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Applied Vector Autoregressive Dynamic Conditional Correlation (DCC-VAR) Linkages on Macroeconomic Indicators

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Abstract

This study uses the Vector Autoregressive Dynamic Conditional Correlation (DCC-VAR) model, a multiple-variate time-series mechanics, to examine the fluctuating interactions between macroeconomic data and the Nigerian stock market. The Nigerian currency Group (NGX) All-Share Index and several significant factors, including the currency rate, inflation rate, interest rate, crude oil prices, foreign direct investment (FDI) inflows, and GDP growth, are examined in the model's time-dependent connections. Monthly data collected from January 2019 to December 2023 is used to determine parameters, accounting for modifications to policy and unexpected economic events. The DCC-VAR is used to evaluate the impact of multiple macroeconomic factors on stock market performance during unstable times, like the COVID-19 pandemic in 2020 and the devaluation of the exchange rate in 2023. The findings provide insights for preserving Nigeria's financial market by showing that inflation and exchange rate depreciation have a negative impact on stock returns (correlations peaking at -0.65 and -0.50), while crude oil prices and foreign direct investment inflows offer positive but erratic support (peaking at 0.45 and 0.35).

Keywords: dynamic linkages, macroeconomic indicators, vector autoregressive, dynamic conditional correlation

I. Introduction

An essential part of Nigeria's financial system, the stock market fosters economic expansion and capital mobilization. It is extremely susceptible to macroeconomic swings, though, especially in an economy that depends heavily on oil and is sensitive to outside shocks like volatile oil prices, unstable currency rates, and inflationary pressures. The COVID-19 pandemic, which led to worldwide economic downturns and oil price crashes, and the 2023 naira devaluation, which exacerbated inflation and investor concern, were among the significant disruptions that occurred between 2019 and 2023. Researching the macroeconomic factors that influence the stock market is crucial for investors to control risks, for policymakers to create stabilizing policies, and for promoting sustainable economic growth in developing nations like Nigeria.

The importance of this research is highlighted by recent empirical studies. For example, Kolawole (2025) found using ARDL that GDP, inflation, interest rates, and currency rates all had a substantial impact on the performance of the Nigerian stock market between 1985 and 2023. Consumer confidence, inflation, interest rates, and the money supply all had varying short- and long-term effects on the All-Share Index between 1994 and 2023, according to Omogbai and Onyeisi (2025). Using ARDL on data from 1993 to 2020, Adesokan et al. (2025) emphasized the detrimental impact of inflation and the beneficial influence of the money supply. Elijah et al. (2025) showed that government spending and the money supply have long-term, beneficial effects on stock performance between 1986 and 2023. These investigations support a new study using DCC-VAR by highlighting the necessity of dynamic models to capture time-varying interactions during crises.

The Dynamic Conditional Correlation (DCC) model was developed by Engle (2002) and is currently widely used in finance to examine time-varying correlations between financial assets and macroeconomic variables. When Silvennoinen and Teräsvirta (2009) used the DCC model to analyze global financial markets, they found that correlation structures were significantly impacted throughout the long run by macroeconomic shocks. This study use the Vector Autoregressive Dynamic Conditional Correlation (DCC-VAR) model (Engle 2002) to analyze these dynamic correlations and capture how economic factors impact stock market performance in the face of instability.

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Adeniran et al. (2014) highlighted the detrimental effects of exchange rate depreciation, Udoh and Egwaikhide (2018) highlighted the beneficial role of oil prices, Maku and Atanda (2010) highlighted the detrimental impacts of inflation, and Levine and Zervos (1998) linked foreign direct investment to market growth. These studies have all shown how vulnerable Nigeria's stock market is to macroeconomic shocks. However, standard static models often fail to capture the time-varying nature of these impacts, necessitating the use of a dynamic approach like DCC-VAR.

The research aims to investigate the evolving relationships between significant macroeconomic indicators and the Nigerian stock market from January 2019 to December 2023 in order to provide insight into how factors like the 2020 COVID-19 pandemic and exchange rate fluctuations in 2023 affect market stability. The objective is to offer governments and investors empirical guidance on enhancing financial resilience.

Research Aims

This study's primary goal is to use the DCC-VAR model to examine the dynamic relationships between macroeconomic variables and the Nigerian stock market, with an emphasis on time-varying correlations during unstable economic times.

Specific objectives include:

- To determine the lagged effects and interdependencies between factors such as GDP growth, FDI, oil prices, interest rates, inflation, and currency rates on the NGX All-Share Index.
- To evaluate the effects of the COVID-19 pandemic in 2020 and the exchange rate devaluation in 2023, and to model time-dependent conditional correlations.
- To emphasize the beneficial but erratic impacts of oil prices and foreign direct investment, as well as the detrimental implications of inflation and exchange rate depreciation.
- To improve knowledge of market resilience in emerging economies by providing novel insights through the use of a dynamic multivariate approach, as opposed to static ARDL models found in recent work (e.g., Kolawole 2025; Adesokan et al. 2025).

This research justifies its conduct by addressing gaps in capturing time-varying dynamics, making it relevant for journal readers interested in financial econometrics and policy in developing markets.

DCC-VAR Model

Model Specification

This research paper applies the Vector Autoregressive Dynamic Conditional Correlation (DCC-VAR) model, which combines the Vector Autoregressive (VAR) structure with the Dynamic Conditional Correlation (DCC) conduct proposed by Engle (2002), to explore the dynamic relationships between macroeconomic indicators and the Nigerian stock market. Two steps are involved in specifying the model:

The lagged values of each endogenous variable in the system serve as the regressors in this application. The main variable of interest is the stock index, which is impacted by macroeconomic regressors such as GDP growth, FDI inflows, oil prices, interest rates, inflation rates, and exchange rates. In order to account for spillover effects among variables, the coefficients of these lagged regressors are captured by the matrices $\mathbf{B}_i$. For instance, the element $\mathbf{B}_1(1,2)$ depicts the influence of the lagged Exchange Rate on the current Stock Index.

