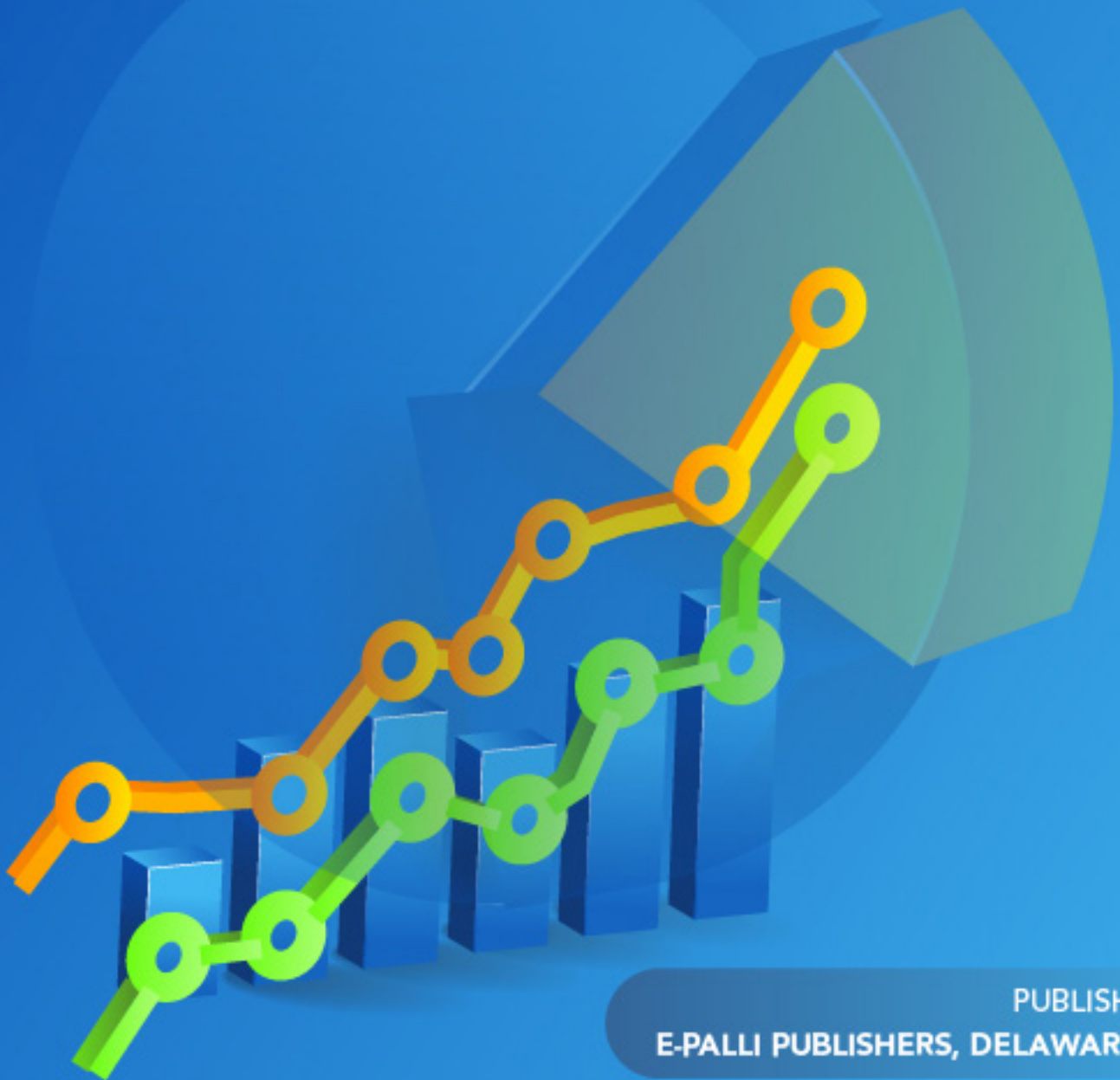




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Modeling the Impact of Interest Rate Volatility on Stock Market Performance: Evidence from Ghana

Emmanuel Chinton^{1*}, Joseph Kofi Senade²

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ABSTRACT

This paper investigates the impact of interest rate fluctuations on the performance of Ghana's stock market using a time series econometric approach. Monthly data on interest rates and stock returns were analyzed to capture both short-run and long-run relationships through the application of ARCH/GARCH and VAR modeling techniques. The empirical results demonstrate that volatility in interest rates significantly influences stock market behavior. Elevated interest rate volatility is found to depress stock returns, indicating that investors react strongly to macroeconomic uncertainty. The analysis also shows that monetary shocks affect the equity market with a delayed response, suggesting that price adjustments occur gradually rather than instantaneously. These findings highlight the importance of understanding the transmission of interest rate volatility to stock returns for effective monetary policy design and strategic investment decision-making in Ghana.

INTRODUCTION

The performance of financial markets is fundamental to economic growth, efficient resource allocation, and sound investment decision-making. In developing economies like Ghana, the stock market plays a key role in mobilizing savings and channeling them into productive investments, thereby enhancing financial inclusion and capital formation. However, the efficiency of these markets largely depends on macroeconomic stability, particularly the behavior of interest rates, which directly affect borrowing costs, investment yields, and portfolio allocation decisions.

Fluctuations in interest rates introduce uncertainty that influences investor confidence and market behavior. Volatility in interest rates can modify discount rates, alter preferences between equities and fixed-income securities, and cause abrupt movements in stock prices. In emerging markets where monetary transmission mechanisms are less developed, such instability can amplify systemic risks and undermine overall market efficiency.

Over the past two decades, Ghana's financial sector has experienced considerable reform marked by liberalization, regulatory strengthening, and growing participation from both domestic and international investors. Despite these advancements, persistent macroeconomic challenges, including variable interest rates, inflationary pressures, and exchange rate fluctuations, continue to affect market stability. Consequently, understanding how variations in interest rate volatility influence stock market performance has become increasingly important for maintaining financial stability and fostering investor confidence.

This paper explores the dynamic relationship between interest rate volatility and stock market performance in Ghana through the use of advanced time series econometric techniques. Specifically, ARCH and

GARCH models are employed to estimate the impact and persistence of interest rate uncertainty on stock returns, while a VAR model is utilized to identify the direction and strength of the causal interactions between the two variables.

