Oil Price Shocks and Stock Market Volatility in Nigeria

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ABSTRACT

This study examines the effect of oil price shocks on stock market volatility in Nigeria using monthly data from February 2010 to December 2025. A stock volatility (SV) series, which is a more accurate indicator of time-varying volatility than raw returns, was first generated using the GARCH model in order to capture the dynamics of volatility in the Nigerian stock market. In accordance with the stylized facts of financial time series data, a correlogram of the stock returns was examined prior to modeling, and the results showed evidence of volatility clustering high volatility followed by high volatility and low volatility intervals followed by calm periods. The Augmented Dickey-Fuller (ADF) test was used to establish the stationarity of the data series. The Johansen cointegration test confirmed the existence of a long-run equilibrium relationship among oil price, exchange rate, inflation, and stock market volatility, which justified the use of the Vector Error Correction Model (VECM). The VECM framework was further complemented with the Impulse Response Function (IRF) to trace the dynamic interactions and adjustment paths among the variables. The empirical results revealed that in the short run, oil price fluctuations have a positive but statistically insignificant impact on stock market volatility, suggesting that the Nigerian stock market does not respond immediately to oil price changes. However, the long-run results show a significant relationship among oil prices, exchange rate, inflation rate, and stock market volatility, indicating gradual adjustment toward equilibrium. This implies that Nigeria's financial market is more sensitive to persistent structural changes in oil prices than to temporary shocks. The study concludes that diversification of the economy, transparent exchange rate management, and the strengthening of market institutions are critical to mitigating the long-term effects of oil price volatility on Nigeria's stock market.

Keywords: Oil Price, Stock Market Volatility, Exchange Rate, Inflation Rate, GARCH, VECM

INTRODUCTION

Oil market has played a significant role in the global economy. Crude oil is an important energy that is used for production and consumption and it is also considered as the most important source of energy both in developed, emerging developed and developing economies (see Cheikh et al., 2018; Fasanya et al., 2021 & Salisu & Gupta, 2020 & Salisu & Fasanya, 2013).

Crude oil was discovered in Nigeria in commercial quantities in 1956 at Oloibiri. Since its inception in 1956 it has been the mainstay and major drive of the Nigerian economy. The crude oil accounted for more than 90% of the Nigerian exports and over 80% of the government revenue. The Nigerian budget is benchmark on the expected revenue from the sale of crude oil on every fiscal year. The oil price is determined by the global supply and demand for crude oil and it's also reacted to unexpected shocks in the market especially geopolitical tension, civil unrest, treat or war from the middle east and OPEC production decisions (see Salisu and Fasanya, 2013). The oil price is also influenced by global financial crises, COVID-19 pandemic and Russia-Ukraine war which brought about the demand and supply shocks in the oil market and this development pose risk and uncertainty to investors and policy makers both in oil exporting and oil importing countries (see Boubaker & Larbi, 2022; Bouslama, 2023 & Umar et al., 2021). The Nigeria economy is vulnerable to oil price volatility such that positive oil price shocks (windfall or good news) bring about increase in stock market returns and this shows that there

is a transmission mechanism between oil to stock markets (see Muhammad, 2023; Adenekan et al., 2020). Also, a negative oil price (bad news) brings about decrease stock market returns (Cheikh et al., 2018).

The interconnected between oil price shocks and stock market volatility has drawn growing interest in macroeconomic and financial literature, mainly as a result of vital role of oil in global production and consumption cycles (Bagchi, 2017). The financial strength of an economy depends on how sound its financial market. A robust and stable financial market is vital for supporting economic growth and stability. Studies have shown that oil market and stocks market are interconnected such that volatility in oil market has a tendency to drive the stock market (Fasanya et al., 2021). The disruption in the oil market posed risk to stock market returns and as such a risk averse investors will diversify their portfolios to less risky assets to hedge against market uncertainty (Salisu and Gupta, 2020; Fasanya et al., 2021 & Ji et al., 2018).

The recent policy change in Nigeria, such as fuel subsidy removal and the unification of the foreign exchange market in 2023, have further heightened market uncertainty and macroeconomic volatility (Nairametrics, 2023). These recent developments combined exchange rate depreciation, increasing interest rate and inflation rate in the economy posing risk and uncertainty to investors (Nairametrics, 2023). The Nigeria economy is exposed to external shocks, therefore, there is need to analyse how external shocks influence domestic stock market.

In the context of methodology, there is a need to identify the advanced econometrics models that consider time varying, structural breaks and asymmetries in data behavioral pattern. The volatility in stock market demonstrates time-varying and asymmetric nature, usually responding more strongly to bad news (negative) than good news (positive) an event called the leverage effect.

Salisu and Fasanya (2013) reveal this using GARCH models, demonstrating that symmetric models fail to account for volatility patterns during periods of financial distress and economic burden. This modeling deficiency can lead to misinformed policy and investment decisions, given their vulnerability to global shocks.

Integrating structural breaks is vital in modelling financial time series analysis, especially for emerging markets. Yildirim and Celik (2020) and Abdennadher and Hallara (2018) indicated that failure to capture structural breaks can lead to biased estimates and mis-specification of volatility dynamics. These breaks often result from geopolitical tensions, economics reforms and global unexpected events such as oil price collapses. Hence, empirical models should capture these changes to improve predictive accuracy. The EGARCH model, propounded by Nelson (1991), is explicitly suited for accounting for asymmetric and nonlinear nature of financial time series. Unlike standard GARCH models, EGARCH allows for the modeling of leverage effects and uses a log-linear form of conditional variance, making it more accurate for forecasting volatility under different economic regimes. Studies such as Kang et al. (2014) have demonstrated the asymmetric responses of oil price shocks to stock markets volatility, where negative oil price shocks enhance higher volatility than positive oil price shocks.

