812 * IR_{t-1} + 0.0042 * M2_{t-1} - 1131.1745 * XR_{t-1} + 125.2022 * PLR_{t-1} + 25909.9238) + C(2) * D(ASI_{t-1}) + C(3) * D(IR_{t-1}) + C(4) * D(M2) + C(5) * D(XR_{t-1}) + C(6) * D(PLR_{t-1}) + C(7) \quad (11)$$

$$D(IR) = C(8) * (ASI_{t-1} + 5657.8812 * IR_{t-1} + 0.0042 * M2_{t-1} - 1131.1745 * XR_{t-1} + 125.2022 * PLR_{t-1} + 25909.9238) + C(9) * D(ASI_{t-1}) + C(10) * D(IR_{t-1}) + C(11) * D(M2) + C(12) * D(XR_{t-1}) + C(13) * D(PLR_{t-1}) + C(14) \quad (12)$$

$$D(M2) = C(15) * (ASI_{t-1} + 5657.8812 * IR_{t-1} + 0.0042 * M2_{t-1} - 1131.1745 * XR_{t-1} + 125.2022 * PLR_{t-1} + 25909.9238) + C(16) * D(ASI_{t-1}) + C(17) * D(IR_{t-1}) + C(18) * D(M2) + C(19) * D(XR_{t-1}) + C(20) * D(PLR_{t-1}) + C(21) \quad (13)$$

$$D(XR) = C(22) * (ASI_{t-1} + 5657.8812 * IR_{t-1} + 0.0042 * M2_{t-1} - 1131.1745 * XR_{t-1} + 125.2022 * PLR_{t-1} + 25909.9238) + C(23) * D(ASI_{t-1}) + C(24) * D(IR_{t-1}) + C(25) * D(M2) + C(26) * D(XR_{t-1}) + C(27) * D(PLR_{t-1}) + C(28) \quad (14)$$

$$D(PLR) = C(29) * (ASI_{t-1} + 5657.8812 * IR_{t-1} + 0.0042 * M2_{t-1} - 1131.1745 * XR_{t-1} + 125.2022 * PLR_{t-1} + 25909.9238) + C(30) * D(ASI_{t-1}) + C(31) * D(IR_{t-1}) + C(32) * D(M2) + C(33) * D(XR_{t-1}) + C(34) * D(PLR_{t-1}) + C(35) \quad (15)$$

The five equations each have the same long-run coefficients as there is only one cointegrating equation which is multiplied to their speed of adjustment to equilibrium coefficients. The rest of the equation is considered the short-run causality.

The result obtained for the least squares estimates of All Share Index is presented in Table 3. The data revealed that the speed of adjustment coefficient (**C**(1)) is negative and the p-value of 0.0085 which is less than 0.05 indicates that it is adjusting very slowly at the rate of about 5.4% with a downward movement towards long-run equilibrium. Thus,it can be infered that there is a long-run causality running from the determinant variables (IR, M2, XR and PLR) to ASI. The Durbin-Watson statistic is greater than R-squared which indicates no spurious regression.

Table 3: Result of the least squares estimates of All Share

Dependent Variable: D(ASI)				
	Coefficient	**Std. Error**	**t-Statistic**	**P-value**
C(1)	-0.05429	0.019842	-2.73614	0.0085
C(2)	0.516139	0.120801	4.272626	0.0001
C(3)	189.2008	136.2097	1.389041	0.1709
C(4)	1.20E-05	0.00121	0.009938	0.9921
C(5)	67.97079	89.86102	0.756399	0.4529
C(6)	262.8709	305.0988	0.861593	0.3929
C(7)	94.35664	565.9819	0.166713	0.8683
R-squared	0.401466	**Sum squared residual**		5.63E+08
Durbin-Watson stat	1.93693	**Log likelihood**		-548.862
F-statistic	5.701369	**P-value (F-statistic)**		0.000136

The VEC Granger Casualty Estimate are presented in Table 4. The estimated values indicate the absence of causal relationship. All the p-values are greater than 0.05, indicating that in the short-run, there is no causal relationship individually or jointly running from IR, M2, XR and PLR to ASI.

Table 4: VEC Granger Causality Estimate

Dependent variable: D(ASI)				
Excluded	**Chi-sq**	**df**	**P-value**	**Null Hypothesis**
D(INFLATION)	1.929434	1	0.1648	C(3)=0
D(M2)	9.88E-05	1	0.9921	C(4)=0
D(XR)	0.572140	1	0.4494	C(5)=0
D(PLR)	0.742342	1	0.3889	C(6)=0
All	4.484232	4	0.3444	C(3)=C(4)=C(5)=C(6)=0

3.3 Impulse Response and Variance Decomposition

The Impulse response of ASI from Fig. 2 indicates a positive response to shocks in ASI, XR and PLR but responds negatively to shocks in IR and M2 over a 16 quarter forecast horizon.

