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Modelling Nigeria stock market dynamics and interdependencies with Bayesian Vector Autoregression Model

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Abstract

Stock market in Nigeria is characterized by significant dynamic entity due to various factors, including economic and geographical instability, political events, regulatory changes, and global market influences. The study developed Vector Autoregressive (VAR) and Bayesian Vector Autoregressive (BVAR) models which allowed a thorough examination of the price dynamics among stock variables and offered insightful information about their interactions and significant influence on the stock price fluctuations in Nigeria. The study employed daily opening and closing prices for Dangote cement, Nestle, UBA, GT Bank and Zenith Bank obtained from the Nigerian Stock Exchange (NGX) at Lagos Island, Lagos State Nigeria. To ensure an extensive comprehension of price index dynamics and interdependence over time, collection of data covers the period of October 2010 to June 2024. The findings highlight the preeminence of the BVAR model as a more reliable and efficient tool for forecasting and analysis, as it accurately captures the complexities and dynamism of the relationship among the variables under study. The impulse response function revealed how changes in Nigerian price index had immediate effects on itself and others. This study provides significant leverage for financial analysts and stock market specialists in forecasting stock prices using the sectoral index's contribution and the relationships between other prices.

Nomenclature and units

BVAR	Bayesian Vector Autoregressive
VAR	Vector Autoregressive
ADF	Augmented Dickey-Fuller
DANGCEM	Dangote Cement.
GTB	Guaranty Trust Bank
UBA	United Bank for Africa

1.0 Introduction

Stock price dynamics is an essential metric in financial markets that illustrates how significantly stock prices change over time. The dynamics and interrelations of the stock market are crucial in shaping corporate investments, as share prices affect the liquidity obtained from trading freshly issued stocks to fund investment expenditures (Adebisi, Odesola, Aromona & Oyenekan, 2025). Numerous studies have investigated the interdependence of stock markets; prior research suggests that the degree of interdependence in market share prices is minimal, with domestic factors, rather than international ones, being the principal determinants (Abdul & Jaweed, 2024; Kumar & Sharma, 2024; Paritosh, 2015).

The Nigeria Stock Market is a dynamic entity; comprehending its variations and accurately forecasting stock price trends is crucial for investors, policymakers, and financial analysts, as it impacts investment strategies, risk management, and economic policy decisions. Several triggers, such as political developments, regulatory changes, impacts on the global market, economic and geographic instability significantly contribute to the pronounced volatility of Nigeria's stock market, Adewole (2024). Recently, researchers such as Akinde (2015); Oyelami, Ogbuagu, & Saibu, (2022), Abdulrauf, A. A., Olajide, Akintunde, & Ebunoluwa, (2025), and Oladejo, Akintoye, Edeh, & Oduwole, F. (2025) employed various statistical methods to evaluate financial price dynamics and interdependence in Nigeria and predict future trends. The strength of the productive sector, investor confidence in various economic sectors, and expectations for the steadiness of the economic system are all reflected in stock markets (Ajibode, & Busari, 2020). Macroeconomic linkages to stock prices in Nigeria emphasize a dynamic interaction where monetary and real economic factors such as exchange rates, inflation, money supply, among others, strongly influence stock market valuations and investment perceptions, (Ayunku, 2019; Okoi, Iheanacho, & Lawal. (2022)

The stock market is a dynamic entity where different indicators show how well different economies are doing. Stock markets are important indications regarding how the economy is doing because they demonstrate what investors across the world anticipate and expect. The stock market is efficient when asset prices reflect all available information, it is assumed that prices fully incorporate all relevant information. The economic condition of the stock market is commonly defined in relation to the efficiency of the stock market; efficiency of the stock market has a role to play regarding the expected returns on stocks traded in the market. (Gbanador, 2018; Gbanador, 2024). Efficient market ensure that assets are fairly priced based on current knowledge, making it challenging for investors to consistently achieve higher returns without adding another risk (Dimson & Mussavian, 1998; Schwert, 2003). Spreading investments across various sectors, classes, and geographical regions can aid in managing risk, navigate the complexities of modern financial markets and improve long term returns (Busse, 2024). Globalization has made the world's financial markets more connected, which is why experts are keeping close tabs on how different stock market indices act and interact within and around the globe. Motivated by an awareness of the interconnectedness and interrelationships of financial markets in general, research has focused on the dynamic interconnections among stock indexes. This connection leads to complicated relationships like response loops, spillover effects, and the risk of contagion. This is because changes in one market can quickly affect how well other markets do. These kinds of changes show how important it is to have sophisticated analytical techniques that can capture the details of these interactions. Nevertheless, there still exist challenges with investigating the dynamic relationships between global and standardized stock market indices.

The investors can build stronger portfolios that can better handle market swings if they learn more about how world stock market indices interact with each other (Tejesh & Khajabee, 2024). Stock market stability is still essential to foreign portfolio investment, which is an important driving force behind Nigeria's economic growth (Ezenduka & Joseph, 2020). Financial econometrics has used a range of techniques, such as panel data analysis, time series analysis, and Ordinary Least Squares (OLS) regression, which rely on linear models in analyzing the behavior of stock market indexes and the interrelationships among variables. Market volatility, investor behavior, and macroeconomic shocks further challenge the traditional approaches, especially in emerging nations like Nigeria where volatility can be impacted by unanticipated and abrupt events.