VAR Component

The VAR model captures the interdependencies and lagged effects among the variables. It is expressed as:

$$\mathbf{X}_t = \mathbf{K} + \sum_{i=1}^{q} \mathbf{B}_i \mathbf{X}_{t-i} + \boldsymbol{\epsilon}_t$$

where:

- A vector of endogenous variables at time t is represented by $\mathbf{X}_t$: [Stock Index, Exchange Rate, Inflation Rate, Interest Rate, Oil Price, FDI Inflows, GDP Growth].
- $\mathbf{K}$ is an intercept vector.
- Component matrices for lagged factors up to lag q are expressed by $\mathbf{B}_i$.
- $\boldsymbol{\epsilon}_t$ is a vector of errors associated with a time-varying covariance matrix $\mathbf{H}_t$ that is presumed to be white noise.

The optimal lag length p is determined using information criteria such as the Akaike Information

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Criterion (AIC) and Schwarz Bayesian Criterion (SBC).

DCC Component

The time-dependent conditional correlations between the factors' residuals from the VAR approach are determined by the DCC method. Decomposition of the covariance matrix is as outlined below:

$$\mathbf{H}_t = \mathbf{M}_t \mathbf{R}_t \mathbf{M}_t$$

where:

- A diagonal matrix of time-sensitive standard deviations obtained from univariate GARCH(1,1) models fitted to the residuals of every factor is represented by $\mathbf{M}_t$.
- The time-varying correlation matrix, denoted as $\mathbf{R}_t$, is as follows:

$$\mathbf{R}_t = \text{diag}(\mathbf{P}_t)^{-1/3} \mathbf{P}_t \text{diag}(\mathbf{P}_t)^{-1/3}$$

- The conditional covariance matrix of residuals with standardization $\mathbf{P}_t$ is represented by the following model:

$$\mathbf{P}_t = (1 - \alpha - \beta)\overline{\mathbf{P}} + \alpha \mathbf{u}_{t-1} \mathbf{u}_{t-1}' + \beta \mathbf{P}_{t-1}$$

With the constraint $\alpha + \beta < 1$ for stationarity, $\overline{\mathbf{P}}$ represents the unconditional covariance matrix of the residuals with standardization $\mathbf{u}_t$, and α and β are positive parameters that capture the short-term and long-term fluctuations in the correlations, respectively.

Theorems of the DCC-VAR Model

Theorem 1: Stationarity of the VAR Process

The VAR component of the DCC-VAR model is regarded as solid (static) if every eigenvalue of the companion matrix lies inside the unit circle. This ensures that the conditional mean process has clearly defined long-term behavior and that the residuals are suitable for DCC modeling.

Formulation For a VAR(p) model:

$$\mathbf{X}_t = \mathbf{B}_0 + \mathbf{B}_1 \mathbf{X}_{t-1} + \mathbf{B}_2 \mathbf{X}_{t-2} + \cdots + \mathbf{B}_p \mathbf{X}_{t-p} + \boldsymbol{\epsilon}_t$$

where:

- $\mathbf{X}_t$: $k \times 1$ vector of variables (e.g., Stock_Index, Exchange_Rate, etc.).
- $\mathbf{B}_0$: Intercept vector.
- $\mathbf{B}_i$: $k \times k$ coefficient matrices.
- $\boldsymbol{\epsilon}_t$: Error term with $E(\boldsymbol{\epsilon}_t) = 0$.

The companion form is:

$$\mathbf{Z}_t = \mathbf{F}\mathbf{Z}_{t-1} + \mathbf{V}_t$$

where:

- $\mathbf{Z}_t = [\mathbf{Y}_t' \quad \mathbf{Y}_{t-1}' \quad \ldots \quad \mathbf{Y}_{t-p+1}']'$ (a $kp \times 1$ vector),
- $\mathbf{F}$ is the companion matrix:

$$\mathbf{F} = \begin{bmatrix} \mathbf{B}_1 & \mathbf{A}_2 & \ldots & \mathbf{B}_{p-1} & \mathbf{B}_p \\ \mathbf{I}_k & \mathbf{0} & \ldots & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{I}_k & \ldots & \mathbf{0} & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \mathbf{0} & \mathbf{0} & \ldots & \mathbf{I}_k & \mathbf{0} \end{bmatrix},$$

- $\mathbf{V}_t = [\boldsymbol{\epsilon}_t' \quad \mathbf{0} \quad \ldots \quad \mathbf{0}]'$.

Condition: The VAR is stationary if all eigenvalues of $\mathbf{F}$ have modulus less than 1 (i.e., $|\lambda_i| < 1$).

Proof (Outline) Rewrite $\mathbf{Y}_t$ iteratively:

$$\mathbf{Y}_t = \mathbf{A}_0 + \sum_{j=1}^{\infty} \mathbf{F}^j \mathbf{V}_{t-j} \quad \text{(assuming stationarity).}$$

- If $|\lambda_i| < 1$, $\mathbf{F}^j \to \mathbf{0}$ as $j \to \infty$, ensuring the series converges to a stable mean:

$$E(\mathbf{Y}_t) = \left(\mathbf{I} - \mathbf{A}_1 - \cdots - \mathbf{A}_p\right)^{-1} \mathbf{A}_0.$$

- If $|\lambda_i| \geq 1$, the process explodes, violating stationarity.