Empirical studies have shown evidence of strong relationship between oil prices and stock market. Ji et al. (2018) integrated copula and risk spillover methods, finding shows that the dependence between BRICS stock returns and oil shocks is time varying and exhibits different behaviors depending on the shocks type in the oil market. Similar study such as Bagchi (2017) indicates an asymmetric response to volatility to both positive and negative shocks and negative correlation that exist between returns and volatility that negative information create greater volatility. The global economic crises such as the COVID-19 pandemic, have further demonstrated sensitivity of stock markets to oil price shocks.

Umar et al. (2021) found that there is medium of connectedness between examined equity markets and oil shocks, in terms of returns and volatility with an unpreceded level during the COVID-19 crisis. Ewing and Malik (2015) opined that there is no volatility spillover between oil prices and stock market when structural breaks in variance are ignored in the model, however, accounting for structural breaks in the model strong volatility spillover between the two market are detected. Therefore, excluding breakpoints tends to underestimate the length and duration of volatility transmission. Salisu and Gupta (2020) also confirmed that there is heterogeneous response of stock market to volatility of alternative oil shocks, including positive and negative shocks. This stress the

need for models that are both dynamic and capture time varying volatility. Similarly, Fasanya et al. (2021) demonstrated the important of leverage effects and structural breaks in resource-based economies, validating the suitability of EGARCH models and also, they emphasized on the need for mutiple breakpoint test using Bai-Perron multiples rather handpicking break point test. This enables better segmentation and improved model accuracy (see Cheikh et al. 2018).

In light of these empirical findings and econometrics models, this study examine the effect of oil price shocks and stock market volatility in Nigeria.

LITERATURE REVIEW

The theoretical relationship between oil price and stock market volatility have been established in the literature. Oil price fluctuations have become a debate for its significant relationship with stock market volatility. The consequences of increases or decrease in the oil price on stock market returns have been a great concern in the field of economics and finance. Understanding the relationship between oil price shocks and stock market volatility is crucial under economics and financial theories. This study reviewed relevant theory that necessitate the study of oil price shocks and its transmission mechanism to stock market volatility in Nigeria.

2.1 Asset Valuation Theory

Asset valuation theory explains how the value of financial assets such as stocks and bonds changes when there is change in economic conditions. For instance, it shows how changes in crude oil price determine stock market prices. When global demand and supply of crude oil changes, it affects companies cost of production, earnings and overall market risk which tends to cause stock market prices to increase or decrease. Trung and Vinh (2011) opined that oil price shocks influence the economy in two folds. First, when oil price increase, firms and households spend more on energy, leading to less money being spend on other goods and investment. This slow down the economy activity. Second, crude oil is an important commodity for production, therefore, higher global oil price increase production costs and reduce output.

2.2 Empirical Review

The relationship between oil price and stock market prices have garnered significant attention in economics and finance. The empirical results of studies show that the effects of oil price on stock market differs across countries.

Studies on the impact of oil price volatility on stock markets in developed economies show mixed but insightful results. Kang et al. (2014), using a VAR model, reported that positive aggregate demand and oil-specific shocks reduce the covariance between U.S. stock returns and volatility, suggesting that certain oil shocks can stabilize investor expectations. Ewing and Malik (2015) applied univariate and bivariate GARCH models with structural breaks and found that volatility spillovers between oil and stock markets only appear when structural breaks are incorporated. Mensi et al. (2013), using an ARMA-GARCH model, established that OPEC announcements strongly influence oil price volatility. Likewise, Yu et al. (2018), employing a VAR-BEKK-GARCH model, observed intensified spillovers between oil and stock markets after the 2008 global financial crisis. Salisu and Fasanya (2013) confirmed volatility persistence and asymmetric effects in Brent and WTI markets using EGARCH, TGARCH, and GARCH-M models.

In emerging markets such as BRICS and GCC countries, studies highlight heterogeneous responses to oil shocks. Salisu and Gupta (2020), applying GARCH-MIDAS, found asymmetric and country-specific stock market reactions. Ji et al. (2018), using Copula GARCH and CoVaR, revealed that oil–stock dependencies vary by shock type. Bagchi (2017), with the APARCH model, showed that negative oil shocks create stronger volatility effects. Umar et al. (2021) demonstrated medium-level connectedness between oil and equity markets during the COVID-19 pandemic. Boubaker and Larbi (2022) reported time-varying hedging effectiveness for BRICS using AFRIMA-FIAPARCH, while Bouslama (2023) found fractional cointegration during crises. Kishor and Singh (2015) showed that U.S. market news significantly affects BRICS markets. Chen et al. (2022) revealed strong volatility absorption by gold in BRICS economies using VAR-BEKK-DCC-GARCH. Yuan et al. (2022) added that policy uncertainty influences oil returns differently across BRICS during oil market booms. In GCC markets,

Cheikh et al. (2018) found stronger effects from negative oil shocks, while Fasanya et al. (2021) reported significant asymmetric long-run relationships using ARDL and NARDL.

African studies remain limited. Yildirim and Celik (2020) found persistent and asymmetric volatility in fragile five markets using GARCH and EGARCH. Tumala et al. (2021), using GARCH-MIDAS, showed that South Africa and Nigeria respond differently to activity and inventory shocks.