The study of interconnectedness and volatility transmission among stock market indices is essential for understanding how the fluctuations and shocks in one stock market may trigger corresponding fluctuations in other markets. This rapid spread of financial instability across global, regional or local market is strongly driven by market interdependence. Volatility transmission is important for determining monetary policy efficiency and in addressing financial stability issues. The extent to which volatility is transmitted across markets could result in a large shock in one market destabilizing another market. It also helps policy- makers to estimate the depth and duration of cross-market impact and common market shocks, which assists in the implementation of timely and effective monetary policy. It can be applied to determine whether financial markets are efficient, and for determining returns and volatility in a market, or between different markets; it can be useful in determining different market price interrelationships. The issues of financial markets volatility transmission study have received sizeable attention in the literature by scholars such as Emenike (2016); Fasanya & Akinde (2019), Kolaiti, Mboya, & Sibbersten (2020); Umar, Jareño, & Escribano, (2021); and Maitra (2025); among others. This has been strengthened over time by new regulatory challenge in securing financial stability and introduction of new technologies that have supported the development of new market structures and practice. The VAR models have been extensively used inmacroeconomic research and forecasting and serve as valuable tools for policymakers. Sadorsky (2020) used a VAR methodology in examining the dynamic connections between the US treasury rate, stock returns, S & P stock index and oil prices within three months, the study provided factual proof that actual stock values were negatively impacted by rising oil costs. Scholars such as Li & Li (2020); Hafner, Herwartz & Stöver (2021) ascertained the VAR model performed better in terms of forecasting accuracy than traditional time-series model and provide accurate projections. Alalaya, Lahsasna, Zairi, & Benajiba (2021) contrasted the VAR model's prediction accuracy with that of machine learning techniques like gradient boosting and random forest. According to Ibrahim, Rasha, Menglu,, Esteban, & Eric (2020) the VAR models outperformed the BVAR models and the conventional autoregression models. Furthermore, these frequentist models do not incorporate expert opinions and prior knowledge, which could be useful in understanding market behavior. Yochanan (2005) examines the transmission of shocks between markets through VAR and BVAR models, analyzing dynamic correlations of daily returns from stock market indexes in the Middle East and the United States. Bayesian Vector Autoregressive (BVAR) is a robust framework and probabilistic approach for modelling data, which enhances evidence by updating the prior assumptions on model parameters. It allows time varying parameters and model uncertainty which provides solution to one of GARCH model identified problem, Jacquier (2004). Bayesian approach facilitates the integration of prior information, which can be advantageous in scenarios with restricted data availability (Adewole & Bodunwa, 2024; Ahelegbey, 2025). Moreover, BVAR permits integration of multiple sources of uncertainty and offers a probabilistic interpretation of volatility estimates, this approach makes modeling more flexible and adaptive in the Nigerian stock market. Several studies have applied Bayesian inference to model stock price volatility in Nigeria. For example, Ramokene, Popoola, Awelewa, Ayokunle, & Ayodele, (2021) employed a Bayesian time-varying parameter model to investigate the determinants of non-oil export volatility in Nigeria. The research highlighted the importance of integrating time-varying dynamics in predicting export volatility and identified GDP and lending rates as key indicators of non-oil export volatility. Rudakouski (2023) investigated the effectiveness of BVAR models in forecasting the precision of key macroeconomic indicators, utilizing the Jeffrey and Minnesota prior. The experimental findings demonstrate that BVAR yields more precise forecasts compared to frequentist VAR, the prediction made by the Minnesota prior seems to be true for all time periods.

Although the BVAR model has potential advantages, its application to modeling the volatility of the Nigerian stock market is still largely unexplored. Considering the unique characteristics and data availability of the Nigerian market, a thorough investigation is necessary to develop and assess Bayesian models tailored to this market. Numerous studies have endeavored to investigate this relationship within the Nigerian context; however, the results have been inconsistence and inconclusive. This study seeks to enhance the current literature by evaluating the viability and effectiveness of the VAR and BVAR models in examining the dynamics and interrelationships of stock market prices in Nigeria. This research centers on utilizing the BVAR model to examine the dynamics and interdependence of specific stock prices in Nigeria. The chosen stocks are Dangote, Nestle, UBA, Zenith Bank, and GT Bank. All of these companies are important in Nigeria's financial and manufacturing sectors. This study also seeks to investigate the intricate interactions and interdependencies among the stock indices constituting global financial markets. The study aims to clarify the behavior of these equities, thereby facilitating a more profound comprehension of market dynamics for both investors and decision-makers.

2.0 Materials and Methods.

The section emphasizes the design, target population, data sources, method of data analysis in analyzing the interdependence and dynamics of stock prices in Nigeria, focusing on five selected stocks: Nestle, Dangote cement, UBA, Zenith Bank, and GT Bank. The methodology incorporates VAR and Bayesian statistical techniques to examine price index dynamics in providing a robust framework for understanding and predicting stock price movement

2.1 Source of Data and Description.

The research employed secondary data sourced from Historical Stock Prices using Daily opening and closing prices for Dangote cement, Nestle, UBA, GT Bank and Zenith Bank obtained from the Nigerian Stock Exchange (NGX) at Lagos Island, Lagos State Nigeria. To ensure a comprehensive understanding of dynamic of stock indices trends over time, the collection of data covers the period of October 2010 to June 2024. Multiple imputation technique was employed in filling the missing values by generating plausible values derived from predictive distribution or relationship among the observed variables in the data set. The series were chosen because of unique and time varying patterns that are essential for analyzing and interpreting market dynamics. The series were selected from the major sectors (Banking, telecommunications and industrial companies) that influence the market dynamics and trends in Nigeria. In examining a thorough investigation of price dynamics of stock indices, the banking series were selected from the leading banks in Nigeria, Nestle and Dangote Cement were chosen from one of the fast-growing industrial sectors in Nigeria. The daily returns of the indices used in each of the stock data series are computed as:

$$R_t = \frac{\log p_t}{\log p_{t-1}} \tag{1}$$

where R_t is the daily returns at time t, p_t can be define as the daily index at time t and p_{t-1} represent daily index at time $t-1$.

2.1.1 Stationarity Test.

The notion of stationarity holds considerable importance when analyzing time series data. This study employs the Augmented Dickey-Fuller (ADF) test to evaluate the stationarity of selected indices, hence preventing the formation of spurious regressions that may arise from the presence of unit roots in nonstationary time series data. The ADF test is an extension of the original Dickey-Fuller test, pioneered by David Dickey and Wayne Fuller in 1979. The null hypothesis of the test posits that the time series under examination possesses a unit root. The ADF test statistic is calculated as follows:

$$ADF = (Y_t - Y_{t-1}) - \gamma \Delta Y_{t-1} \tag{2}$$

Where: Y_t stands for the time series at time t, Y_{t-1} is the time series at time $t-1$, ΔY_{t-1} represents the first difference of the time series at time $t-1$ and γ indicates the coefficient.

2.2 Estimation Procedure

The casual links among the selected indices will be examined using the Vector Autoregression (VAR) and Bayesian Vector Autoregressive (BVAR). VAR model developed by Christopher Sims (1980), is a widely applied stochastic process for multivariate time series analysis. It is essential in understanding and forecasting economic and financial time series behavior (Campbell, Lo, & Mackinlay, 1996). The VAR model extends the univariate autoregression model to multivariate time series data, wherein each variable is expressed as a linear function of its own past lags as well as those of other variables. In BVAR, models are treated as random variables and prior probability is assigned to those variables, unlike the standard VAR. However, BVAR models also require stationarity conditions, just like the VAR model.

2.3 Model Specification

2.3.1 Vector Autoregressive (VAR) Model

VAR is a system of equations where each variable is dependent on its lags and other variables. As a result, each VAR model has equal number of independent variables, as established by standard least squares approaches.