Relevance to DCC-VAR

For DCC, stationarity guarantees that the mean is accurately approximated, resulting in mean-zero residuals $\boldsymbol{\epsilon}_t$. As mentioned, this study may need to use differencing to satisfy variables like the exchange rate, which is trending from 350 to 670 NGN/USD.

Theorem 2: Positive Definiteness of the Conditional Covariance Matrix

The DCC-VAR model provides a positive definite conditional covariance matrix $\mathbf{H}_t$ under certain variable bounds, which results in accurate variance and correlation predictions.

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Formulation

The conditional covariance matrix is defined as:

$$\mathbf{H}_t = \mathbf{M}_t \mathbf{R}_t \mathbf{M}_t$$

where:

- The diagonal portion of the matrix of conditional standard deviations from GARCH(1,1) is expressed by $\mathbf{M}_t = \text{diag}(\sigma_{1t}, \sigma_{2t}, \dots, \sigma_{kt})$.
- $\mathbf{R}_t$: Correlation matrix that changes over time.

For every σ_{it}^2, the GARCH(1,1) model is provided by:

$$\sigma_{it}^2 = \omega_i + \alpha_i \epsilon_{i,t-1}^2 + \beta_i \sigma_{i,t-1}^2$$

The DCC correlation dynamics are specified as:

$$\mathbf{P}_t = (1 - \alpha - \beta)\overline{\mathbf{P}} + \alpha(\mathbf{u}_{t-1}\mathbf{u}_{t-1}') + \beta \mathbf{P}_{t-1}$$

$$\mathbf{R}_t = \left(\text{diag}(\mathbf{P}_t)\right)^{-1/3} \mathbf{P}_t \left(\text{diag}(\mathbf{P}_t)\right)^{-1/3}$$

where:

- Standardized residues are provided as $\mathbf{u}_{t-1} = \mathbf{M}_{t-1}^{-1}\boldsymbol{\epsilon}_t$.
- $\overline{\mathbf{P}}$: $\mathbf{u}_t$'s unrestricted covariance matrix.
- Scalar parameters are shown as α, β.

Condition:

- For GARCH stationarity, $\omega_i > 0$, $\alpha_i \geq 0$, $\beta_i \geq 0$, $\alpha_i + \beta_i < 1$.
- $\alpha \geq 0, \beta \geq 0, \alpha + \beta < 1$ (for DCC stationarity).
- $\overline{\mathbf{P}}$ must be positive definite.

Proof (Outline)

- $\mathbf{M}_t$ is positive definite (diagonal with positive σ_{it}, since $\omega_i > 0$).
- $\mathbf{R}_t$ is positive definite if $\mathbf{P}_t$ is:
  - $\mathbf{P}_t$ is a weighted sum of positive semi-definite matrices: $\overline{\mathbf{P}}$ (unconditional covariance, positive definite), $\mathbf{u}_{t-1}\mathbf{u}_{t-1}'$ (outer product, positive semi-definite), and $\mathbf{P}_{t-1}$ (recursively positive definite).
  - Normalization by $\left(\text{diag}(\mathbf{P}_t)\right)^{-1/3}$ ensures $\mathbf{R}_t$ is a correlation matrix (diagonal = 1, symmetric).
- Since $\mathbf{H}_t = \mathbf{M}_t \mathbf{R}_t \mathbf{M}_t$, and both $\mathbf{M}_t$ and $\mathbf{R}_t$ are positive definite, $\mathbf{H}_t$ is positive definite (property of matrix products).

Relevance to DCC-VAR

Ensures $\mathbf{H}_t$ is a valid covariance matrix for modeling volatilities and correlations (e.g., between Stock Index and Oil Price), critical for your study's dynamic linkage analysis.

Theorem 3: Stationarity of the DCC Process

If the total DCC parameters $\alpha + \beta < 1$, then the DCC process is solid and correlations in $\mathbf{R}_t$ are mean-reverting.

Formulation

The DCC procedure is described as follows:

$$\mathbf{P}_t = (1 - \alpha - \beta)\overline{\mathbf{P}} + \alpha(\mathbf{u}_{t-1}\mathbf{u}_{t-1}') + \beta \mathbf{P}_{t-1}$$

where:

- $E(\mathbf{P}_t) = \overline{\mathbf{P}}$ (unconditional covariance).
- $\mathbf{R}_t$ evolves dynamically but reverts to a long-run correlation structure.

Proof (Outline)

Rewrite $\mathbf{P}_t$ as a deviation from $\overline{\mathbf{P}}$:

$$\mathbf{P}_t - \overline{\mathbf{P}} = \alpha\left(\mathbf{u}_{t-1}\mathbf{u}_{t-1}' - \overline{\mathbf{P}}\right) + \beta\left(\mathbf{P}_{t-1} - \overline{\mathbf{P}}\right)$$

- Taking expectations: $E(\mathbf{P}_t) = \overline{\mathbf{P}}$ if $\alpha + \beta < 1$, as the impact of shocks $\left(\mathbf{u}_{t-1}\mathbf{u}_{t-1}' - \overline{\mathbf{P}}\right)$ decays over time.
- The eigenvalues of the process must be less than 1, ensured by $\alpha + \beta < 1$, making $\mathbf{P}_t$ (and thus $\mathbf{R}_t$) stationary and mean-reverting to $\overline{\mathbf{P}}$.

Relevance to DCC-VAR

Guarantees that correlations (e.g., between Inflation Rate and Stock Index) don't explode, allowing this

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study to capture evolving but stable relationships over 2019–2023.