In Nigeria, Muhammad (2023) identified asymmetric effects of oil prices, interest rates, and exchange rates on stock performance using NARDL. Adenekan et al. (2020) found unidirectional effects from oil prices to stock returns via VAR and cointegration tests. Nwude et al. (2021) observed minimal oil price influence using variance decomposition. Agbo et al. (2021) reported significant asymmetric impacts using NARDL, while Odu et al. (2023) confirmed asymmetry in EGARCH models.

The existing literature on oil prices and stock market volatility in Nigeria largely focuses on short-run effects, offering limited insight into long-term dynamics. Only a few studies use frameworks capable of capturing both short- and long-run relationships, leaving important adjustment mechanisms unexplored. Additionally, little attention has been given to how exchange rate and inflation transmit oil price shocks to stock market volatility.

These gaps highlight the need for a more comprehensive and up-to-date study that incorporates inflation and exchange rate as key transmission variables while using post-2020 data to capture both short- and long-run dynamics. This study aims to close these gaps by using appropriate econometrics approach to investigate the intertonnectedness between oil price shocks and volatility of the Nigerian stock market.

METHODOLOGY

The Data Source

This study used secondary data covering financial and macroeconomics variables to examine the effects of oil price shocks on stock market volatility in Nigeria between February 2010 and December 2024. The variables under consideration are oil price (Bonnylight), stock market prices (ASI), exchange rate (EXR) and inflation rate (INF). All data were source from Central Bank Statistical Bulletin.

Generation of Stock Returns

The All-Share Index (ASI) data from the Nigerian Stock Exchange (NSE) was used to generate the stock returns used in this study. The continuously compounded (logarithmic) returns, which quantify the percentage change in stock prices over time, were used to calculate the return series. By stabilizing the variance, this transformation improves the series' suitability for volatility estimation and time-series modelling.

The following formula is used to calculate the stock return:

$$R_t = \ln\left(\frac{ASI_t}{ASI_{t-1}}\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

Where:

R_t: Stock Returns at time t

ASI_t: All-Share Index at time t

ASI_{t-1}: All-Share Index at t-1

Model Specification

This study used the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model to generate stock market volatility. The volatility series is generated from the stock market return data using the GARCH model, which records the variations in market uncertainty over time.

The fundamental GARCH (1,1) model is described as follows:

$$R_t = \mu + \varepsilon_t,\ \varepsilon_t|\Omega_{t-1} \sim N(0, h_t) \ldots\ldots\ldots\ldots\ldots\ldots (2)$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_t^2 + \beta_1 h_{t-1} \ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

Where:

R_t: Stock Return

ε_t: Error term

h_t: Conditional Variance (Proxy for volatility)

α_0: Constant term

α_1: Coefficient of past squared residuals (ARCH term)

β_1: Coefficient of past variance (GARCH term)

Data Analysis Procedure

The preliminary analysis involves descriptive statistics, lag selection using standard information criteria, and essential pre-tests. Stationarity is first checked with the ADF test to confirm that the variables are integrated of order one. Given this outcome, the Johansen cointegration approach is employed to identify long-run equilibrium relationships among the series. This framework also provides the cointegrating vectors needed to model both long-run adjustment and short-run dynamics.

Vector Error Correction Model (VECM)

Both the short-run dynamics and the long-run equilibrium among cointegrated variables are captured by the VECM, which was created by Engle and Granger (1987). The error correction term (ECT), which measures the speed of adjustment back to equilibrium, is how the model accounts for disequilibrium.

The long run cointegration relationship and the short run are specified as:

$$\Delta SV_t = \beta_1 SV_{t-1} + \beta_2 LOP_{t-1} + \beta_3 LCP_{t-1} + \beta_4 LEX_{t-1} + \sum_{i=1}^{k-1} \Delta\, SV_{t-i} + \sum_{i=1}^{k-1} \Delta\, LOP_{t-i} + \sum_{i=1}^{k-1} \Delta\, LEX_{t-i} + \sum_{i=1}^{k-1} \Delta\, LCP_{t-i} + \varepsilon_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$

Table 1: Measurement of Variables

Variable	Measurement	Data Source
SV	GARCH series	Nigerian exchange Group
OP	Monthly average price of Bonny light crude oil (USD Per Barrel)	Central Bank of Nigeria
LEX	Monthly official Naira/US dollar exchange rate (average rate)	Central Bank of Nigeria
LCP	Monthly Consumer Price Index, used as a proxy for inflation rate	Central Bank of Nigeria