A general VAR model with m dependent and n independent variables and p lags can be written in form of equation (3) below;

$$\begin{bmatrix} y_{1t} \\ y_{2t} \\ \vdots \\ y_{mt} \end{bmatrix} = \begin{bmatrix} \alpha_{11}^{p} & \dots, & \alpha_{1m}^{p} \\ \alpha_{21}^{p} & \dots, & \alpha_{2m}^{p} \\ \vdots & & \\ \alpha_{m1}^{p} & \dots, & \alpha_{nm}^{p} \end{bmatrix} \begin{bmatrix} y_{1,t-p} \\ y_{2,t-p} \\ \vdots \\ y_{m,t-p} \end{bmatrix} + \begin{bmatrix} a_{11} & \dots, & a_{1n} \\ a_{21} & \dots, & a_{2n} \\ \vdots & & \vdots \\ a_{n1} & \dots, & a_{mn} \end{bmatrix} \begin{bmatrix} u_{1,t-1} \\ u_{2,t-2} \\ \vdots \\ u_{n,t-1} \end{bmatrix} + \begin{bmatrix} \mu_{1t} \\ \mu_{2t} \\ \vdots \\ \mu_{mt} \end{bmatrix} \tag{3}$$

The matrix representation of VAR model in equation 1 can be rewritten as

$$y_t = C_1 y_{t-1} +, \dots, + C_p y_{t-p} + a u_t + \mu_t \tag{4}$$

y_t denotes a m × 1 vector of explanatory variables, C is a matrix with dimensions of m × m, a signifies a m × n matrix, and u_t represents an n × 1 vector of explanatory variables that comprises constant, time or explanatory variables, μ_t denotes vector of error terms following multivariate normal distribution by mean zero and variance-covariance matrix Σ.

Equation (5) below shows the collection of regressors in a single matrix

$$\begin{bmatrix} y_t \\ . \\ . \\ . \\ y_T \end{bmatrix} = \begin{bmatrix} y_0 & y_{1-p} & u_1 \\ . & . & . \\ . & . & . \\ . & . & . \\ y_{t-p} & y_{T-p} & u_T \end{bmatrix} \begin{bmatrix} C_1 \\ . \\ . \\ a_p \\ C_T \end{bmatrix} + \begin{bmatrix} \mu_1 \\ . \\ . \\ . \\ \mu_T \end{bmatrix} \tag{5}$$

T signifies the regression sample space. Applying vector transformation, stacking all VAR coefficient in a single line, equation (5) above takes the form in equation (6) below;

$$Y = \bar{U}\beta + \mu \tag{6}$$

where y represent vector $\bar{y}$ and $\bar{U}$ signifies $I_m \times U, \mu$ is the vector $\bar{\mu}$ with $N(0, \Sigma)$. The estimation of parameters in equation (6) can be achieved by a consistent and asymptotically efficient methods of ordinary least square expressed in equation (7).

$$\hat{\beta} = (U'U)^{-1} U'Y \tag{7}$$

2.3.2 The Bayesian Vector Autoregressive (BVAR) Model

It incorporates prior knowledge about the parameters with the observed data (likelihood function) in order to make inferences. Considering bayes rules;

$$P(\varphi|Y) = \frac{P(Y|\varphi).P(\varphi)}{P(Y)} \tag{8}$$

The posterior distribution $P(\varphi|Y)$ defined as the product of the likelihood function $P(Y|\varphi)$ with a prior distribution $P(\varphi)$, divided by the data density $P(Y)$. Since $P(Y)$ is a normalizing constant, equation (8) can be rewritten as;

$$P(\varphi|Y) \sim P(Y|\varphi).P(\varphi) \tag{9}$$

Bayesian Inferences were made by updating prior beliefs about the VAR parameters in Eq. (4), VAR coefficients are described by a probability density function (p.d.f.) using Bayes Law;

$$P(C, \Sigma | Y_{T-p,t}) = \frac{P(Y_{T-p,t} | C_p, \Sigma).P(C_p, \Sigma)}{P(Y_{T-p,t})} \tag{10}$$

$$\Rightarrow P(Y_{T-p,t} | C_p, \Sigma).P(C_p, \Sigma)$$

The product of the likelihood function $P(Y_{T-p,t}|C_p, \Sigma).P(C_p, \Sigma)$and the priors $P(C_p, \Sigma)$ is the joint posterior distribution of the VAR coefficients $P(C, \Sigma|Y_{T-p,t})$. The likelihood function can be represented as a conditional distribution of each observed data point; the VAR residuals are independent and identically distributed;

$$P(Y_{T-p,t}|C_p, \Sigma, Y_{T-p,t}) = \prod_{t=1}^{T} P(Y_t|C_p, \Sigma, Y_{T-p,t-1}) \quad (11)$$

The likelihood in equation (11) can be expressed as (12) aligning with Gaussian errors assumptions

$$P(Y_{T-p,t}|C_p, \Sigma, Y_{T-p,0}) = \prod_{t=1}^{T} \frac{1}{2\pi^{\frac{In}{2}}} |\Sigma|^{\frac{1}{2}} \exp^{-\frac{1}{2}(y-C'u)\Sigma^{-1}(y-C'u_t)}$$

(12)

Aligning with equation (6) above, equation (12) can be expressed as;

$$P(Y_{T-p,t}|C_p, \Sigma, Y_{T-p,0}) = \prod_{t=1}^{T} \frac{1}{2\pi^{\frac{In}{2}}} |\Sigma|^{\frac{1}{2}} \exp^{-\frac{1}{2}(y-\bar{U}\beta)'\Sigma^{-1}(y-\bar{U}\beta)}$$

(13)

Bayesian method allows the integration of some information about parameters via the use of priors. Bayesian inference necessitates understanding the random parameter distribution, the population parameters are random, but the data is assumed to be fixed. Effective Bayesian inference depends on the choice of a suitable prior, Priors come in a variety of forms and serve a variety of functions, including changing parameters over time, reducing weak parameters, and addressing residual heteroscedasticity among others. In Bayesian VAR, coefficient matrices distribution is uncertain. Based on the VAR model in equation (13), a brief discussion on the prior adopted in this paper is given below:

2.3.2.1 Prior Selection and Description.

Minnesota Prior: It is a commonly type of prior in BVAR models that uses the assumption of variables following a random walk method. And Minnesota prior, which known as Litterman prior, is a shrinkage prior for AR parameters in VAR models. Once the priors are specified, the Bayesian estimation process updates them with the observed data to form posterior distributions. These posterior distributions provide a comprehensive view of the parameter estimates, accounting for both prior beliefs and the data.

Considering the VAR coefficients $\theta = (\theta'_1, \ldots, \theta'_n)'$ are priori independents across equations, and each θ_i, for i = 1,. . ., n, has a normal prior:

$$\theta_i \sim N(m_i, Q_i) \quad (14)$$

Let $m\boldsymbol{i}$ = 0 for growth rate data in order to reduce the VAR coefficients to zero. For level data, $m\boldsymbol{i}$ is likewise set to zero, with the exception of the first own lag coefficient, which is set to one.

Also, let $Q\boldsymbol{i}$, be diagonal with the z-th diagonal element; zz is set to be:

$$Vizz = \begin{cases} -\frac{z_1}{l^2}, \text{for the coefficient of i} - \text{th lag of variable} \\ -\frac{z_2\ Si^2}{l^2\ Sj^2}, \text{for the coefficient of i} - \text{th lag of variable} \\ -\frac{z_3\ Si^2}{Sj^2} \text{for the j} - \text{th element of } \alpha i; \\ -z_4 Si^2, \text{for the intercept;} \end{cases}$$

(15)

The sample variance of the residuals from an AR(p) model for the variable r is Sr^2, where r ranges from 1 to n.