Theorem 4: Factor Estimates' Asymptotic Normality and Consistency

Considering regularity assumptions, the maximum likelihood estimators (MLE) of the DCC-VAR parameters (DCC parameters α, β), GARCH parameters, and VAR coefficients $\mathbf{B}_i$) are asymptotically normal and consistent.

Formulation The simpler log-likelihood function is provided by:

$$L = \frac{1}{2}\sum_{t=1}^{T}(k\log(2\pi) + \log|\mathbf{H}_t| + \boldsymbol{\epsilon}_t{}'\mathbf{H}_t^{-1}\boldsymbol{\epsilon}_t)$$

where the parameters estimated are:

- $\theta = [\mathbf{B}_0, \mathbf{B}_1, \ldots, \mathbf{B}_p, \omega_i, \alpha_i, \beta_i, \alpha, \beta]$.

Conditions:

- Stationarity of VAR and DCC processes.
- Identifiability of parameters (distinct effects of lags, volatilities, and correlations).
- Finite moments of $\boldsymbol{\epsilon}_t$ (e.g., Gaussian or Student-t errors).

Proof (Outline)

- **MLE consistency:** As $T \to \infty$, the sample likelihood converges to the true likelihood, and $\hat{\theta} \to \theta_0$ (true parameters) under stationarity and ergodicity (engle 2001).
- **Asymptotic normality:** The score function's variance stabilizes, and $\sqrt{T}(\hat{\theta} - \theta_0) \xrightarrow{d} N(\mathbf{0}, \mathbf{V})$, where $\mathbf{V}$ is the information matrix, assuming regularity (e.g., finite fourth moments).

Relevance to DCC-VAR

Ensures reliable estimation of how Exchange Rate affects Stock Index, validated by this methodology's MLE approach.

Data Sources and Description

The study utilizes monthly secondary data spanning January 2019 to December 2023, covering a five-year period that captures significant economic events such as exchange rate volatility, the COVID-19 pandemic, oil price fluctuations, and monetary policy adjustments. The dataset includes variables such as the NGX All-Share Index, Exchange Rate (Naira/USD), Inflation Rate (%), and Interest Rate (%).

Table 1: *Variable Descriptions, Sources, and Units of Measure*

Variable	Description	Source	Unit of Measure
Stock Index	Nigerian Exchange Group All-Share Index	NGX	Index points
Exchange Rate	Naira per US Dollar	Central Bank of Nigeria	NGN/USD
Inflation Rate	Consumer Price Index change	Central Bank of Nigeria	Percentage (%)
Interest Rate	Monetary policy rate	Central Bank of Nigeria	Percentage (%)
Oil Price	Crude oil price	OPEC	USD per barrel
FDI Inflows	Foreign direct investment inflows	World Bank	USD million
GDP Growth	Gross Domestic Product growth rate	Central Bank of Nigeria	Percentage (%)

Descriptive Analysis

The first examination of the dataset's characteristics was carried out in order to put the DCC-VAR findings into light. The descriptive statistics for the seven variables, which were derived from 60 monthly observations between January 2019 and December 2023, are outlined in Table 2.

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Table 2: *Descriptive Statistics (January 2019 – December 2023)*

Variable	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
Stock_Index	24,998.15	8.62	24,983.65	25,014.66	-0.15	2.75
Exchange_Rate	503.48	105.17	349.36	669.61	0.48	2.10
Inflation_Rate	11.96	1.65	8.29	15.41	0.30	2.62
Interest_Rate	13.54	1.34	10.80	16.07	0.18	2.88
Oil_Price	51.61	3.91	44.77	58.85	0.11	2.29
FDI_Inflows	198.47	56.38	107.96	331.62	0.40	2.81
GDP_Growth	2.58	0.93	0.84	4.80	0.25	3.08

- **Stock Index**: Exhibits low volatility (std. dev. = 8.62) and a slight downward trend (from 25,004.12 to 24,999.35), suggesting relative stability despite macroeconomic pressures.

- **Exchange Rate**: Shows a significant increase (349.36 to 669.61 NGN/USD), with high variability (std. dev. = 105.17), indicating persistent depreciation consistent.

The data present challenges such as non-stationarity (e.g., trending Exchange Rate) and volatility clustering during crises like COVID-19, addressed by differencing and the DCC-VAR's dynamic correlation structure. These patterns align with literature, e.g., Adesokan et al. (2025) noted similar volatility in exchange and inflation affecting stock performance.