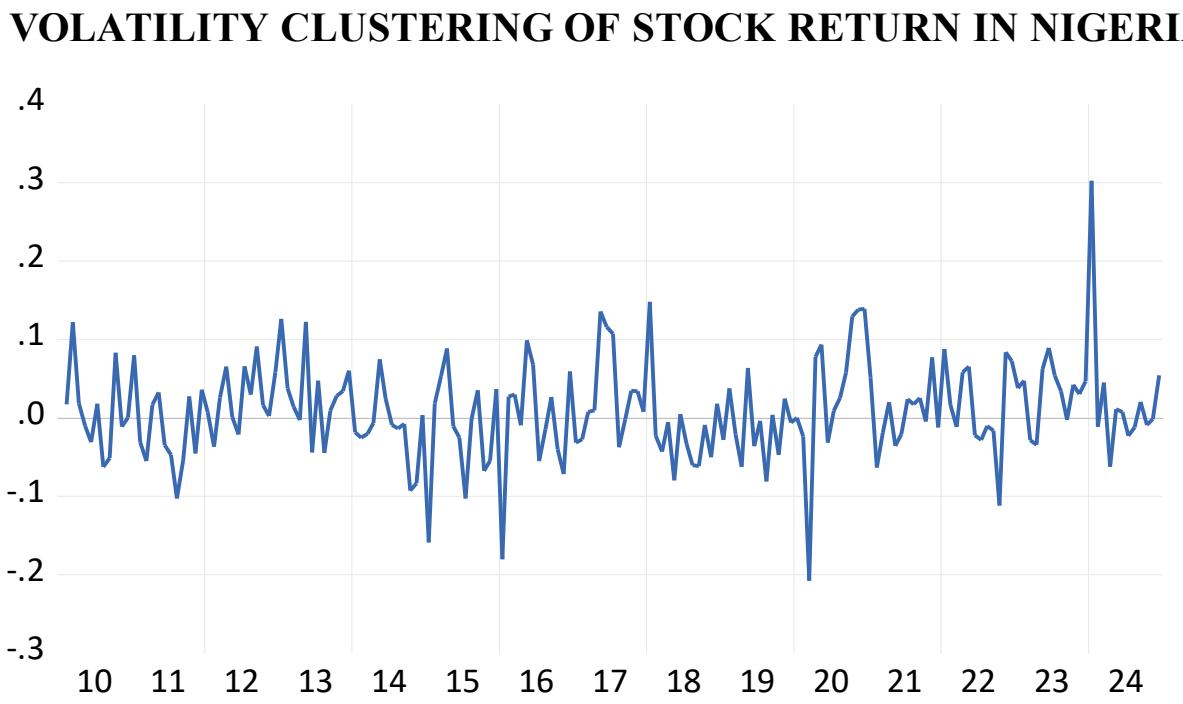
Source: Author's Compilation (2025)

Data Analysis

The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model is used to construct the volatility series based on the evidence of volatility in the Nigerian stock market, which is shown in this section.

Financial time series volatility is frequently characterized by return series deviations from the normal distribution and by periods of persistent high and low variations, a phenomenon referred to as volatility clustering.

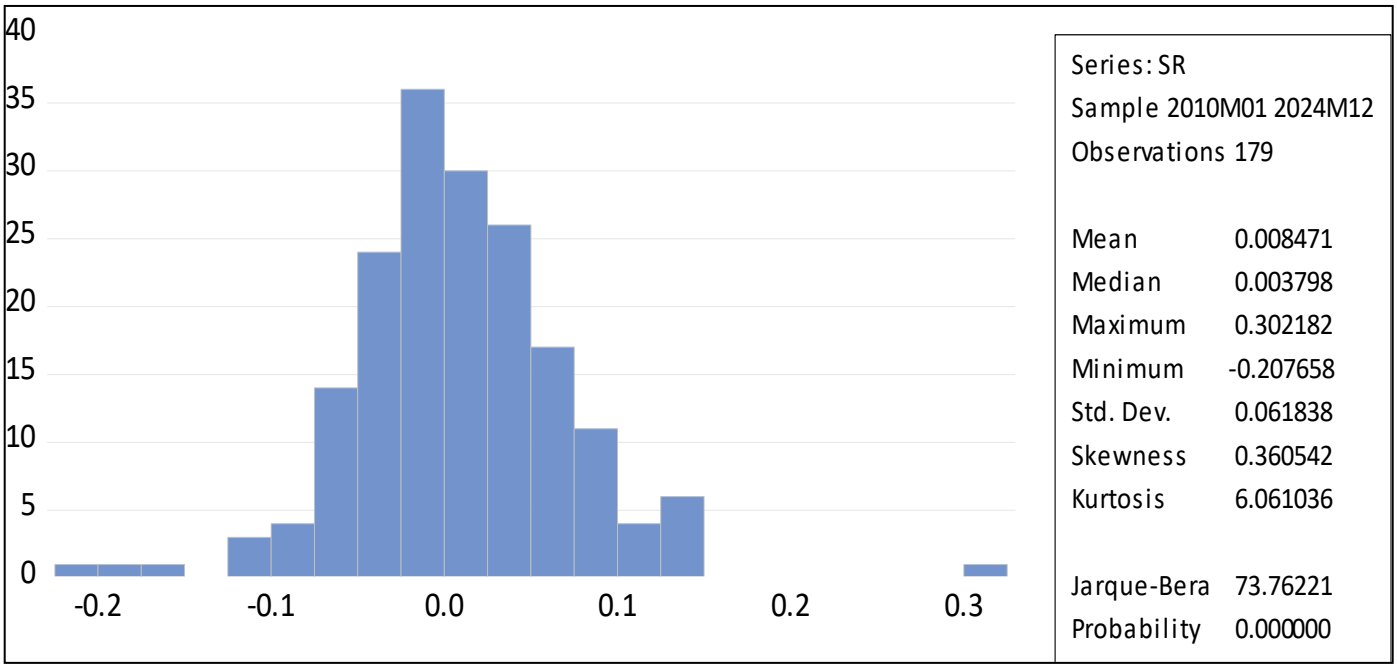
Fig 1: Volatility Clustering of Stock Returns in Nigeria.



The fig 1 indicates clear volatility clustering in Nigerian stock returns, with calm periods followed by sharp swings rather than a steady pattern. Most returns hover around zero, but occasional spikes especially around 2023–2024 signal episodes of heightened instability. This shows that once volatility rises, it tends to persist rather than occur randomly. Such behaviour underscores the need for ARCH-type models that capture time-varying risk in the market.

Normality Test

Fig 2: Histogram of Stock Return Series



The distributional analysis using the histogram, kurtosis, and Jarque–Bera statistics shows strong evidence of volatility in Nigerian stock returns. The high kurtosis value (6.061) indicates fat tails and frequent large price swings, while the Jarque–Bera statistic rejects normality at the 1% level. These features confirm volatility clustering in the series and justify the use of a GARCH model to generate the volatility measure employed in the study.