Q_i is prior covariance matrix that relies on four hyper parameters, $z_1, \ldots, z_4$, which regulate degree of shrinkage for various types of coefficients, $z_3 = 1$ and $z_4 = 100$ for simplification, these suggested values imply virtually no shrinkages for the intercepts and coefficients.

Hyperparameter $z_1$controls the overall shrinkage strength for coefficients on their own lags, whereas $z_2$controls the on lags of additional variables. They are recognized as the unknown parameters subject to evaluation.

2.4 The Price Index Dynamics Analysis

The study of price dynamics in times series showcases the magnitude of unexpected price swings over time and measures the strength and frequency of fluctuations in data points over time. It serves as a crucial indicator of risk and uncertainty in financial and economic forecasting. The price index dynamics can be understood as the fluctuations of returns which serve as a measure of return uncertainty in financial market, it can be used to evaluate the possible profit or loss from investing in an asset and typically signify the level of risk connected with it. Price dynamics and the interdependence of the stock variables were evaluated with, correlation matrix, Granger causality test, Cointegration test, variance covariance approach and impulse response function analysis.

2.4.1 Variance Covariance Matrix

The Variance covariance matrix of a random vector X is given by

$$Cov(X) = E(X - E(X)(X - E(X)^T) \quad (16)$$

$Cov(X)$ can also be presented as

$$Cov(X) = E(XX)^T - E(X)\, E(X)^T) \quad (17)$$

Covariance measures the degree to which two variables vary together. The covariance of two random variables X_m and X_n can be presented mathematically as

$$Cov(X_m X_n) = E(X_m - \mu_m)(X_n - \mu_n) \quad (18)$$

Where μ_m is $E(X_m)$ and μ_n is the $E(X_n)$. Furthermore, this relationship can extend to a generalized multivariate situation using matrix notations.

Variance covariance matrix is expressed as

$$\Sigma = \begin{bmatrix} \sigma^2(X_1) & \sigma(X_1, X_2) \dots & \sigma(X_1, X_n) \\ \sigma(X_2, X_1) & \sigma^2(X_2) \quad \dots & \sigma(X_2, X_n) \\ . & \dots \quad\quad \dots & . \\ . & \quad\quad\quad \dots & . \\ \sigma(X_n, X_1) & \sigma(X_n, X_2) & \sigma^2(X_n) \end{bmatrix} \quad (19)$$

Variance covariance matrix is a square matrix that contains the variances and covariance associated with several variables. The diagonal elements of the matrix contain the variances of the variables and off diagonal element contain the covariance between all possible pairs of variables. Variance covariance in BVAR model represents the contemporaneous relationship among the error terms of the endogenous variables. The estimation of the parameters involves the Bayesian techniques with Minesota prior, the Bayesian approach incorporate prior beliefs about the coefficients and the error terms. The variance covariance matrix accounts the interrelationship movement of the variance covariance matrix using BVAR models, the fluctuations of the various stock index is treated as parameter with its own prior distribution estimated jointly with the vector autoregressive models producing more robust inferences.

2.5 Optimum Selection Criteria

Constructing a VAR or BVAR model requires a critical step of carefully selecting the optimal lag order. This process involves determining the most suitable number of lags for each variable in the VAR model. The best lag is determined using model selection criteria with minimum values of Final Prediction Error (FP) Sequential Modified LR test statistic (LR), Hannan-Quinn Information Criterion (HQ), Schwarz Information Criterion (SC), and Akaike Information Criterion (AIC). These criteria serve as measures of the relative goodness of fit of a statistical model, penalizing excessive complexity by accounting for the number of parameters and the sample size.

2.6 Model Forecasting and Performance Evaluation

validation criterion such as Akaike Information criteria (AIC), Schwarz information criterion (SC), Hannan-Quinn information criterion (HQ), Final prediction error (FPE) and adjusted R^2 were employed for examining and comparing the predicting performances of the selected VAR and BVAR models

$$AIC = 2T - m \quad (20)$$

$$\mathrm{SIC} = 2\mathrm{Tlogn} - \mathrm{logm} \quad (21)$$

where T symbolizes the total of estimable parameters, m denotes the maximum

likelihood and n is the digits of samples.

$$R^2_{adj} = 1 - \frac{(1-R^2)(n-1)}{n-p-1} \quad (22)$$

R^2 is the R-square, n is the number of samples in the data set and p symbolize the number of predictors.

The Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) are also used to check how accurate the forecasts from the fitted BVAR and VAR models are.

MAE is the absolute value of the difference between the predicted and actual values. It figures out the average absolute difference between what was predicted and what actually happened.

MAE is estimated as follow:

$$MAE = \frac{1}{n} \sum_{t=1}^{n} \left| \hat{\tilde{y}}_f - y_t \right| \quad (23)$$

MAPE is projected as the computation of the percentage of mean absolute error occurred in the model formation. It is given by;

$$MAPE = \frac{100}{n} \sum_{t}^{n} \left| \frac{\hat{\tilde{y}}_f - y_t}{y_t} \right| \quad (24)$$

RMSE, which is calculated as follows, shows how well the model fits the observed data:

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^{n} \hat{\tilde{y}}_f - y_t} \quad (25)$$

n is the sample size, while $\hat{\tilde{y}}_f$ *and* y_t are the estimated and the real values respectively. The model with the lowest value is probably the one high forecast precision.

3.0 Results and Discussions

Table 1 depicts the descriptive statistics of shares Stock returns of Dangote Cement PLC, Nestle PLC, GT Bank PLC, UBA PLC and Zenith Bank PLC on the platform of Nigeria Stock Exchange in Nigeria respectively from October 26, 2010 to June 6, 2024. It can be deduced from Table 1 that all the variables show sign of positive skewness. The Jarque-Bera statistic with its associated p-value indicated that all the variables were not normally distributed at 5% significant level.

3.1 Trend and Pattern of Stock Prices Returns in Nigeria

	DANG CEM	GTB	NESTLE	UBA	ZENITH
Mean	0.1464	0.1975	0.0021	0.0105	0.1906
Median	0.1452	0.1913	0.0018	0.0113	0.1899
Maximum	1.7486	1.2737	1.6142	1.6651	1.7263
Minimum	0.0505	0.0434	0.1161	0.0567	0.2445
SD.	0.0051	0.0047	0.0312	0.0175	0.0029
Skewness	0.0218	0.1672	0.2816	0.0251	0.1765
Kurtosis	3.1117	5.0745	3.2294	6.0732	5.8764
Jarque-Bera	1.4355	1.2326	0.7520	1.3484	0.5885
P-value	0.000	0.000	0.000	0.000	0.000
N	3310	3310	3310	3310	3310

Figure 1 to 5 below show the trend patterns of shares Stock Price returns of Dangote Cement PLC, GT Bank PLC, Nestle PLC, UBA PLC and Zenith Bank PLC on the platform of Nigeria Stock Exchange in Nigeria respectively from October 26, 2010 to June 6, 2024. The figures revealed the non-stability of shares prices of the variables over the period considered.