The empirical outcomes provide valuable insights into how monetary fluctuations transmit to the equity market. These findings are expected to guide policymakers, financial regulators, and institutional investors in formulating strategies that promote macroeconomic stability and enhance the resilience of Ghana's capital market.

LITERATURE REVIEW

The interaction between interest rates and stock market performance is well established in financial economics and macro-financial theory. Within the discounted cash flow (DCF) framework, a firm's stock value represents the present value of its expected future earnings discounted at the prevailing interest rate. Accordingly, an increase in interest rates raises the discount rate, thereby lowering the present value of future cash flows and depressing stock prices. Conversely, a reduction in interest rates tends to boost equity valuations by lowering the opportunity cost of holding stocks (Mishkin, 2019).

In addition, the portfolio balance theory suggests that investors distribute their wealth among financial assets according to risk–return trade-offs. When interest rates rise, fixed-income assets such as bonds become more appealing relative to equities, prompting a shift of capital away from the stock market (Fama, 1981). In emerging economies with underdeveloped capital markets, such portfolio reallocations can intensify market volatility and constrain liquidity conditions.

Empirical research on this relationship has produced

¹ Department of Statistics, University of Cape Coast, Ghana

² Department of Mathematics & Statistics, Wichita State University Kansas, USA

* Corresponding author's e-mail: emmanuelchinton7@gmail.com

mixed outcomes. In advanced economies, studies including those by Flannery and Protopapadakis (2002) and Rigobon and Sack (2004) document a strong inverse relationship between unexpected interest rate movements and stock returns. In contrast, evidence from developing economies is less consistent. For instance, Adam and Tweneboah (2008) report that in Ghana, the long-run influence of interest rate changes on stock prices is relatively weak, whereas short-term fluctuations have a more pronounced impact—largely due to limited market depth and slower information diffusion.

This study contributes to the existing literature by employing ARCH/GARCH and VAR models to quantify both the extent and persistence of volatility within Ghana's financial system. By analyzing these dynamics in a developing market setting, the research offers fresh empirical evidence on how monetary fluctuations transmit to stock market performance, providing insights that are valuable for policymakers and investment practitioners alike.

MATERIAL AND METHODS

This research employs a quantitative time series approach based on monthly observations covering the period 2010 to 2023. The analysis integrates Autoregressive Conditional Heteroskedasticity (ARCH) and Generalized ARCH (GARCH) models with a Vector Autoregressive (VAR) framework to examine volatility dynamics and the interdependence between interest rate movements and stock market returns in Ghana.

The dataset was compiled from reputable national sources, including the Bank of Ghana, the Ghana Stock Exchange, and the Ghana Statistical Service. The GARCH (1,1) specification was utilized to assess the persistence and magnitude of volatility in the time series, while the VAR model was applied to capture short- and long-term causal linkages between the variables. Standard econometric diagnostics including the Augmented Dickey-Fuller (ADF) test for stationarity, the ARCH-LM test for heteroskedasticity, and the Jarque–Bera test for normality—were conducted to validate the robustness of the model estimations.

Data Processing and Transformation

The study employed daily closing data on the 91-Day Treasury Bill rates and the Ghana Stock Exchange (GSE) Composite Index, covering the period from January 1, 2016, to December 31, 2023. To capture market fluctuations, the raw price series were converted into daily logarithmic returns, expressed in percentage terms, to ensure stationarity and accurately represent return variability in the data:

$$R_t = 100 \times \ln\left(\frac{P_t}{P_{t-1}}\right) \quad (1)$$

The analysis employed daily Treasury bill interest rates for where:

- R_t is the daily return at time t (in %),
- P_t is the GSE closing price at time t ,
- $P_{(t-1)}$ is the closing price from the previous trading day.

To measure daily rate changes, the series was transformed using the first difference:

$$\Delta P_t = P_t - P_{t-1} \quad (2)$$

where:

- ΔP_t is the change in the Treasury bill rate at time t ,
- P_t is the daily Treasury bill rate at time t ,
- $P_{(t-1)}$ is the daily Treasury bill rate at time $t-1$.

Test for Stationarity

The stationarity of time series variables is a critical prerequisite for reliable econometric modeling. It can be assessed using tests such as the Augmented Dickey-Fuller (ADF), Phillips–Perron (PP), and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) procedures. In this study, the ADF test was specifically employed to examine the stationarity properties of both the interest rate and stock return series, ensuring that the variables are suitable for subsequent time series analysis.

Augmented Dickey-Fuller (ADF) Test

The Augmented Dickey-Fuller (ADF) test was applied to assess the stationarity of the time series by evaluating the existence of a unit root. This approach enhances the traditional Dickey-Fuller framework by including additional lagged differences of the dependent variable, which helps to account for serial correlation and capture higher-order autoregressive dynamics within the dataset. The test evaluates the null hypothesis (H_0): that the series possesses a unit root—implying non-stationarity against alternative hypothesis (H_1): that the series is stationary. The ADF model is specified as:

$$\Delta Y_t = \alpha + \beta t + \gamma Y_{t-1} + \sum_{i=1}^p \delta_i \Delta Y_{t-i} + \varepsilon_t \quad (3)$$

where ΔY_t represents the first difference of the series, t denotes the time trend, p is the lag order, and ε_t is the error term. The optimal lag length (p) is determined using information criteria such as the Akaike Information Criterion (AIC) or the Bayesian Information Criterion (BIC).

If the computed ADF test statistic is less than the critical value, the null hypothesis of a unit root is rejected, indicating that the series is stationary. Conversely, if the statistic exceeds the critical value, the null cannot be rejected, suggesting non-stationarity. The test also provides p-values that indicate the likelihood of observing the test statistic under the null hypothesis, thereby guiding the level of statistical significance.

Diagnostic Test for ARCH Effects

Volatility clustering was examined using the Ljung–Box Q-statistic on the squared residuals of the fitted models. Both the Treasury bill interest rate and GSE stock return series recorded p-values of 0.0000, below the 5% significance level, leading to the rejection of the null hypothesis of no ARCH effects. This confirms the presence of conditional heteroskedasticity and validates the application of the EGARCH model to capture the asymmetric volatility dynamics in the data.

Univariate Time Series

A univariate time series refers to a sequence of data points collected over time, where each data point corresponds to a single variable or measurement. In other words, it involves the observation of a single variable at different points in time.