Table 2: Correlogram of Stock Volatility (Before-GARCH)

	AC	PAC	Q-Stat	Prob*
1	0.141	0.141	3.6288	0.057
2	0.067	0.048	4.4494	0.108
3	0.082	0.067	5.6797	0.128
6	0.124	0.128	8.7478	0.188
12	0.124	0.114	14.353	0.279

NB: Prob* represents the probability value and it is significant at 5%.

The correlogram of stock volatility before applying GARCH shows low autocorrelations across lags 1, 2, 3, 6, and 12. The Ljung–Box Q-statistics are not significant at the 5% level, indicating no strong linear dependence in the raw volatility series. This suggests that volatility clustering is not captured by simple autocorrelations, supporting the use of GARCH models for time-varying volatility.

Generation of Stock Market Volatility Using the GARCH Model

This study generates the stock market volatility series using the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model based on the evidence of volatility clustering and non-normality in the stock return series.

Table 3: GARCH (1,1) Estimation Results

Dependent Variable: SR				
Method: ML ARCH - Student's t distribution (BFGS / Marquardt steps)				
Date: 09/29/25 Time: 05:04				
Sample (adjusted): 2010M02 2024M12				
Included observations: 179 after adjustments				
Convergence not achieved after 500 iterations				
Coefficient covariance computed using outer product of gradients				
Presample variance: backcast (parameter = 0.7)				
t-distribution degree of freedom parameter fixed at 4				
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.004745	0.003757	1.26305	0.2066
	Variance Equation			
C	5.09E-05	0.000117	0.436218	0.6627
RESID(-1)^2	-0.09943	0.049989	-1.98903	0.0467
GARCH(-1)	1.067092	0.047578	22.42825	0
R-squared	-0.00365	Mean dependent var		0.008471

Adjusted R-squared	-0.00365	S.D. dependent var	0.061838
S.E. of regression	0.06195	Akaike info criterion	-2.86061
Sum squared resid	0.683137	Schwarz criterion	-2.78938
Log likelihood	260.0244	Hannan-Quinn criter.	-2.83173
Durbin-Watson stat	1.708202		

Source: Author's Computation using E-views 13 (2025)

The GARCH(1,1) estimation of Nigerian stock returns shows that the mean return is positive but not statistically significant (C = 0.004745, p = 0.2066), indicating no substantial average return. The ARCH term (RESID(-1)² = -0.0994, p < 0.05) is significant, suggesting that past shocks have a small but detectable effect on current volatility. The GARCH term (GARCH(-1) = 1.0671, p < 0.01) is highly significant, reflecting that past volatility strongly influences current volatility. The sum of the ARCH and GARCH coefficients is close to one, indicating high persistence of volatility, meaning that periods of high (or low) volatility tend to continue over time, with current volatility largely driven by its own past behavior rather than previous shocks alone.

Table 4: Correlogram of Stock Volatility (Post-GARCH)

	AC	PAC	Q-Stat	Prob*
1	0.096	0.096	1.673	0.196
2	0.063	0.055	2.409	0.3
3	0.084	0.074	3.696	0.296
6	0.11	0.119	6.4884	0.371
12	0.101	0.099	11.275	0.506

NB: Prob* represents the probability value and it is significant at 5%.

The correlogram of stock volatility after applying GARCH shows low autocorrelations across all selected lags (1, 2, 3, 6, 12). The Ljung–Box Q-statistics are not significant at the 5% level, indicating that the GARCH model has successfully captured the time-varying volatility. This suggests that remaining linear dependence in the residuals is minimal, confirming the adequacy of the GARCH specification.

Table 5: Ljung–Box Q-statistics of Standardized Residuals

	AC	**PAC**	**Q-Stat**	**Prob***
1	-0.009	-0.009	0.0139	0.906
2	-0.004	-0.004	0.0175	0.991
3	0.065	0.065	0.7909	0.852
6	0.019	0.013	5.2451	0.513
12	-0.007	0.009	6.177	0.907

NB: Prob* represents the probability value and it is significant at 5%.

The post-GARCH correlogram shows very low autocorrelations and partial autocorrelations across lags 1, 2, 3, 6, and 12. The Ljung–Box Q-statistics are all insignificant (p > 0.05), indicating no remaining linear dependence in the volatility series. This confirms that the GARCH model has effectively captured the time-varying volatility in the Nigerian stock market.

Table 6: ARCH LM Test for GARCH Residuals

Test	Statistic	Prob.
F-statistic (Lag 1)	0.013502	0.9076
ARCH (Lag 1)	0.013655	0.907

F-statistic (Lag 4)	0.692373	0.5982
ARCH (Lag 4)	2.805249	0.5909

Source: Author's Computation using E-views 13 (2025)

The ARCH LM test for the GARCH(1,1) residuals shows that all p-values for F-statistics and observed R-squared at lags 1 and 4 are well above 0.05, indicating no remaining ARCH effects. This confirms that the GARCH model has adequately captured volatility clustering in Nigerian stock returns, and the standardized residuals show no evidence of residual heteroskedasticity. Overall, the conditional variance dynamics are well specified, validating the use of the GARCH(1,1) model.

Discussion of GARCH Results

The GARCH(1,1) estimation indicates that Nigerian stock market volatility, rather than mean returns, drives return fluctuations, with a positive but insignificant mean (C = 0.004745, p = 0.2066) and low baseline variance (C = 0.0000509, p = 0.6627). The significant negative ARCH term (-0.0994, p = 0.0467) reflects modest mean reversion, while the highly significant GARCH term (1.0671, p < 0.01) shows strong volatility persistence, confirmed by the ARCH and GARCH sum (0.9677) near one. Diagnostic tests reveal no serial correlation or residual ARCH effects, indicating the model is well-specified, and the generated volatility series reliably captures time-varying volatility for forecasting purposes.