Fig. 1: Stock Price of Dangote Cement PLC

Fig. 2: Stock Price of GTB Bank

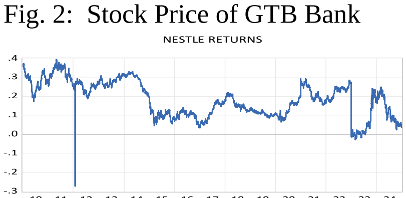

Fig. 3: Stock Price of Nestle PLC

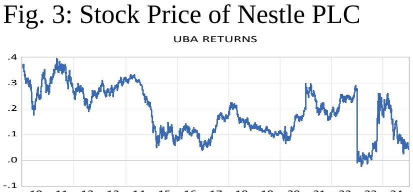

Fig. 4: Stock Price of UBA Bank

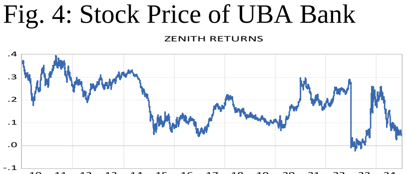

Fig. 5: Stock Price of ZENITH Bank

3.2 Stationarity Test

The stationarity test of the stock indices dataset was evaluated by a process described by Dickey and Fuller (1979). The results were presented in Table 2. All the variables in the model were made stationary at first difference which implied that the series are integrated of order 1 process.

Table 2: Unit Root Test

	I(0)		I(1)	
	ADF stat	Constant + Trend	Constant	Constant + Trend
Dangote	-0.2655	-0.1754	-1.4327	-1.3268*
Nestle	-0.4277	-1.0755	-0.5326	-0.3568*
GTBank	-1.9943	-0.9853	-2.0532	-2.8491*
UBA	0.2168	-0.1186	-0.3317	-1.5481*
Zenith	-0.2146	-0.1575	-2.1198	-1.1177*

* Indicates Stationary (i.e. p < 5%)

3.2.1 Co-integration Analysis

The Johansen cointegration Trace and Maximum Eigenvalue test results in Table 3 do not reject the null hypotheses of no cointegration at ranks $r = 0$, $r \leq 1$, and $r < 2$. At the 5% significance level, both tests show that there are no cointegrating equations. This means that the stock indices do not have a long-term relationship that holds up over time. Consequently, the variables exhibit neither a stable long-term equilibrium nor a common stochastic trend, indicating that they are not inherently connected and may ultimately diverge.

Table 3: Co-integration Test

No. of CE (s) in hypothesized	Trace statistics	Critical value (0.05)	Prob.
Trace			
None	7.3365	9.3295	0.4762
At most 1	25.1364	28.9641	0.2459
At most 2	0.7145	1.1137	0.3325
Maximum Eigenvalue			
None	6.5925	8.7621	0.4442
At most 1	22.1628	27.2906	0.2531
At most 2	0.7145	1.1136	0.3325

3.2.2 Granger Causality Test

The Granger causality test, derived from the modified Wald test procedure, examines the direction of causality among the study's variables; results are presented in Table 4 above. In banking, UBA and GTB have a one-way causal relationship, while Zenith and GTB have a two-way causal relationship. The Dangote Cement and Nestle indices demonstrated a unidirectional causal relationship within the industrial sectors.

Table 4: Granger Causality Test

Null Hypothesis	Obs	F-Statistic	Prob.	Decision

GTB BANK does not Granger Cause DANGCEM	3310	0.8798	0.0934	Causality
DANGCEM does not Granger Cause GTB BANK	3310	0.9383	0.0744	Causality
NESTLE does not Granger Cause DANGCEM	3310	1.9260	0.0697	Causality
DANGCEM does not Granger Cause NESTLE	3310	1.1059	0.5258	No causality
UBA does not Granger Cause DANGCEM	3310	0.1899	0.9242	No causality
DANGCEM does not Granger Cause UBA	3310	0.6998	0.6598	No causality
ZENITH does not Granger Cause DANGCEM	3310	0.8506	0.6034	No causality
DANGCEM does not Granger Cause ZENITH	3310	0.6062	0.0147	Causality
NESTLE does not Granger Cause GTB_BANK	3310	0.8648	0.5985	No causality
GTB_BANK does not Granger Cause NESTLE	3310	1.3218	0.4736	No causality
UBA does not Granger Cause GTB BANK	3310	0.3804	0.8133	No causality
GTB_BANK does not Granger Cause UBA	3310	0.3398	0.0363	Causality
ZENITH does not Granger Cause GTB BANK	3310	3.2113	0.0513	Causality
GTB_BANK does not Granger Cause ZENITH	3310	0.8963	0.0079	Causality
UBA does not Granger Cause NESTLE	3310	0.5261	0.7371	No causality
NESTLE does not Granger Cause UBA	3310	1.7145	0.4006	No causality
ZENITH does not Granger Cause NESTLE	3310	7.7720	0.0172	Causality
NESTLE does not Granger Cause ZENITH	3310	2.1461	0.0422	Causality
ZENITH does not Granger Cause UBA	3310	84.4355	0.0117	Causality
UBA does not Granger Cause ZENITH	3310	1.5784	0.0233	Causality

The Granger causality test, derived from the modified Wald test procedure, examines the direction of causality among the study's variables; results are presented in Table 4 above. In banking, UBA and GTB have a one-way causal relationship, while Zenith and GTB have a two-way causal relationship. The Dangote Cement and Nestle indices demonstrated a unidirectional causal relationship within the industrial sectors. Correlation coefficient for daily returns of the chosen indices is shown in Table 5 above. The correlation matrix displays the correlation coefficients between pairs of stock price indices. The outcome in Table 5 demonstrated negligible interdependencies among the indices.

Table 5: Correlation coefficient of the stock indices.

	DANGCEM	GTB	NESTLE	UBA	ZENITH
DANGCEM	1	0.6124	0.3683	0.1075	0.2491
GTB	0.6124	1	0.5258	0.0749	0.2623
NESTLE	0.3683	0.5258	1	0.4036	0.0364
UBA	0.1075	0.0749	0.4036	1	0.2916
ZENITH	0.2491	0.2623	0.0364	0.2916	1

3.3 VAR Model Lag Selection

The selection of the optimal lag order is crucial in time series analysis, as it significantly impacts the model's accuracy and predictive capability. This study employs various information criteria to evaluate different lag orders, as illustrated in Table 6. The FPE metric measures forecast error variance, with lower values implying better forecasting performance. The third lag order exhibits the lowest FPE value, suggesting that it may provide the most reliable forecasts as confirmed by the minimum values of AIC, SC, and HQ in lag 3. Hence, the optimum lag order of 3 is used for the estimation of VAR model to capture the essence of interconnected global financial markets.