Autoregressive (AR) Model

An autoregressive model is one where the current value of a variable, y_t , depends upon only the values that the variable took in previous periods plus an error term. A simple way to model dependence between consecutive observations is $Y_t = \phi_0 + \phi_1 Y_{t-1} + \epsilon_t$ where ϵ is white noise. Such a process is called a first-order autoregressive process or AR (1) process. It is stationary if the coefficient $\phi_1 < 1$. Since $E[\epsilon] = 0$ it follows that under the stationarity condition the mean of the process $E[Y_t] = \phi_0 / (1 - \phi_1)$ and variance $\text{var}[Y_t] = (\sigma_\epsilon^2) / (1 - \phi_1^2)$ where $\sigma_\epsilon^2 = \text{var}(\epsilon)$.

A more general representation of the autoregressive process is,

$$Y_t = \phi_0 + \phi_1 Y_{t-1} + \dots + \phi_p Y_{t-p} + \epsilon_t \quad (4)$$

called an autoregressive process of order p , or in short, AR(p).

Autocovariance Function

The autocovariance measures the linear dependence between two points on the same series observed at different times. For a stochastic process $Y_t : t = 0, \pm 1, \pm 2, \pm 3, \dots$, the mean function is defined by $\mu_t = E(Y_t)$ for $t = 0, \pm 1, \pm 2, \pm 3, \dots$. That is μ_t is just the expected value of the process at time t . In general, μ_t can be different at each time point t . The autocovariance function,

$$\begin{aligned} \gamma_{t,s} &= \text{Cov}(Y_t, Y_s) \\ \text{for } s, t &= 0, \pm 1, \pm 2, \pm 3, \dots \\ \text{Cov}(Y_t, Y_s) &= E[(Y_t - \mu_t)(Y_s - \mu_s)] = E(Y_t Y_s) - \mu_t \mu_s \end{aligned} \quad (5)$$

Autocorrelation Function

The autocorrelation function (ACF) is employed to evaluate the degree of correlation between a time series and its own lagged observations. It quantifies the linear dependence between current values of the series and their past values across different lag intervals, providing insight into the persistence and temporal structure of the data. The autocorrelation function is given by;

$$\begin{aligned} \rho_{t,s} &= \text{corr}(Y_t, Y_s) \\ \text{for } s, t &= 0, \pm 1, \pm 2, \pm 3, \dots \text{ where} \\ \text{corr}(Y_t, Y_s) &= \frac{\text{cov}(Y_t, Y_s)}{\sqrt{\text{var}(Y_s) \text{var}(Y_t)}} = \frac{\gamma_{t,s}}{\sqrt{\gamma_{s,s} \gamma_{t,t}}} \end{aligned} \quad (6)$$

The values of $\rho_{(t,s)}$ near ± 1 indicate strong linear dependence, whereas values near zero (0) indicate weak linear dependence. If $\rho_{(t,s)} = 0$ we say Y_t and Y_s are uncorrelated.

Partial Autocorrelation Function

The Partial Autocorrelation Function (PACF), closely related to the autocorrelation function, is a key diagnostic tool in time series analysis. It measures the

direct relationship between observations separated by a specific lag while controlling for the influence of intermediate lags. The PACF is particularly useful for identifying the appropriate order of an autoregressive (AR) process, as it isolates the unique contribution of each lag to the current observation. Given a time series Y_t , the partial autocorrelation of lag k denoted $\phi_{(k,k)}$, is the autocorrelation between Y_t and $Y_{(t+k)}$ with the linear dependence of Y_t on $Y_{(t+k)}$ through $Y_{(t+k-1)}$ removed. Equivalently, it is the autocorrelation between Y_t and $Y_{(t+k)}$ that is not accounted for by lags 1 through $k-1$ inclusive.

$$\begin{aligned} \phi_{1,1} &= \text{corr}(Y_{t+k}, Y_t) \text{ for } k = 1, \\ &= \text{corr}(Y_{t+k} - Y_{t+k}^\wedge, Y_t - Y_t^\wedge) \text{ for all } k \end{aligned} \quad (7)$$

where $Y_{(t+k)}^\wedge$ and $Y_t^\wedge$ are linear combinations of $\{Y_{(t+1)}, Y_{(t+2)}, \dots, Y_{(t+k-1)}\}$ that minimize the mean square error of $Y_{(t+k)}$ and Y_t , respectively.

Multivariate Time series

Multivariate time series analysis involves the simultaneous examination of two or more interrelated time-dependent variables. Compared to univariate analysis, it presents greater complexity, particularly as the number of variables increases. Among the most effective approaches for modeling such data are the ARIMA–EGARCH and Vector Autoregressive (VAR) frameworks. The VAR model, in particular, serves as a natural extension of the univariate autoregressive process, allowing for the exploration of dynamic interactions and mutual dependencies among multiple time series variables.

Definition of ARIMA (p, d, q) Model

$\{y_t\}$ is an Autoregressive Integrated Moving Average model of order (p, d, q) if the d^{th} order differenced process,

$$x_t = \nabla^d y_t = (1 - L)^d y_t$$

is an ARMA (p, q) process, where p is the order of the autoregressive process, d denotes the degree of differencing and q represent order of the moving average process.

Deriving the ARIMA (p, d, q) Model

Let $\{y_t\}$ denote the observed series. Define the lag (backshift) operator L by $Ly_t = y_{(t-1)}$. The difference operator is $\nabla = (1 - L)$, and the d^{th} difference is

$$\nabla^d y_t = (1 - L)^d y_t$$

Let

$$\Phi(L) = 1 - \phi_1 L - \dots - \phi_p L^p \text{ and } \Theta(L) = 1 + \theta_1 L + \dots + \theta_q L^q \quad (8)$$

be autoregressive (AR) and moving-average (MA) polynomials, respectively. Innovations $\{\epsilon_t\}$ are a zero-mean, serially uncorrelated process with variance σ^2 (often assumed i.i.d. Gaussian or Student-t when heavy tails are present).

If x_t is stationary, an ARMA (p, q) model is,

$$\Phi(L)x_t = c + \Theta(L)\epsilon_t \quad (9)$$

where c is a constant (mean component). Stationarity requires the roots of $\Phi(L) = 0$ lie outside the unit circle; invertibility requires the roots of $\Theta(L) = 0$ lie outside the unit circle.