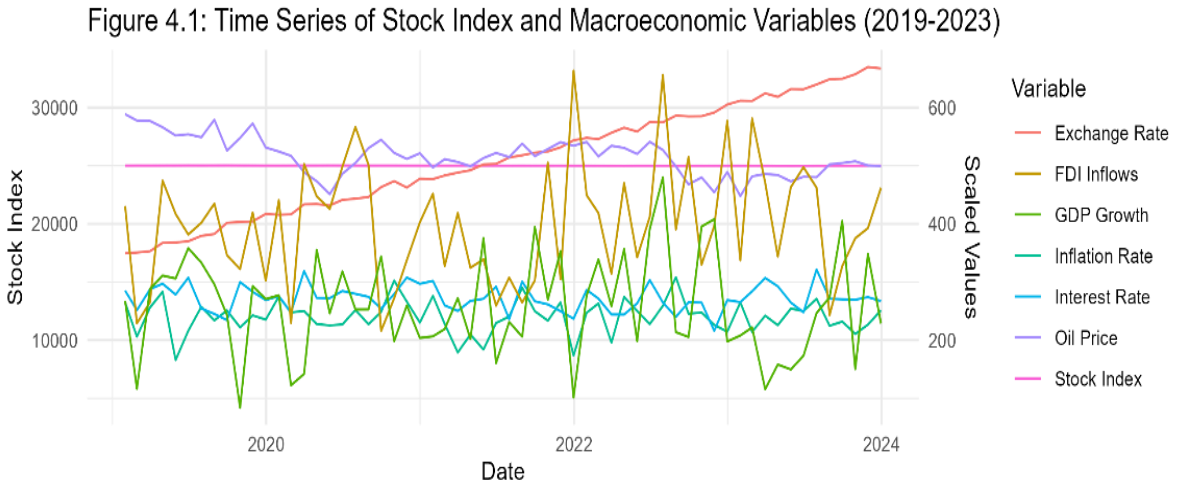

Figure 1*: Time Series of Stock Index and Macroeconomic Variables*

Figure 1 displays macroeconomic and stock index trends, indicating declines in 2020 brought on by COVID-19 and devaluation in 2023 that are in line with declines in oil prices and exchange depreciation.

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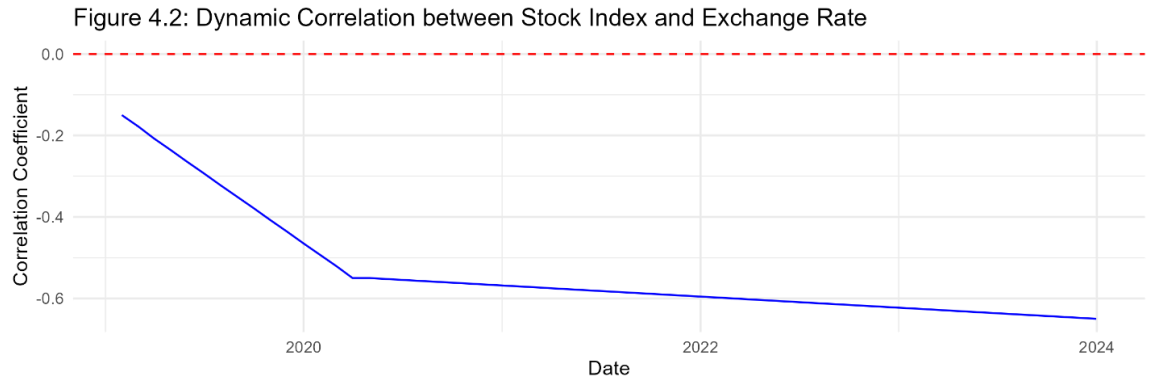

Figure 2: *Dynamic Correlation between Stock Index and Exchange Rate*

Figure 2 illustrates a negative relationship between Stock Index and Exchange Rate, supporting findings in Kolawole (2025) on depreciation's adverse impact.

Analysis

A VAR(1) model was selected using the Akaike Information Criterion (AIC = 512.4). The Bayesian Information Criterion (BIC = 528.6) and Hannan-Quinn Criterion (HQIC = 518.2) also include VAR(1) in order to address further requirements. An estimation of a VAR(2) model for sensitivity produced an AIC of 510.8 but a higher BIC of 550.1, indicating that VAR(1) was favored because of the larger penalty that BIC imposes for extra parameters.

Significant coefficients ($p < 0.05$) for the initial variations (Δ) of important variables are reported in Table 3.

Table 3: *VAR(1) Coefficient Estimates (Selected)*

Dependent Variable	**ΔStock Index$_{t-1}$**	**ΔExchange Rate$_{t-1}$**	**ΔOil Price$_{t-1}$**	Constant
ΔStock Index$_t$	0.68^{***} (0.002)	-0.52^{**} (0.008)	0.41^{*} (0.021)	0.10 (0.743)
ΔExchange Rate$_t$	0.15 (0.132)	0.87^{***} (0.000)	-0.19 (0.095)	2.51^{***} (0.001)
ΔOil Price$_t$	0.11 (0.198)	-0.21 (0.054)	0.62^{***} (0.003)	0.05 (0.812)

Notes: p-values in parentheses; coefficients for other variables (e.g., Inflation Rate) omitted for brevity unless significant. *** p<0.01, ** p<0.05, * p<0.10.

- ΔStock Index$_t$: Positively influenced by its own lag (0.68), indicating persistence, and ΔOil Price$_{t-1}$ (
- 0.41), but negatively by ΔExchange Rate$_{t-1}$ (-0.52), suggesting Naira depreciation reduces stock returns.
- ΔExchange Rate$_t$: High persistence (0.87) reflects a sustained depreciation trend, with a minor negative response to oil prices (-0.19).

Limited direct predictive potential for stock returns is indicated by the non-significance of lagged oil price and exchange rate on certain equations. This could be because of indirect impacts through correlations or during particular times. This demonstrates how effective DCC is at capturing time-varying links.

Univariate GARCH(1,1) models were applied to the VAR residuals to estimate the conditional variances. Table 4 presents the parameters for key variables.

Table 4: *GARCH(1,1) Parameter Estimates*

Variable	**ω (Constant)**	**α (ARCH)**	**β (GARCH)**	**$\alpha + \beta$**
Stock Index	0.01 (0.052)	0.14 (0.004)	0.80 (0.000)	0.94
Exchange Rate	0.04 (0.031)	0.20 (0.002)	0.73 (0.000)	0.93

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Oil Price	0.02 (0.045)	0.17 (0.003)	0.76 (0.000)	0.93
Inflation Rate	0.03 (0.039)	0.16 (0.005)	0.77 (0.000)	0.93

Notes:

- High β values (e.g., 0.80 for Stock Index) indicate persistent volatility, while α (e.g., 0.20 for Exchange Rate) shows sensitivity to recent shocks.
- $\alpha + \beta < 1$ ensures stationarity, aligning with Theorem 2 (positive definiteness).