Table 6: VAR Lag Order Selection Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	217.0750	NA	0.5621	0.5711	0.5627	0.5625
1	353.0070	15.3371	0.5902	0.5825	0.5809	0.5559
2	438.0320	16.0643	0.6021	0.5994	0.6024	0.5770
3	451.7430	15.1755	0.5574*	0.5508*	0.5529*	0.5517*
4	495.3610	16.2197	0.5520	0.5628	0.5774	0.5790
5	529.6540	15.9264	0.5654	0.5722	0.5719	0.5894
6	306.3180	15.4968	0.5990	0.5815	0.6123	0.5807
7	486.0660	15.2900	0.5721	0.5745	0.5883	0.5622
8	629.3050	15.2531	0.5628	0.5531	0.5722	0.5831

* Indicates lag order selected by the criterion.

3.3.1 Vector Auto Autoregressive (VAR) Model Fitting

The estimated results of the VAR model among various stock market indices, namely Dangote cement, Nestle, GTBANK, UBA bank and Zenith bank are presented in Table 7. The VAR models revealed that determination of future performance of each variable is being influenced by past records of each variable jointly with the past records of other variables.

	D(DANGCEM)	**D(NESTLE)**	**D(GTBANK)**	**D(UBA)**	**D(ZENITH)**
D(DANGEM(-1))	-0.0603 (0.3610) [-0.1670]	0.00534 (0.0169) [0.3175]	0.0005 (0.0022) [0.2141]	-0.0025 (0.0142) [-0.1785]	0.0008 (0.0025) [0.3206]
D(DANGEM(-2))	0.0740 (0.0175) [4.2449]	0.1322 (0.1138) [1.1658]	0.0001 0.00231 [0.2800]	0.0025 (0.0001) [2.6811]	0.0031 (0.0017) [1.8881]
D(DANGEM(-3))	0.1949 (0.8905) [0.1653]	-0.2666 (0.3708) [-0.7189]	0.0414 (0.045) 0.8670]	-0.0029 (0.3057) [-0.0092]	-0.0489 (0.0551) [-0.8821
D(NESTLE(-1))	0.0817 (0.0869) [1.6484]	0.3508 (0.3939) [-0.8906]	-0.0156 0.0505) -0.3088]	-0.0673 (0.3262) [-0.2014]	-0.0281 (0.0585) [-0.4791]
D(NESTLE(-2))	-0.2815 (0.2287) [-1.2307]	-0.0035 (0.0108) [-0.3273]	-0.0005 0.0013) -0.3704]	-0.0067 (0.0091) [-0.7344]	0.0047 (0.0015) [2.9880
D(NESTLE(-3))	-0.2200 (0.1337) [-1.1617]	0.9538 (2.5081) [0.3803]	-0.1358 0.3217) -0.4222]	1.3842 (2.0849) [0.6685]	0.0956 (0.3726) [0.2564]
D(GTBANK(-1))	-0.5049 (0.6811) [-0.7225]	0.7268 (2.3081) [0.3149]	-0.3215 0.2960) -1.08615]	-0.8529 (1.9145) [-0.4459]	-0.0749 (0.3425) [-0.2179]
D(GTBANK(-2))	0.3886 (0.6923) [0.1410]	0.2423 (0.5133) [0.4721]	0.0055 0.0654) -0.0873]	0.3762 (0.4278) [0.8510]	0.0649 (0.0760) [0.8516]
D(GTBANK(-3))	0.5612 (0.4717) [0.8642]	-1.9555 (1.4905) [-1.3120]	0.2368 (0.1912) 1.2385]	-1.2389 (1.2336) [-1.0205]	0.4895 (0.2218) [2.211]
D(UBA(-1))	1.0891 (0.8576) [1.8198]	1.2612 (1.7790) [0.7089]	-0.0891 (0.2282) [-0.3903]	1.8817 (1.4757) [1.2747]	-0.2137 (0.2641) [-0.8936]
D(UBA(-2))	-0.3102 (-0.1527) [-2.0322]	-0.2070 (-1.5804) [-0.5193]	-4.1385 (-1.0611) [-0.2567]	0.2451 (-1.2836) [0.4876]	-0.6539 (-0.9726) [-0.6704]
D(UBA(-3))	0.0006 (-0.0012) [0.1519]	-0.0939 (-0.1802) [0.3437]	-0.4454 -0.1834) [-0.5209]	-0.0136 (-0.1434) [-2.4254]	-0.8369 (-0.7336) [-0.0761]
D(ZENITH(-1))	0.0014 (-0.0034) [0.4001]	-0.6127 (-0.3564) [-1.7189]	0.5508 (-0.3633) [1.5159]	0.2395 (-0.2894) [1.0138]	0.8599 (-0.6221) [0.1749]
D(ZENITH(-2))	-0.0001 (-0.0030) [-0.2101]	0.0798 (-0.3123) [0.2554]	1.0422 (-0.3189) [3.2739]	0.1340 (-0.2358) [0.5249]	-0.3339 (-1.9306) [-0.8470]
D(ZENITH(-3))	-0.0002 (-0.0023) [0.3097]	0.9371 (-0.3027) [1.0945]	-0.7046 (-0.3085) [0.2261]	-0.3199 (-0.2579) [-0.0017]	-0.4613 (-0.8876) [0.0394]
C	0.6100 (0.1200) [-0.3056]	0.5450 (0.3101) [1.3482]	0.2345 (0.6952) [1.9649]	0.1697 (0.5438) [0.4802]	0.8251 (0.3725) [0.2979]
R-squared	0.7086	-0.0619	-0.3150	0.1859	0.7380
Adj. R-squared	0.7902	0.5863	0.3663	0.1901	0.7524
Sum sq. resids	32160.4200	1511.3080	193.8649	1253.6290	224.3704
S.E. equation	6.3485	0.8717	0.4731	1.5025	7.1974
F-statistic	-263.8590	-193.5310	-146.2990	-189.2310	-149.66
Log likelihood	23.9008	17.7853	13.6781	17.4114	13.9704
Akaike AIC	1.0530	8.2267	8.2653	7.8101	21.0860
Schwarz SC	1.0363	8.6434	8.6819	8.2268	21.5026
Mean dependent	0.1831	95.3560	32.2602	25.0713	13679.87
S.D. dependent	0.1546	116.6584	35.1195	26.1802	15566.20

Standard errors in ( ) and t-statistics in [ ],

3.4 Bayesian Vector Autoregressive (BVAR) Model Lag Selection

Table 8: Lag Selection Criteria for the BVAR

Lag	**LogL**	**LR**	**FPE**	**AIC**	**SC**	**HQ**
0	-2523.9880	NA	2.83e+37	103.2648	103.4965	103.3527
1	-2321.7860	346.6329	3.25e+34	96.4811	98.1026	97.0963
2	-2292.8030	42.58734	4.62e+34	96.7675	99.7789	97.9100
3	-2263.2610	36.17402	7.19e+34	97.0310	101.4324	98.7009
4	-2328.1800	355.0981	7.87e+38	96.1407*	98.0064*	97.0217*
5	-2219.0320	43.32603	7.49e+34	96.6952	102.4865	98.8924
6	-2516.0530	46.1673	5.22e+35	96.9034	101.9356	99.0003

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

As evidenced by the lowest values of AIC, SC, and HQ in lag 4 from Table 8, the fourth lag order has the lowest FPE value, indicating that it might offer the most accurate forecasts. In order to reflect the essence of interconnected global financial markets, the BVAR model is estimated using the optimal lag order of 4.