When the original series y_t is non-stationary (e.g., has stochastic trend), apply differencing d times:

$$x_t = \nabla^d y_t = (1 - L)^d y_t. \quad (10)$$

By choosing a suitable d , x_t becomes (covariance) stationary.

Substituting (10) into (9) gives the ARIMA (p, d, q) mean specification:

$$\Phi(L) \nabla^d y_t = c + \theta(L) \varepsilon_t. \quad (11)$$

Equation (3) is the compact form of ARIMA (p, d, q) . It states that the d^{th} differences of y_t follow an ARMA (p, q) with innovations ε_t .

Interpretations

- If $d = 0$ (no differencing), c is just the intercept/mean component of the stationary process.

- If $d \geq 1$, c becomes a drift term in the level series y_t . For example, with $d = 1$, the implied mean change per period is $\mu = c$ so y_t has a deterministic linear trend in expectation.

Writing (11) out:

$$(1 - \phi_1 L - \dots - \phi_p L^p)(1 - L)^d y_t = c + (1 + \theta_1 L + \dots + \theta_q L^q) \varepsilon_t \quad (12)$$

Special cases

- ARIMA $(0, d, 0)$: $\nabla^d y_t = c + \varepsilon_t$ (random walk with drift when $d = 1$).

- ARIMA $(p, 0, q) = \text{ARMA}(p, q)$ (already stationary).

- ARIMA $(0, 1, 1)$ (common for macro/finance): $(1 - L) y_t = c + (1 + \theta_1 L) \varepsilon_t$.

Model Specification

The modeling followed a two-stage ARIMA–EGARCH framework to capture both mean dynamics and conditional volatility.

Mean Equation – ARIMA (3,2,3) and ARIMA (1,0,1) for volatility of interest rates and stock market returns respectively

The conditional mean was modeled as:

$$\Phi(L)(1 - L)^2 P_t = \theta(L) \varepsilon_t \quad (13)$$

where $\Phi(L)$ and $\Theta(L)$ are autoregressive and moving average lag polynomials, L is the lag operator, and ε_t are residuals.

Variance Equation – EGARCH (1,1,1) with Student's t-distribution

The ARIMA residuals were modeled with EGARCH $(1,1,1)$. The variance equation is:

$$\ln(\sigma_t^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \alpha \left(\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} - \sqrt{\frac{2}{\pi}} \right) + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \quad (14)$$

where:

- β measures volatility persistence,
- α captures magnitude effects,
- γ captures asymmetry (leverage effect).

The logarithmic specification in Equation (15) ensures

$\sigma_t^2 > 0$ without non-negativity constraints and Student's t errors accommodate heavy tails in the residuals.

The Vector Autoregressive Model

The Vector Autoregressive (VAR) model, originally proposed by Sims (1986), provides a flexible framework for analyzing the joint dynamic relationships among multiple time series variables. Unlike structural models that impose restrictive identifying assumptions, the VAR approach captures interdependencies without requiring prior specification of causal directions. In a VAR system comprising m endogenous variables, each variable is represented as a linear combination of its own past values and the lagged values of all other variables in the system, along with a stochastic error term.

VAR(p)

Let $y_t = (y_{1t}, \dots, y_{kt})'$; $t \in \mathbb{Z}$ be a k -variable random process. We say that the process $\{y_t; t \in \mathbb{Z}\}$ follows a vector autoregressive model of order p , denoted as VAR(p) if

$$y_t = V + A_1 y_{t-1} + \dots + A_p y_{t-p} + \varepsilon_t, t \in \mathbb{Z}; \quad (15)$$

where p is a positive integer

A_i are $(K \times K)$ coefficient matrices

$V = (V_1, \dots, V_k)$ is a fixed $(K \times 1)$ vector of intercept terms and $\varepsilon_t = (\varepsilon_{1t}, \dots, \varepsilon_{kt})'$ is a K -dimensional white noise with covariance matrix Σ_ε

VAR (2) Model Estimates

The general form of the VAR (2) model can be written as:

$$\begin{bmatrix} \text{StockVol}_t \\ \text{RateVol}_t \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \end{bmatrix} + A_1 \begin{bmatrix} \text{StockVol}_{t-1} \\ \text{RateVol}_{t-1} \end{bmatrix} + A_2 \begin{bmatrix} \text{StockVol}_{t-2} \\ \text{RateVol}_{t-2} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} \quad (16)$$

where c_1 and c_2 are constants, A_1 and A_2 are 2×2 coefficient matrices for lag 1 and lag 2, and $\varepsilon_{1t}, \varepsilon_{2t}$ are white-noise error terms.

Assumptions of the VAR Model

The Vector Autoregressive (VAR) model relies on several key assumptions to ensure valid estimation and meaningful interpretation of results:

- **Stationarity:** The time series variables are expected to exhibit constant mean and variance over time. This property ensures that the relationships among variables remain stable, allowing for consistent and reliable parameter estimation.

- **Absence of Perfect Multicollinearity:** The explanatory variables in the model should not be perfectly linearly correlated. Violations of this condition can distort coefficient estimates and undermine the precision of the model.

- **Zero Conditional Mean of Errors:** The residuals are assumed to have an expected value of zero, indicating that the model captures all systematic components of the data.

- **Limited Presence of Outliers:** The data are assumed to be free from extreme or abnormal observations that could disproportionately influence the estimation process or bias the results.

Optimal Lag Selection

An effective approach for determining the optimal lag length in a Vector Autoregressive (VAR) model is to estimate several VAR(p) specifications with varying lag orders, where p ranges from 0 up to a predetermined maximum value (p_{max}). The most appropriate lag length is then selected based on model selection criteria that balance goodness of fit with model parsimony. Commonly used criteria include the Akaike Information Criterion (AIC), the Schwarz–Bayesian Information Criterion (BIC), and the Hannan–Quinn (HQ) criterion, each providing a statistical basis for identifying the lag structure that best represents the underlying data dynamics.

$$AIC(p) = \ln \Sigma(p) + \frac{2}{T} pn^2 \quad (17)$$

$$BIC(p) = \ln \Sigma(p) + \frac{\ln T}{T} pn^2 \quad (18)$$

$$HQ(p) = \ln \Sigma(p) + \frac{2 \ln T}{T} pn^2 \quad (19)$$

Granger Causality Test

One of the principal uses of the Vector Autoregressive (VAR) model lies in its capacity to analyze predictive relationships and dynamic interactions among time series variables. This framework enables researchers to determine whether historical values of one variable contribute to forecasting another.