Preliminary Test

Table 7: Descriptive Statistics

	SV	LOP	LEX	LCP
Mean	0.004704	4.314947	5.666748	5.50156
Median	0.004557	4.34614	5.722768	5.468145
Maximum	0.009576	4.868303	7.42086	6.76595
Minimum	0.000619	2.65886	5.009168	4.653008
Std. Dev.	0.001725	0.366601	0.63064	0.569089
Skewness	-0.00065	-0.87385	1.110221	0.420028
Kurtosis	3.249154	4.329849	3.906118	2.15132
Jarque-Bera	0.463011	35.97101	42.89595	10.63521
Probability	0.793338	1.55E-08	4.84E-10	0.004904
Sum	0.841994	772.3755	1014.348	984.7792
Sum Sq. Dev.	0.00053	23.92251	70.79191	57.64749
Observations	179	179	179	179

Source: Author's Compilation using E-views 13 (2025)

Table 7 presents the descriptive statistics for stock returns (SV), oil prices (LOP), exchange rate (LEX), and consumer prices (LCP). The average stock market volatility was moderate (mean SV = 0.0047), while oil prices (4.3149), exchange rates (5.6667), and consumer prices (5.5016) were relatively higher and more stable. SV shows small dispersion (SD = 0.0017), whereas LOP, LEX, and LCP exhibit greater variability, reflecting sensitivity to domestic and global shocks. Skewness indicates near symmetry in SV, negative skew in LOP, and positive skew in LEX and LCP, consistent with oil price declines, currency depreciation, and inflation trends. Kurtosis values reveal leptokurtic distributions for SV, LOP, and LEX, implying fat tails and extreme fluctuations, while LCP is platykurtic. Normality tests show SV is approximately normal, but LOP, LEX, and LCP significantly deviate from normality, reflecting typical financial and macroeconomic time series behavior.

Unit Root Tests

Augmented Dickey Fuller Test

Table 8: Unit Root Test

Variable	Augmented Dickey-Fuller test statistic	Test critical values:			Order of Integration
		1% level	5% level	10% level	
SV	-13.6397	-2.57809	-1.94263	-1.61551	I(1)
	(0.0000)				
LOP	-10.6798	-2.57809	-1.94263	-1.61551	I(1)
	(0.0000)				
LEX	-12.4675	-2.57809	-1.94263	-1.61551	I(1)
	(0.0000)				
LCP	-3.61508	-3.46742	-2.87773	-2.57548	I(1)
	(0.0000)				

Probability values are in parentheses

Source: Author's Compilation using E-views 13 (2025)

The Augmented Dickey-Fuller (ADF) test shows that stock market volatility (SV), oil prices (LOP), exchange rate (LEX), and inflation (LCP) are all non-stationary at levels but become stationary after first differencing, indicating they are integrated of order one, I(1). All ADF statistics exceed their 1% critical values in absolute terms, confirming stationarity after differencing. These results satisfy the requirements for Johansen cointegration and VECM analysis, ensuring the variables can be used to explore both short- and long-term relationships.

Johansen Cointegration Test

The Johansen cointegration test indicates a stable long-term relationship between oil price shocks, exchange rate, inflation, and stock market volatility in Nigeria. While the Maximum Eigenvalue test identifies one cointegrating equation, the Trace statistic suggests two, confirming that these variables are interdependent and move together over the long run.

Table 9: Unrestricted Cointegration Rank Test (Trace)

Hypothesized		Trace	0.05	Prob.**
No. of CE(s)	Eigenvalue	Statistic	Critical Value	Critical Value
None *	0.14657348	60.24636619	47.85612716	0.002268711
At most 1 *	0.109449956	32.35109968	29.79707334	0.02486656
At most 2	0.038823386	11.94988718	15.49471288	0.159354441
At most 3 *	0.027903287	4.980796649	3.841465498	0.025623376

Source: Author's Compilation using E-views 13 (2025)

The Johansen cointegration test reveals a stable long-term relationship among oil price shocks, stock market volatility, exchange rate, and inflation. While the Maximum Eigenvalue test suggests one cointegrating equation, the more robust Trace statistic identifies two, confirming significant long-term interdependence. This indicates that oil price fluctuations have lasting effects on stock market volatility, partly transmitted through inflation and exchange rate movement.

Lag Length Selection

Information criteria such as AIC, SIC, HQ, and FPE were used to select the optimal lag length for the VAR model. The lag minimizing most criteria was chosen, ensuring that the Johansen cointegration test and subsequent VECM are correctly specified, avoiding misspecification and autocorrelation issues.

Table 10: VAR Lag Length Selection Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	714.8211421	NA	2.88E-09	-8.313698	-8.240208	-8.283879
1	2027.681177	2548.945	7.45E-16	-23.48165	-23.11421*	-23.33256
2	2064.39397	69.56108	5.85e-16*	-23.72391*	-23.0625	-23.45554*
3	2079.266129	27.48305*	5.93E-16	-23.71071	-22.75536	-23.32307
4	2087.628642	15.0623	6.5E-16	-23.62139	-22.37207	-23.11447
5	2094.683068	12.37619	7.23E-16	-23.51676	-21.97349	-22.89057
6	2104.299243	16.4206	7.82E-16	-23.4421	-21.60487	-22.69663
7	2113.717535	15.64208	8.48E-16	-23.36512	-21.23393	-22.50037
8	2129.228632	25.03546	8.59E-16	-23.3594	-20.93426	-22.37538

Source: Author's Compilation using E-views 13 (2025)

Table 10 shows that multiple information criteria LR, FPE, AIC, SC, and HQ were used to select the optimal VAR lag length. While SC suggested lag 1 and LR indicated lag 3, AIC, FPE, and HQ favored lag 2. Lag 2 was chosen for further analysis, balancing model simplicity and capturing variable dynamics, and is applied in the VECM and Johansen cointegration tests.