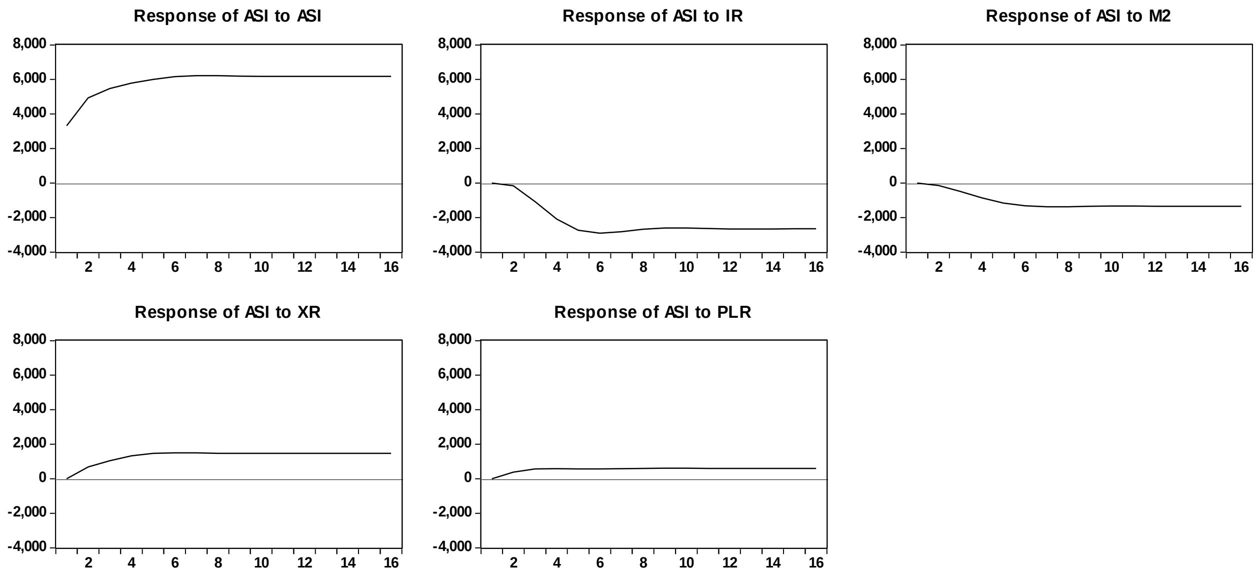

Fig. 2: Impulse Response of All Share Index (ASI)

The estimated results of the variance decomposition presented in Table 5 showed proportion of variance due to ASI shock as well as shocks to IR, M2, XR and PLR over a 16 quarter forecast horizons. In the first quarter, shocks to ASI explained 100 percent of changes in itself. However, in the long-run, shocks to IR, M2, XR and PLR explained about 13.11%, 3.16%, 4.19% and 0.72% of the changes in ASI at the 16th quarter forecast horizon with PLR having an insignificant effect (less than 1%) on ASI.

Table 5: Variance Decomposition of All Share Index (ASI)

FH	ASI	IR	M2	XR	PLR	FH	ASI	IR	M2	XR	PLR
1	100.00	0.00	0.00	0.00	0.00	**9**	80.49	12.11	2.70	3.99	0.71
2	98.15	0.07	0.06	1.32	0.40	**10**	80.12	12.32	2.81	4.04	0.71
3	94.97	1.705	0.38	2.27	0.69	**11**	79.81	12.50	2.90	4.08	0.71
4	90.24	5.06	0.91	3.04	0.74	**12**	79.53	12.67	2.97	4.11	0.72
5	86.01	8.29	1.49	3.50	0.72	**13**	79.30	12.82	3.03	4.13	0.72
6	83.26	10.34	1.97	3.73	0.70	**14**	79.11	12.94	3.08	4.15	0.72
7	81.77	11.37	2.31	3.85	0.70	**15**	78.95	13.03	3.13	4.17	0.72
8	80.97	11.85	2.54	3.93	0.70	**16**	78.81	13.11	3.16	4.19	0.72

4.0 Discussion

This study employed unit root test, Johansen's cointegration, VECM, LSR, VEC Granger Causality, IRF and FEVD to examine the impact of the macroeconomic indicators considered on the Nigerian equity market data. The findings from the study revealed that all the variables were not stationary but were integrated of order one (I(1)). The results showed the presence of a long-run relationship between the variables considered in the study. The Inflation Rate and Money Supply were found to have negative and significant effects while the Exchange Rate and Prime Lending Rate had positive effect on the All Share Index with shocks to Exchange Rate having a significant effect and shocks to Prime Lending Rate showing no significant effect on All Share Index. All Share Index adjusts negatively towards equilibrium, but an increase in Exchange Rate and a decrease in Money Supply and Inflation, will influence All Share Index to adjust positively towards equilibrium.

The present study also revealed that Inflation Rate has an adverse negative effect on All Share Index and particularly serve as a major hindrance to business growth in Nigeria. The All Share Index (ASI) benefits from high Exchange Rate because it makes stock exchange less expensive for foreigners to invest in, while Nigerian investors rush to buy shares with the hope that the currency will regain its value. Low interest rate results to an increase in All Share Index as it becomes cheaper for firms to finance their investment via equity because each share issued produce more funds. However in this study, Prime Lending Rate has an insignificant effect on All Share Index.

Findings from this study have implications for policy makers, investors and stock market regulators on ways to achieve economic development sustainability in the long-run via the use of macroeconomic indicators as important factors in explaining equity market movement. It can therefore be concluded that in order to monitor and control stock prices in Nigeria through macroeconomic variables, emphasis should be given to innovations on Money Supply, Exchange Rate and Inflation Rate rather than Prime Lending Rate in the long-run.

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