Building on the concept introduced by Granger (1969), a variable y_1 is considered to Granger-cause another variable y_2 if past fluctuations in y_1 enhance the prediction accuracy of y_2 .

In this study, the Granger causality technique embedded within the VAR structure was utilized to investigate the directional influence between interest rate volatility and equity market performance in Ghana. The VAR is a natural framework for examining the Granger causality. The VAR is expressed as;

$$\Delta \ln GSE_t = \alpha_0 + \sum \alpha_{1i} \Delta \ln GSE_{t-1} + \sum \alpha_{2i} \Delta \ln IR_{t-1} + u_t \quad (20)$$

$$\Delta \ln IR_t = b_0 + \sum b_{1i} \Delta \ln GSE_{t-1} + \sum b_{2i} \Delta \ln IR_{t-1} + v_t \quad (21)$$

RESULTS AND DISCUSSIONS

Findings and Discussion of Ghana T-Bill Interest Rates Volatility

To measure the volatility of interest rates in Ghana over time the modelling followed a two -stage ARIMA EGARCH framework to capture both mean dynamics and conditional volatility with mean equation -ARIMA

(3,2,3) and Variance Equation – EGARCH (1,1,1).

Interpretation of Data Transformation of Ghana T-Bill Interest Rates in Ghana. Equation (1) ensures stationarity and reduces heteroscedasticity in the raw index series.

Augmented Dickey–Fuller (ADF) Test for Stationarity on T-bill Interest Rates

Table 1 is the output of the ADF test statistic, p-value, and critical values.

Table 1: ADF Test Results

ADF Statistic	-24.4929
p-Value	0.0000
Critical Value (1%)	-3.4326
Critical Value (5%)	-2.8625
Critical Value (10%)	-2.5673

Test Results Null Hypothesis: There is a unit root (The mean is not stationary).

Alternative Hypothesis: There is no unit root (The mean is stationary).

The p-value 0.00000 indicates strong evidence against the null hypothesis of a unit root, confirming stationarity in the differenced series.

Ljung–Box Test for ARCH Effects (Squared Changes) on T-bill Interest Rates

Table 2 presents the output results of the Ljung–Box

Table 2: Ljung–Box Test for ARCH Effects

Lag	LB Statistic	p-Value
10	700.5601	4.76×10^{-144}

statistic for lag 12 applied to the squared rate changes. The extremely low p-value confirms significant ARCH effects, justifying the use of an ARCH-family volatility model.

EGARCH Parameter Estimates

Table 3 reports the output results of the estimated parameters of the EGARCH (1,1,1) model.

Table 3: Estimated Parameters of EGARCH (1,1,1) Model for Ghana T-Bill Rate Changes (2016–2023)

Parameter	Coefficient	Std. Error	t-Statistic	p-Value	95% Confidence Interval	
6-7					Lower	Upper
α_1	12.4455	0.537	23.158	<0.001	11.392	13.499
γ_1	-0.5377	0.0879	-6.118	<0.001	-0.710	-0.365
β_1	0.4679	0.0201	23.317	<0.001	0.429	0.507
ν	2.0500	0.0141	144.993	<0.001	2.022	2.078

Interpretation of Key Findings

From Table 3:

High α_1 indicates that unexpected changes in Treasury bill rates have a strong and immediate effect on money market volatility, showing the sensitivity of the T-bill market to policy announcements and macroeconomic shocks, and it is statistically significant.

Negative γ_1 confirms that adverse fiscal or inflationary shocks cause a larger volatility response in Treasury bill rates than positive ones, making the money market more unstable during economic downturns, and it is statistically significant. $\beta_1 < 1$ suggests that while Treasury bill volatility shocks are persistent, they gradually decay over time rather than remaining indefinitely, showing that market stabilization is possible after

policy adjustments, and it is statistically significant. Low ν confirms fat-tailed behavior, meaning Treasury bill rates are more likely to experience extreme upward or downward changes than a normal distribution would predict, reflecting vulnerability to both domestic and external shocks, and it is statistically significant.

Conditional Volatility Analysis of Ghana T-Bill Rate Changes (2016-2023)

Figure 1 shows the estimated conditional volatility.

Observation:

In 2016–2017, volatility in Treasury bill rates was moderate, reflecting gradual adjustments in monetary policy and

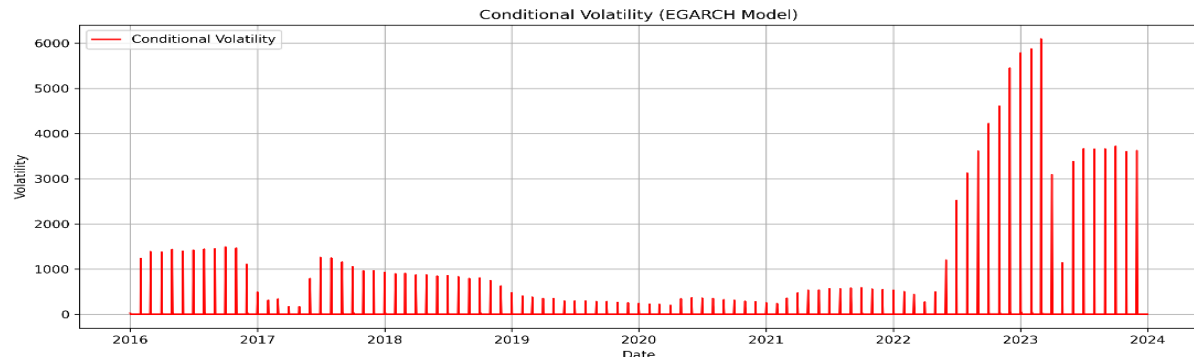


Figure 1: Estimated Conditional Volatility of Ghana T-Bill Rate Changes (2016–2023)

relatively stable market conditions.

From mid-2017 to mid-2019, volatility trended downward, showing reduced uncertainty in money market instruments as inflation stabilized.

Between mid-2019 and early 2022, the Treasury bill market entered a low-volatility phase, consistent with more predictable policy directions and improved liquidity conditions.