3.4.1 Bayesian Vector Autoregressive (BVAR) Model Fitting

Table 9: Bayesian Vector Autoregressive model coefficient for the five variables.

Lag	Dangcem	GTB	Nestle	UBA	Zenith
Constant	-0.086	0.078	-0.087	-0.030	0.106
Dangcem(-1)	2.116	0.016	0.125	0.029	0.000
GTB(-1)	0.024	0.033	0.061	0.230	0.502
Nestle (-1)	0.000	0.060	0.042	0.003	0.291
UBA (-1)	0.055	0.031	0.017	0.242	0.074
Zenith (-1)	0.172	0.311	0.010	0.000	0.226
Dangcem(-2)	-0.205	-0.000	-0.132	-0.054	-0.000
GTB(-2)	-0.000	-0.018	-0.491	-0.000	-0.640
Nestle (-2)	0.044	0.205	0.287	0.100	0.330
UBA (-2)	0.000	0.044	0.171	-0.000	0.002
Zenith (-2)	-0.026	0.065	0.269	0.015	0.000
Dangcem(-3)	0.173	0.040	0.006	0.019	0.024
GTB(-3)	-0.014	0.000	-0.053	0.000	0.004
Nestle (-3)	-0.007	0.009	0.301	0.029	0.031
UBA (-3)	-0.843	0.061	-0.252	0.000	0.000
Zenith (-3)	0.000	0.006	-0.036	0.000	0.007
Dangcem(-4)	0.008	-0.000	0.104	0.050	0.000
GTB(-4)	0.000	-0.037	0.058	0.000	0.026
Nestle (-4)	0.031	0.006	-0.440	0.100	0.090
UBA (-4)	-0.148	0.072	0.000	0.029	0.000
Zenith (-4)	-0.360	0.043	0.061	0.000	0.016

R-squared: 0.96291; Adjusted R squared: 0.9560

Table 9 shows the main results of a detailed study on Bayesian Vector Autoregressive (BVAR) models for five chosen Nigerian stocks. BVAR treats parameters of the variables as random variables with Minnesota prior probabilities. BVAR Model overcomes the curse of dimensionality by applying shrinkage via informative priors. The model was employed in analyzing the stock market dynamics and interdependence of the variables under study due to effectiveness of solving overfitting problems related to standard VAR models when analyzing multiple financial series. Comparing VAR of lag 3 and BVAR of lag length (4), using DANGOTE CEMENT, NESTLE, GTBANK, UBA and ZENITH variables. The BVAR model has a hyperparameter lambda after optimization of 0.14563 with an acceptance draw rate of 62.36%. BVAR model demonstrates that the fluctuations in stock price indices are influenced not only by their own dynamics but also by dynamics of other stock price indices. The model elucidates the effects of a single variable on itself and on other variables. Almost all of the indices showed that their own previous value had a positive and significant effect on their future value. This shows strong autoregressive behavior, where the past value is a good predictor of future values.

The general error metrics showed that BVAR models were more effective in predicting how the prices of Nigerian stocks would fluctuate. Furthermore, the results demonstrated that BVAR model consistently outperforms VAR model in terms of the higher Adjusted-R^2 and general model performance evaluation metrics in Table 10, corroborating the findings of Israel, Kingdom, Yvonne, Da- wariboko & Ike (2023). This suggests that variance found in the data was better explained by BVAR model.

Table 10: Model Performance Evaluation

Model	RMSE	MAE	MAPE	R^2	Adj R^2
VAR	0.7236	0.2908	0.0348	0.9240	0.8805
BVAR	0.4527	0.0361	0.4486	0.9639	0.9560

Table 11 below shows the results of checking if the residuals of the joint BVAR model have constant variance, which is important for making sure that the model estimation is strong and efficient. The residuals show homoscedasticity with a high p value of 0.8614, which supports the model's stability and the reliability of the estimated parameters. Moreover, the BVAR residuals are multivariate normal and not correlated. Figure 6 below shows the roots of the BVAR system, which is a way to check how stable the system is. The BVAR system meets the stability condition because there are no roots outside of the unit circle.

Table 11: BVAR Residual Diagnostics

Diagnostic Test	Test Stat. Value	Prob	Remark
BVAR Residual Heteros kedcity test	4183.0000	0.8614	No heteroskedacity
BVAR Residual Corr elation LM Test	31.0613	0.3437	No Serial Correlation
Normality Test (Jarque Bera)	29.1097	0.7249	Residuals are multivar iate Normal.

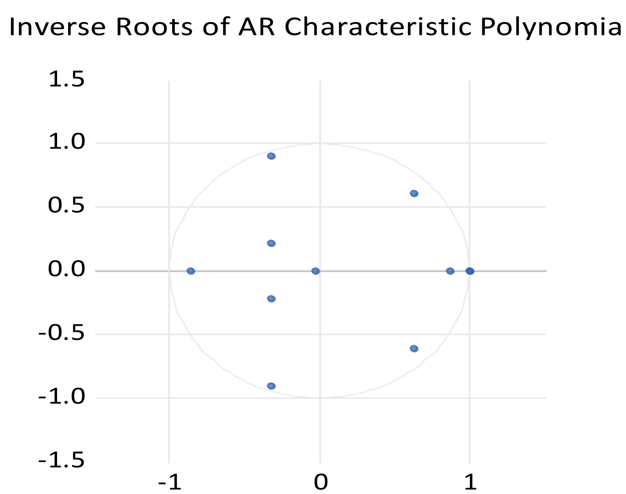

Table 12 below shows that the fast-Moving Consumer Goods FMCG (Nestle) have the highest price returns dynamics with 0.7822, followed by the Building Materials (Dangote cement) with 0.4816 while the service companies (banking sectors) have the least dynamics.

Table 12: Numeric array (dimensions 5, 5) of variance-covariance values from a BVAR models.