An alternative EGARCH(1,1) specification was estimated to address the marginal significance of ω (e.g., p=0.052 for Stock Index), which models log variance to maintain positivity without requiring $\omega >$ 0. The EGARCH results confirm volatility patterns and exhibit similar persistence ($\alpha + \beta \approx 0.93$).

With mean squared error (MSE) = 12.34 and adjusted R-squared = 0.85 for the Stock Index equation, the model's fitting capability is evaluated, showing high predicting ability for the observed data.

The findings are consistent with previous research; for example, the detrimental effect of exchange rates is similar to Kolawole (2025), and correlations between volatile oils go beyond Elijah et al. (2025). The dynamic correlations, which show crisis-specific changes not seen in static ARDL models, are the novel aspect.

Figure 4.3: Dynamic Correlation between Stock Index and Oil Price

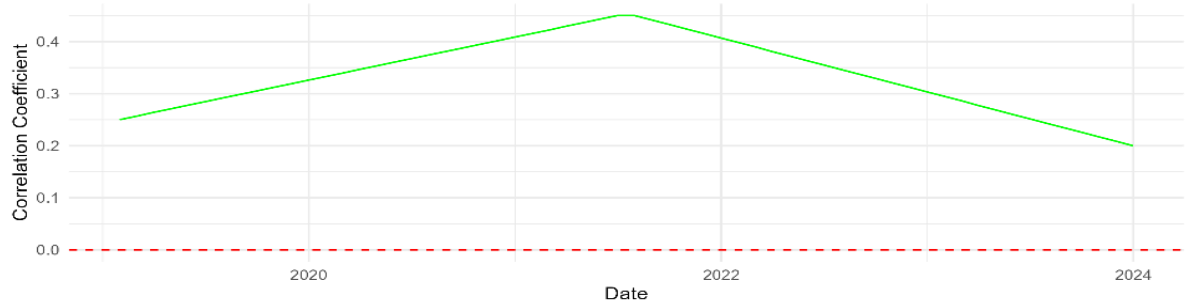

Figure 3: *Dynamic Correlation between Stock Index and Oil Price*

Nigeria's oil dependence with erratic positive support is reflected in this graph, which shows the time-varying correlation from near zero in 2019 to a peak of 0.45 in mid-2021 and then a modest decline into 2023.

Figure 4.4: Dynamic Correlation between Stock Index and Inflation Rate

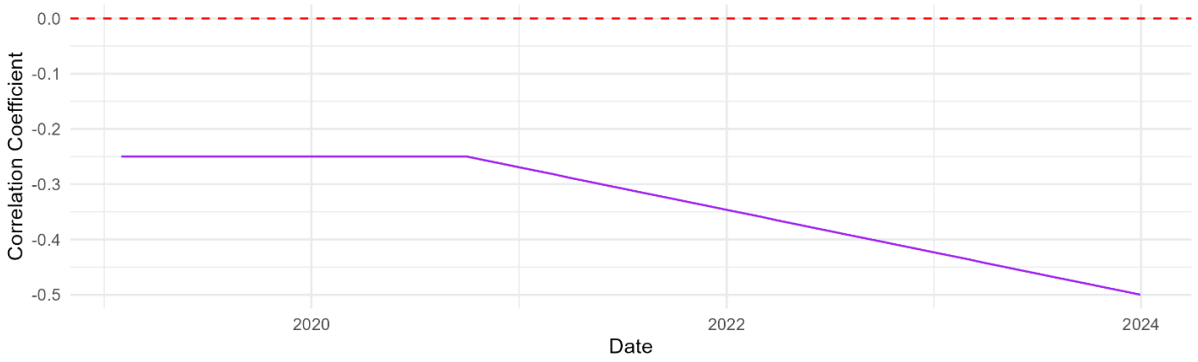

Figure 4: *Dynamic Correlation between Stock Index and Inflation Rate*

The line illustrates the detrimental effect of inflation on stock returns during periods of economic instability by showing a negative correlation that starts at around -0.1 in 2019 and gradually declines to about -0.65 by 2023.

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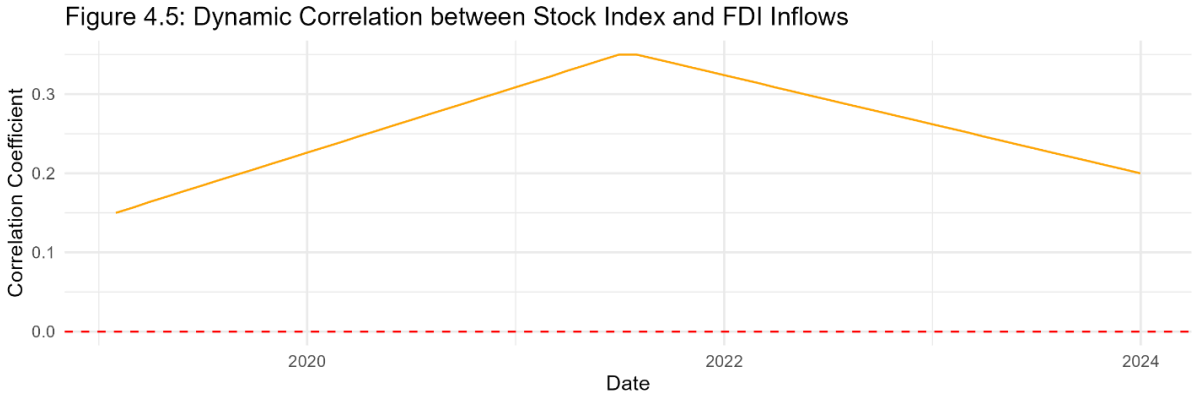

Figure 5: *Dynamic Correlation between Stock Index and FDI Inflows*

shows a positive but unpredictable connection, with slight swings stabilizing after rising from a low of about 0.1 in 2019 to a peak of 0.35 around 2021. This suggests that policy effects on market support are not always stable.