From mid-2022 to the end of 2023, volatility surged sharply, indicating heightened instability in the money market, driven by fiscal pressures, inflationary shocks, and global uncertainties.

Model Diagnostic Testing for Treasuring Bill Interest Rates

Two sets of Ljung–Box tests were conducted to evaluate the adequacy of the EGARCH model.

Ljung–Box Test on Standardized Residuals (Autocorrelation)

Table 4 shows the output of the Ljung–Box statistics and

Table 4: Ljung–Box Test on Standardized Residuals

Lag	LB Statistic	p-Value
1	0.000028	0.995752
2	0.290002	0.865022
3	0.820918	0.844457
4	0.822473	0.935410
5	0.853038	0.973528
6	0.881540	0.989707
7	0.926281	0.995932
8	0.938524	0.998608
9	0.985469	0.999470
10	1.006674	0.999823
11	1.053604	0.999934
12	1.063606	0.999980

corresponding p-values for lags 1 to 12.

High p-values (>0.05) indicate no significant autocorrelation in the standardized residuals.

Ljung–Box Test on Squared Standardized Residuals (Remaining ARCH Effects)

Table 5 presents the output of the Ljung–Box statistics for squared standardized residuals. High p-values confirm the absence of remaining ARCH effects.

Table 5: Ljung–Box Test on Squared Standardized Residuals

Lag	LB Statistic	p-Value
1	0.038480	0.844481
2	0.076202	0.962616
3	0.114030	0.990102
4	0.152516	0.997236
5	0.190922	0.999208
6	0.229039	0.999770
7	0.267490	0.999932
8	0.306028	0.999980
9	0.344553	0.999994
10	0.382892	0.999998
11	0.421499	0.999999
12	0.460197	1.000000

The consistently high p-values in Tables 4 and 5 confirm that the model adequately captures both autocorrelation and conditional heteroscedasticity.

Observation

The ACF and PACF plots of residuals and squared residuals (Figure 2) showed no significant spikes beyond the 95% bounds. The absence of significant autocorrelations confirms that the EGARCH (1,1,1) model adequately describes the volatility dynamics.

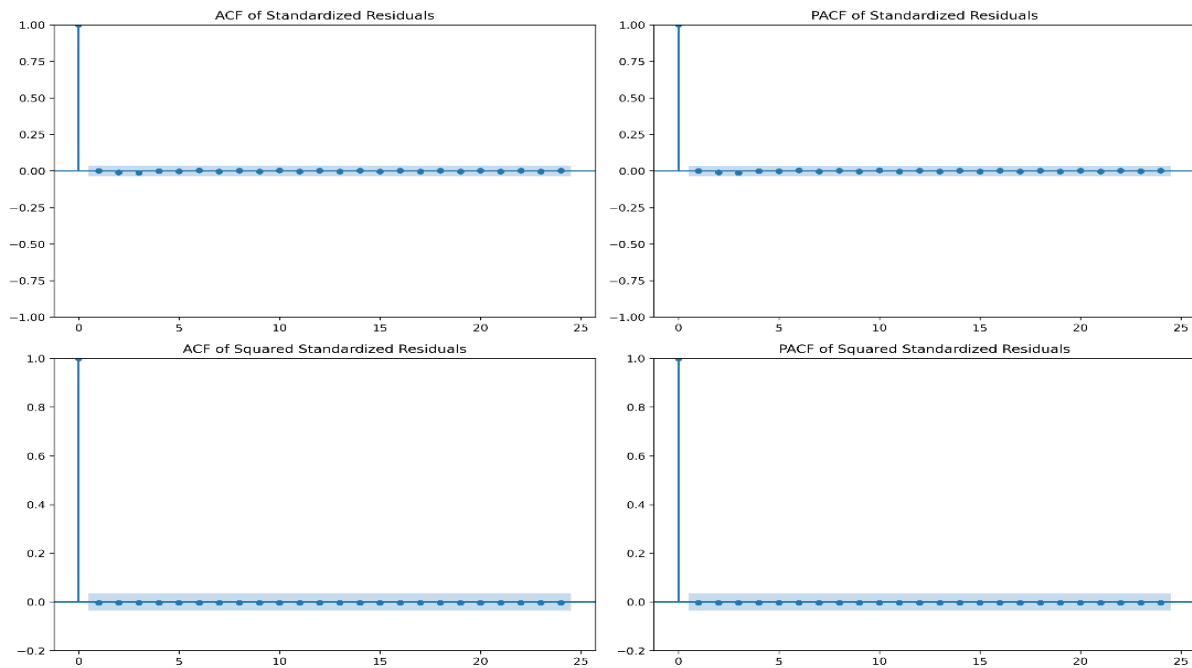


Figure 2: ACF and PACF of Standardized and Squared Standardized Residuals.

Conclusion

The results show that,

- Volatility of Treasury bill interest rates is not constant but responds strongly to macroeconomic shocks and monetary policy shifts.
- High-volatility phases coincided with fiscal pressures and inflationary developments, highlighting the instability of the money market.
- The findings confirm that Treasury bill rate volatility is a key reflection of Ghana's broader monetary and financial conditions.

Findings and Discussion of GSE Stock Returns Volatility

To assess the volatility of stock market returns in Ghana the modelling followed a two -stage ARIMA EGARCH framework to capture both mean dynamics and conditional volatility with mean equation -ARIMA (1,0,1) and Variance Equation – EGARCH (1,1,1)

Interpretation of Data Transformation of GSE Stock Returns in Ghana. Equation (2) captures absolute rate movements (in percentage points) which is suitable when interest rates are already in percentage form to reduces heteroscedasticity and ensures the statistical properties are suitable for conditional volatility modeling.

Augmented Dickey–Fuller (ADF) Test for Stationarity on (GSE) Stock Returns

Table 6 reports the output of the ADF test statistic, p-value, and critical values.

Table 6: ADF Test Results

ADF Statistic	-6.3522
p-Value	$2.59 \times 10^{(-8)}$
Critical Value (1%)	-3.4326
Critical Value (5%)	-2.8625
Critical Value (10%)	-2.5673

Test Results Null Hypothesis: There is a unit root (The mean is not stationary)

Alternative Hypothesis: There is no unit root (The mean is stationary)

The p-value 0.00000 indicates strong evidence against the null hypothesis of a unit root, confirming stationarity in the differenced series.