Variable	Dangcem	GTB	Nestle	UBA	Zenith
Dancem	0.4816	0.1810	-0.2205	0.1300	0.1051
GTB	0.1810	0.0229	-0.3634	0.2090	0.8719

Nestle	-0.2205	-0.3634	0.7822	0.6129	0.0502
UBA	0.1300	0.2090	0.6129	0.0641	0.0091
Zenith	0.1051	0.8719	0.0502	00091	0.1418

GGLog-Likelihood: -220462.14.

The observed variance- covariance matrix in Table 12 above confirms an interdependence and significant relationship between the individual stock prices of the selected variables most especially among the banking sectors. The performance of Nigeria's banking sectors can be attributed to their policies on market capitalizations, trading platforms, quick development, and consistent dividend payouts. The results highlight that GT Bank (GTB) and Zenith Bank (ZEN) stock prices exhibit a particularly strong relationship compared to UBA bank stocks. This is supported by the variance-covariance values indicating higher covariance between GTB and ZEN compared to UBA bank. However, there is a weak relationship among the industrial sector as it was revealed in the variance covariance value between Dangote cement and Nestle price returns. This suggests that movements in the overall price indices in Nigeria markets have a significant connection to fluctuations in the stock prices of the selected sectors. The banking and manufacturing sectors directly influence the stability of other stock indices by regulating the flow, cost, and availability of capital. These sectors operate as principal financial intermediaries propelling the broader economy, as evidenced in Nigeria's evolving stock market.

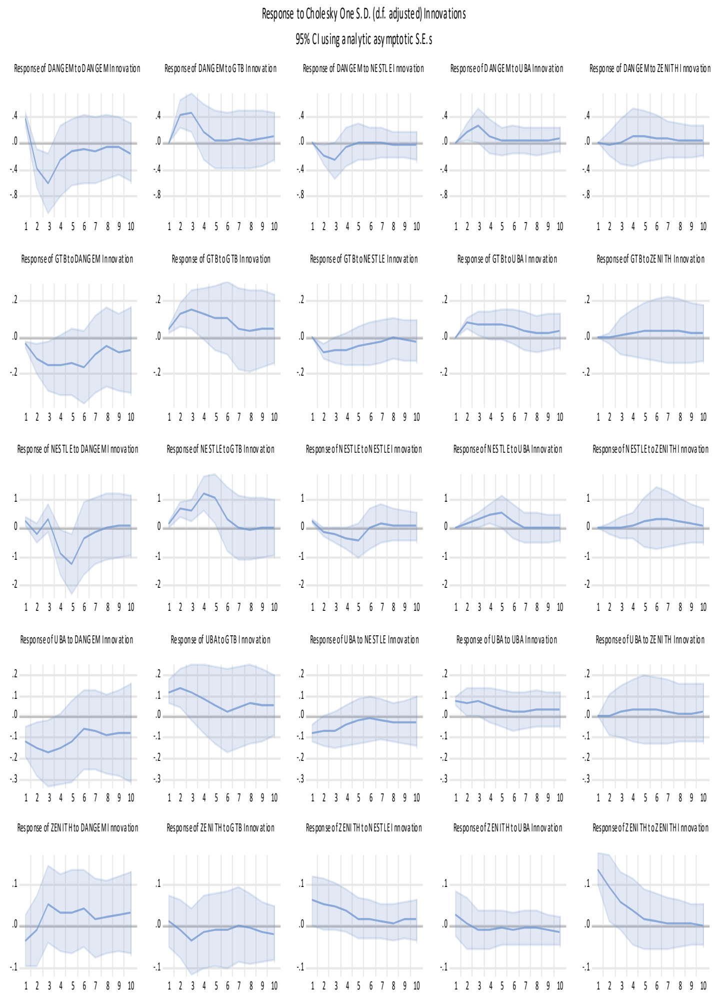

Figure 7: Plot of the shocks for each variable

The plot illustrates the response of the stock prices of DANGCEM, GTB, Nestle, UBA, and Zenith over time to a standard deviation shock in any of the variables. The IRFs in this study track these changing responses in Nigeria over a ten-year period. The impulse response research in Figure 7 shows that the stock market return prices for GTB and Zenith banks are very resistant to their own shocks. Over time, they gradually fall, which is a sign of capital market inertia. DANGCEM stock price returns, on the other hand, don't change much when other stock prices change, which means that other factors don't have much of an effect in the short term. However, DANGCEM stock price returns do change a lot and positively when its own prices change, showing that it is self-dependent and persistent.

Additionally, Nestle PLC's stock price exhibits statistically significant negative reactions to shocks from DANGCEM, indicating that short-term variations in DANGCEM returns have a substantial impact on Nestle's stock price. However, similar to how UBA Bank's stock returns barely respond to shocks, Zenith Bank's price returns and UBA's price returns support the idea that these stock price returns in Nigeria function mostly independently in the short term. Generally, the shocks among the sectors revealed that banking sectors significantly influence the manufacturing sector while the industrial sector exhibits least influence. This result is consistent with Emenike and Ali (2014) findings in their studies of nature of domestic volatility between sectors of Nigeria Economy where they discovered that banking sector significantly influence the risk and price movements in consumer goods sector. Mostly, the result of granger causality testing indicates the presence of bidirectional causality between the banking sector and Manufacturing sector supporting the result of Simiyu, Korir, . & Gabriel, (2020).

4.0 Conclusions

Market uncertainty serves as a crucial gauge for assessing the traits of market fluctuations, understanding these fluctuations and accurately predicting stock price trend is essential for investors, policymakers, and financial analysts. The study developed Vector Autoregressive model (VAR) and Bayesian Vector Autoregressive (BVAR) models, which allowed for a thorough examination of the price dynamics and interdependence between stock variables. It presented insightful findings about their interactions and implications for Nigerian price index BVAR models postulated a more accurate and dependable depiction of the price dynamics among Dangote cement, Nestle, UBA, GT Bank and Zenith Bank stock variables due to its stability and homoskedasticity evidences of the residuals, suggesting a consistent connection between the variables. The results demonstrate the superiority of the BVAR model as a more dependable and effective forecasting and analysis tool because it effectively captures the complexity and dynamism of the relationship between the variables under investigation in Nigeria. These findings align with Agunbiade, Ayodeji, Funmi, & Obadina, (2019)., which demonstrated that the BVAR model is more precise and preferable than the VAR model in modelling econometric variable. The result revealed the existence of multidirectional relationship among the variables, potentially influenced by factors such as corporate governance, political instability, market dynamics, and regulatory frameworks.

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Declaration of conflict of interest

The authors have collectively contributed to the conceptualization, design, and execution of this journal. They have worked on drafting and critically revising the article to include significant intellectual content. This manuscript has not been previously submitted or reviewed by any other journal or publishing platform. Additionally, the authors do not have any affiliation with any organization that has a direct or indirect financial stake in the subject matter discussed in this manuscript.

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