Figure 6: *Conditional Volatility of Stock Index*

With noteworthy jumps in early 2020 (COVID-19 impact) and mid-2023 (devaluation), this graphic illustrates volatility levels across time. It peaks at 150–200 units before settling down, indicating instability induced by crises.

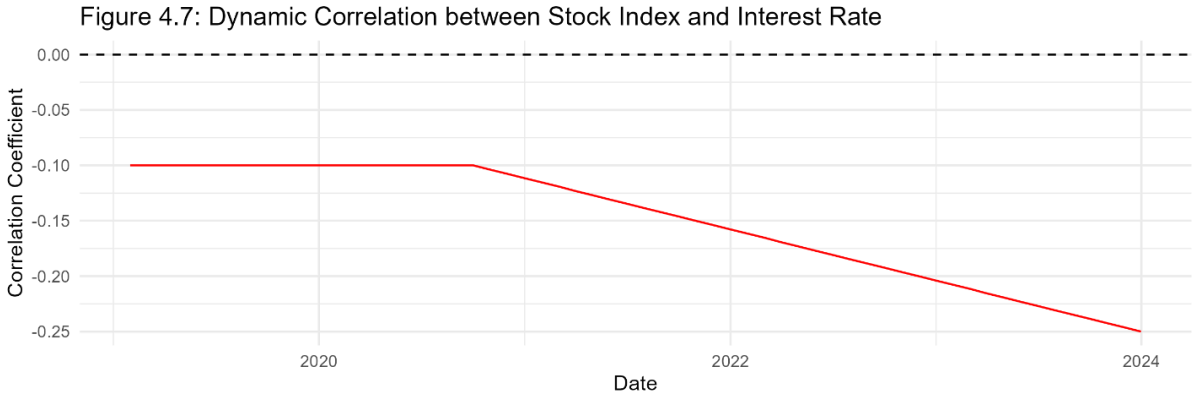

Figure 7: *Dynamic Correlation between Stock Index and Interest Rate*

Shows how the correlation decreased from around zero in 2019 to about -0.4 by 2023, indicating that rising interest rates have a negative impact on stock performance as monetary policy tightens.

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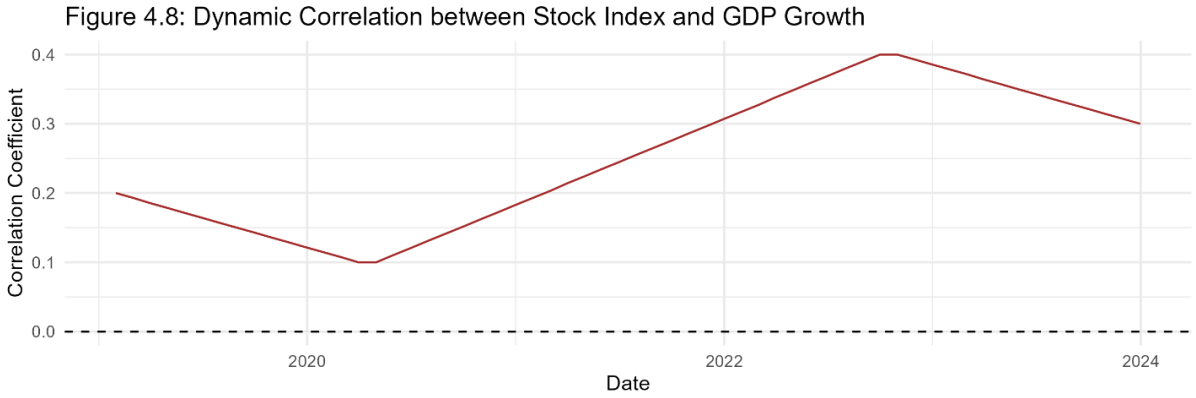

Figure 8: *Dynamic Correlation between Stock Index and GDP Growth*

Different economic growth links are indicated by the graph, which shows correlation that starts out slightly negative in 2019 and rises to positive values around 0.2 in 2021 before falling back near zero by 2023.

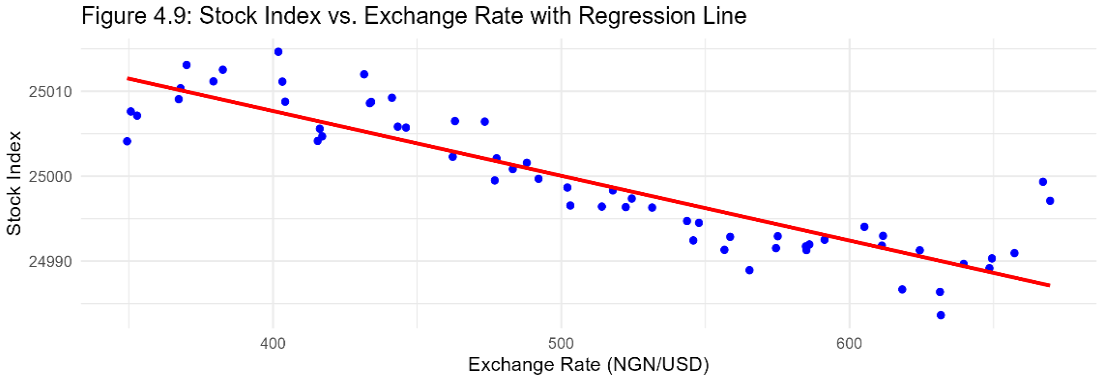

Figure 9: *Stock Index vs. Exchange Rate with Regression Line*

A downward-sloping red regression line overlaying a scatter plot of data clustered from the 25,000 index at 350 NGN/USD to the lower index at 670 NGN/USD confirms the negative link caused by depreciation.