Ljung–Box Test for ARCH Effects (Squared Changes) on GSE Stock Returns

Table 7 presents the output of the Ljung–Box statistic for lag 12 applied to the squared rate changes.

Table 7: Ljung–Box Test for ARCH Effects

Lag	LB Statistic	p-Value
10	20412.45	0.0000

The extremely low p-value confirms significant ARCH effects, justifying the use of an ARCH-family volatility model.

EGARCH Parameter Estimates

Table 8 reports the output of the estimated parameters of the EGARCH (1,1,1) model.

Table 8: Estimated Parameters of EGARCH (1,1,1) Model for Ghana GSE Stock Returns (2016–2023)

Parameter	Coefficient	Std. Error	t-Statistic	p-Value	95% Confidence Interval	
6-7					Lower	Upper
ω	2.6700	0.0001744	15310.00	0.001	2.670	2.670
α_1	11.3377	0.004157	2727.26	0.001	11.330	11.346
γ_1	-0.3229	0.0001664	-1940.35	0.001	-0.323	-0.323
β_1	0.5677	0.00006417	8847.45	0.001	0.568	0.568
ν	2.0882	0.001727	1209.27	0.001	2.085	2.092

Interpretation of Key Findings

From Table 7:

High α_1 indicates that unexpected changes in stock prices have a strong and immediate effect on equity market volatility, showing how sensitive the GSE is to new information and investor reactions, and it is statistically significant.

Negative γ_1 confirms that negative economic news or shocks trigger larger volatility in stock returns than positive developments, highlighting the fragile nature of investor confidence in Ghana's equity market, and it is statistically significant.

$\beta_1 < 1$ suggests that volatility shocks in stock returns are

highly persistent, meaning that once the market becomes turbulent, the effects can last for a prolonged period before fading out, and it is statistically significant.

Low ν confirms fat-tailed behavior, meaning the Ghanaian stock returns are prone to sudden sharp fluctuations, including spikes and crashes, making equity investments riskier compared to a normal distribution, and it is statistically significant.

Conditional Volatility Analysis of GSE Stock Returns (2016-2023)

Figure 3 shows the estimated conditional volatility.

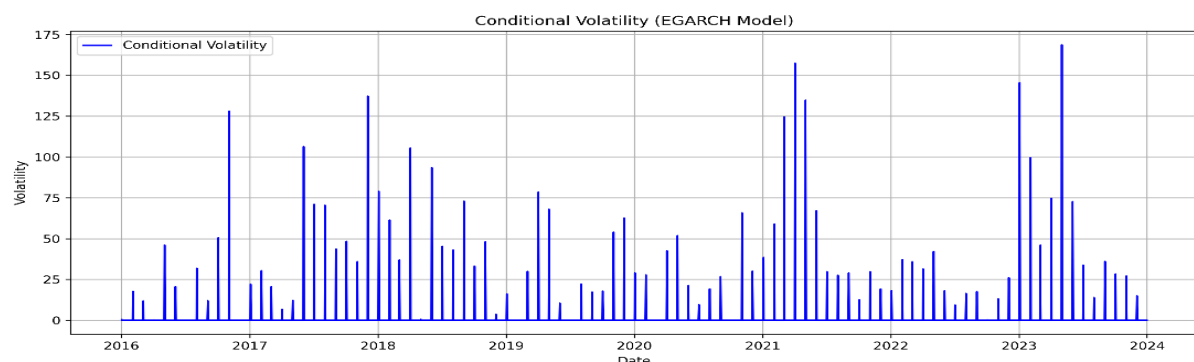


Figure 3: Estimated Conditional Volatility of Ghana GSE Stock Returns (2016–2023)

Observation

In 2016 to early 2017, stock market volatility was generally low, reflecting subdued trading activity and stable investor sentiment.

From late 2017 to 2018, sharp volatility spikes emerged, indicating heightened speculative activity and strong reactions to both local and external market news.

Between 2019 and mid-2021, the market displayed relatively calm conditions, with only moderate fluctuations, consistent with cautious investor behavior during the pre- and early-COVID periods.

From late 2021 to the end of 2023, volatility rose significantly, with several high peaks, reflecting investor uncertainty in the post-COVID recovery period, exchange rate pressures, and shifts in corporate performance expectations.

Model Diagnostic Testing for Ghana Stock Exchange (Stock Return)

Two sets of Ljung–Box tests were conducted to evaluate the adequacy of the EGARCH model.

Ljung–Box Test on Standardized Residuals (Autocorrelation)

Table 9 shows the Ljung–Box statistics and corresponding p-values for lags 1 to 10. High p-values (0.05) indicate no significant autocorrelation in the standardized residuals.

Table 9: Ljung–Box Test on Standardized Residuals

Lag	LB Statistic	p-Value
1	0.001033	0.974356
2	0.002479	0.998761
3	0.023987	0.999019
4	0.058332	0.999583
5	0.083940	0.999895
6	0.114934	0.999970
7	0.141154	0.999992
8	0.170064	0.999998
9	0.196362	0.999999
10	0.223643	1.000000

Ljung–Box Test on Squared Standardized Residuals (Remaining ARCH Effects)

Table 10 presents the output of the Ljung–Box statistics for squared standardized residuals. High p-values confirm the absence of remaining ARCH effects.

Table 10: Ljung–Box Test on Squared Standardized Residuals

Lag	LB Statistic	p-Value
1	0.001422	0.969914
2	0.002846	0.998578
3	0.004266	0.999926
4	0.005687	0.999996
5	0.007109	1.000000
6	0.008533	1.000000
7	0.009958	1.000000
8	0.011385	1.000000
9	0.012813	1.000000
10	0.014242	1.000000

The consistently high p-values in Tables 9 and 10 confirm that the model adequately captures both autocorrelation and conditional heteroscedasticity.

Observation

The ACF and PACF plots of residuals and squared residuals (Figure 4) showed no significant spikes beyond the 95% bounds. The absence of significant autocorrelations confirms that the EGARCH (1,1,1) model adequately describes the volatility dynamics.