Vector Error Correction Model (Vecm) Results

The VECM framework is estimated to analyze both the short-run dynamics and the long-run relationship between oil price shocks and stock market volatility, with exchange rate and inflation rate as control variables.

Table 4.9: Short-run and Long-Run Results of Vector Error Correction Model.

Variable	**Coefficient**		
LOP(-1)	0.001886 (2.90764)		
LEX(-1)	0.006029 (4.40590)		
LCP(-1)	-0.00518 (-3.70265)		
Constant	-0.01851		
Error Correction	D(SV)	D(LOP)	D(LEX)
COINTEQ	-0.12933 (0.0002)	-28.132 (0.0000)	-2.78310 (0.1854)
D(SV(-1))	0.037168 (0.6526)	0.082522 (0.2675)	0.45040 (0.6458)
D(SV(-2))	0.154992 (0.0406)	0.075552 (0.7485)	2.05145 (0.8592)
D(LOP(-1))	0.000888 (0.0609)	0.000473 (0.2925)	1.87717 (0.1774)
D(LOP(-2))	0.000432 (0.3496)	0.000461 (0.2794)	0.93610 (0.2013)
D(LEX(-1))	-0.00457 (0.0000)	0.00102 (0.0887)	-4.47963 (0.0000)

D(LEX(-2))	0.002407 (0.0229)	0.001056 (0.2815)	2.27946 (0.0000)
D(LCP(-1))	-0.00569 (0.6081)	0.011094 (0.0320)	-0.51297 (0.7638)
D(LCP(-2))	0.007876 (0.4781)	0.011096 (0.4052)	0.70975 (0.7857)
Constant	-0.0000002 (0.9988)	0.000136 (0.2132)	-0.00147 (0.0002)

Source: Author's Compilation using E-views 13 (2025)

NOTE: The values in the parentheses represent probability values.

The VECM results show that oil price shocks, exchange rate, and inflation significantly influence Nigerian stock market volatility. Long-run results indicate that oil price increases are positively and significantly associated with higher stock market volatility, consistent with Nigeria's dependence on oil exports and the resulting liquidity and speculative trading effects. Exchange rate depreciation also raises volatility by affecting foreign investment valuations and import costs, while higher inflation exhibits a stabilizing effect by discouraging speculative trading and prompting tighter monetary policy. The error correction mechanism confirms that deviations from long-term equilibrium are gradually corrected, with about 12.9% adjustment per period, reflecting a moderate speed of convergence.

Short-run dynamics show volatility clustering, with lagged stock volatility significantly influencing current volatility, consistent with GARCH results. Oil price changes have limited immediate effects, suggesting that structural market rigidities and little market depth delay their impact. Exchange rate shocks exhibit a two-phase effect: appreciation temporarily reduces volatility, while depreciation later increases uncertainty, highlighting delayed transmission mechanisms. Inflation has no significant short-term impact, emphasizing that its effects are indirect and long-term.

These findings align with asset pricing theory, which posits that asset values reflect both fundamental information and risk expectations. Shocks to macroeconomic fundamentals, such as oil prices and exchange rates, alter risk perceptions and expected returns, driving volatility in both immediate and persistent ways. The results emphasize the importance of maintaining macroeconomic stability and mitigating external shocks to enhance stock market resilience in an emerging economy like Nigeria.