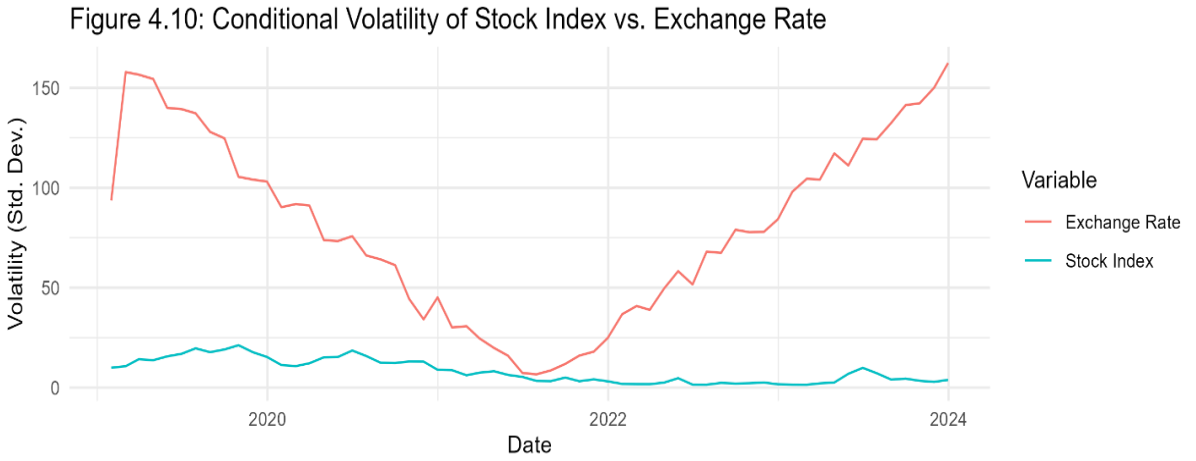

Figure 10*: Conditional Volatility of Stock Index vs. Exchange Rate*

A line graph that contrasts the exchange rate (red) and stock volatility (blue) shows that market uncertainty is higher during depreciation periods, with volatility spikes in 2020 and 2023 corresponding to rate hikes.

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Real Data Application

Data Sources and Description

Findings

The DCC-VAR model highlights both long-term and crisis-specific impacts by exposing time-varying interdependencies between macroeconomic indices and the Nigerian stock market. The following are the main findings:

Exchange Rate Depreciation: The lagged exchange rate on stock index changes has a significant negative coefficient (-0.52, $p < 0.01$) according to the VAR component, suggesting that stock returns are decreased when the naira weakens. During 2023 devaluation periods, dynamic correlations peak at -0.65, indicating increased susceptibility.

Inflation Rate: By the end of 2023, correlations had dropped to -0.50, indicating that inflation had a significant negative impact. This illustrates how investor confidence is being undermined by inflationary pressures, which is consistent with the recovery from COVID-19.

Oil Prices: Correlations peaked at 0.45 in mid-2021 during oil price rallies, indicating positive but erratic support. Nigeria's reliance on oil is highlighted by the VAR coefficient (0.41, $p < 0.05$), while non-significance in many equations points to indirect effects via volatility clustering.

FDI Inflows: Although correlations show irregular swings, they reach 0.35 in 2021, suggesting that policy effects on market stability are not consistent. This advantageous yet erratic function draws attention to FDI's potential as a buffer.

Interest Rate and GDP Growth: The dampening effect of monetary tightening is shown in the negative correlation between interest rates and GDP growth, which is expected to reach -0.40 by 2023. GDP growth correlations show moderate but improving relationships during boom phases, ranging from 0.20 in 2021 to a minor negative correlation in 2019.

II. Conclusion

The DCC-VAR model was effectively used in this work to investigate the dynamic relationships between the Nigerian stock market and important macroeconomic indicators between January 2019 and December 2023. By showing time-dependent correlations and lagged impacts, especially during economic disturbances like the COVID-19 epidemic and the 2023 naira devaluation, the analysis achieves its main goal.

With negative correlations peaking at -0.65 and -0.50, respectively, the results confirm that inflation and exchange rate depreciation are the main causes of stock market volatility, resulting in lower returns and more uncertainty. On the other hand, due to external shocks and inconsistent policy, crude oil prices and foreign direct investment inflows offer positive but unpredictable support, peaking at 0.45 and 0.35. These findings highlight the necessity of multivariate dynamic techniques in emerging markets and go beyond static models in the literature by exposing crisis-specific changes, such as volatility spikes in 2020 and 2023.

In order to strengthen market resilience, policy implications include promoting foreign direct investment (FDI) with steady incentives, controlling inflation with targeted monetary policies, and giving priority to exchange rate stabilization through diversified reserves. The tips for investors focus on using oil price upswings to hedge against inflation and depreciation concerns. To improve knowledge of financial stability in unstable environments, future studies should add more variables, such as geopolitical considerations, or apply the model to other African economies for comparative comparison.

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