Conclusion

The results show that,

- Volatility of stock market returns is not constant and changes with investor confidence and market expectations.
- Periods of extreme volatility were associated with major events such as COVID-19 and the post-crisis recovery phase.
- The findings confirm that stock return volatility is largely driven by investor reactions to shocks and uncertainty in the equity market.

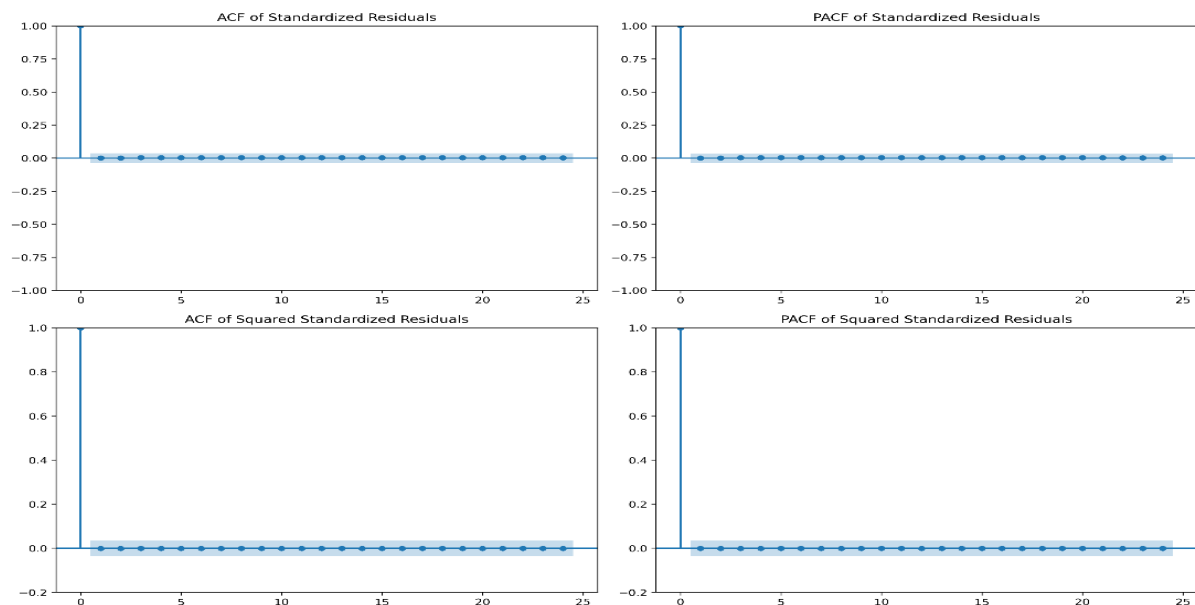


Figure 4: ACF and PACF of Standardized and Squared Standardized Residuals

Findings and Discussion of Interest Rate Volatility Influences on Stock Returns

To investigate whether interest rate volatility influences stock returns, a Vector Autoregression (VAR) model and Granger causality tests were conducted.

Lag Order Selection

The lag order selection results show that the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC), the Final Prediction Error (FPE), and the Hannan–Quinn Information Criterion (HQIC) all select lag 2 as the optimal lag length.

This indicates that a VAR (2) model is the most appropriate specification.

VAR Estimation Results

Table 11 is the output of the VAR (2) Estimates for Stock Volatility Equation.

Table 11: Estimation results for the equation of Stock Prices (GSE)

Variable	Coefficient	p-value
Constant	0.7767	< 0.001
L1. Stock Volatility	-0.0051	0.748
L1. Rate Volatility	-0.0003	0.584
L2. Stock Volatility	-0.0110	0.487
L2. Rate Volatility	0.0152	0.000

Result: Only the second lag of Rate Volatility is statistically significant and positive.

Table 12 is the output of the VAR (2) Estimates for Rate Volatility Equation.

Table 12: Estimation results for the equation of Ghana T-Bill Rates

Variable	Coefficient	p-value
Constant	45.1121	< 0.001
L1. Stock Volatility	-0.4876	0.440
L1. Rate Volatility	-0.0131	0.479
L2. Stock Volatility	-0.5872	0.352
L2. Rate Volatility	-0.0105	0.569

Result: None of the lagged terms are statistically significant.

Residual Correlation

The residual correlation between the two equations is -0.011, which is very close to zero.

To further assess the directional influence between the variables, Granger causality tests were performed.

Table 13 is the output of the Granger Causality Test Results.

Table 13: Granger Causality Tests

Null Hypothesis	Test Statistic	p-value	Decision
Rate Volatility does not Granger-cause Stock Volatility	539.71	0.000	Reject H_0
Stock Volatility does not Granger-cause Rate Volatility	0.721	0.486	Fail to Reject H_0

Discussion and Policy Implications

Descriptive analysis indicates that both interest rates and stock market returns in Ghana display patterns of volatility clustering. Estimates from the GARCH model reveal a high degree of shock persistence, as evidenced by elevated values of the α_1 and β_1 parameters, suggesting that disturbances have enduring effects. The mean equation further identifies a negative association between fluctuations in interest rate volatility and stock market performance.

Results from the VAR model and Granger causality tests point to a one-way causal link from interest rate volatility to stock returns, implying that shifts in monetary policy exert a significant influence on equity price movements. Impulse response analysis shows that stock returns tend to decline in the short-term following upward shocks in interest rate volatility, with the impact fading within approximately three months. Variance decomposition suggests that interest rate shocks account for roughly 25–30% of the variability in stock returns.

These findings underscore the importance of maintaining a coherent and transparent monetary policy framework to reduce uncertainty and stabilize investor sentiment. It is recommended that the Bank of Ghana prioritize consistency in policy rate decisions and enhance communication strategies. Additionally, regulatory bodies such as the Securities and Exchange Commission (SEC) and the Ghana

Stock Exchange (GSE) should work to improve market liquidity. Investors are advised to adopt diversification and hedging strategies to mitigate exposure to interest rate risks. Overall, sound macroeconomic governance and targeted financial sector reforms are essential to strengthening the resilience of Ghana's capital markets.

CONCLUSION

The analysis demonstrates that fluctuations in interest rates exert a negative influence on stock market performance in Ghana. Through the application of GARCH and VAR models, the study identified sustained volatility patterns and a one-way causal relationship from interest rate movements to equity returns. These findings highlight the critical role of maintaining monetary stability and coordinating policy effectively to foster long-term market development and bolster investor confidence.

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