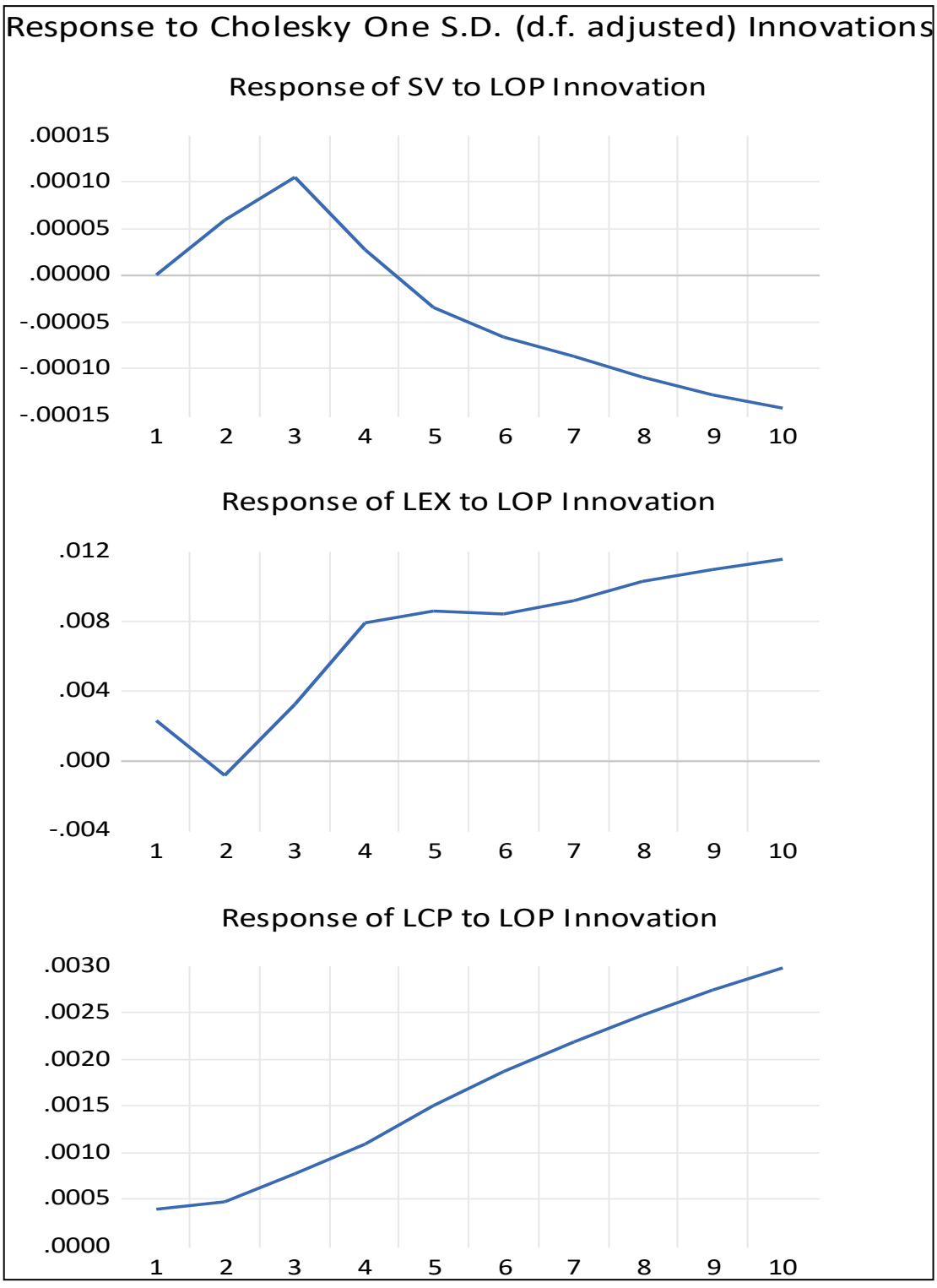
Table 11: VECM Residuals Serial Correlation LM Test

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	14.78088	16	0.540742	0.924477	(16, 486.4)	0.540827
2	15.59515	16	0.481556	0.976215	(16, 486.4)	0.481645
Cumulative (lags 1-2)	39.67634	32	0.165041	1.24995	(32, 573.2)	0.165326

Source: Author's Compilation using E-views 13 (2025)

The VECM Residual Serial Correlation LM Test shows that all p-values for lags 1, 2, and the cumulative test exceed 0.05, indicating no evidence of serial correlation in the residuals. This confirms that the VECM is well-specified, and its dynamic structure accurately captures the relationships among stock market volatility, oil prices, exchange rate, and inflation. Consequently, the estimated parameters are robust and reliable for inference and policy analysis.

Fig 4.2 Impulse Response Function (IRF)



The impulse response analysis shows that oil price shocks (LOP) have distinct effects on Nigerian stock market volatility (SV), exchange rate (LEX), and inflation (LCP). SV initially declines in response to rising oil prices, peaking negatively around the second period, but the effect diminishes after five periods, indicating a short-term and transient impact driven by investor uncertainty and market sentiment. In contrast, LEX responds positively and significantly to oil price increases, reflecting currency appreciation from higher oil export revenues, though the effect gradually weakens over time due to macroeconomic factors like inflation and fiscal imbalances. LCP exhibits a delayed but persistent positive response, with inflation rising steadily and peaking around the fourth or fifth period, highlighting the long-term inflationary effect of oil price shocks in an oil-dependent economy with weak fiscal and monetary absorption mechanisms.

DISCUSSION OF FINDINGS

The study finds that short-run fluctuations in oil prices have a positive but statistically insignificant effect on Nigerian stock market volatility, reflecting slow market adjustments due to structural characteristics like little market depth, low liquidity, and partial market efficiency. Exchange rate fluctuations exhibit a mixed short-term effect: depreciation initially stabilizes volatility, but delayed impacts eventually raise it, while short-term inflation shows no significant influence.

In contrast, long-run results reveal a strong interconnectedness between oil prices, exchange rates, inflation, and stock market volatility. Rising oil prices increase fiscal revenue and foreign exchange inflows, stabilizing the Naira and boosting investor confidence, whereas falling prices trigger currency depreciation, fiscal deficits, and heightened volatility. The negative and significant error correction term confirms that deviations from long-term equilibrium are gradually corrected, illustrating the persistent influence of oil shocks.

Therefore, while immediate oil price shocks have limited impact, their long-term effects on volatility are substantial, mediated through macroeconomic factors. The findings highlight the importance of macroeconomic stability, policy coordination, economic diversification, and financial market reforms to mitigate volatility and strengthen investor confidence in Nigeria.

CONCLUSION

The study analyzed the effects of oil price shocks on Nigerian stock market volatility using a VECM framework with exchange rate and inflation as controls. Findings reveal a long-term equilibrium relationship, where rising oil prices and Naira depreciation increase volatility, while stable inflation reduces it. Short-run oil price effects are insignificant due to structural market limitations, though exchange rate changes significantly affect short-term volatility. To enhance financial stability and reduce vulnerability to external shocks, the study recommends diversifying the economy beyond oil, ensuring exchange rate stability through sound monetary policies, deepening and improving capital market efficiency, strengthening oil revenue stabilization mechanisms, and promoting broader domestic investor participation. These measures underscore the need for long-term macroeconomic stability, coordinated policy, and structural reforms to mitigate oil price shocks on the stock market.

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