Innovation in Computer and Data Sciences
2(1), 43–62
DOI: https://doi.org/10.64389/icds.2026.02167
https://sphinxsp.org/journal/index.php/icds/

Research article

Volatility Modeling, Persistence and Half-Life Measures of Selected Financial Equities on the Ghana Stock Exchange

Dogbire Emmanuel Sobil[1,*], **John Abonongo**[1]

[1,*] Department of Statistics and Actuarial Science, School of Mathematical Science, C. K. Tedam University of Technology and Applied Sciences, UK-0215-5322, Navrongo, Ghana

* **Correspondence:** sobilism85@gmail.com

ARTICLE INFO

Keywords:
Volatility
GARCH
EGARCH
Half-Life
Ghana Stock Exchange
Principal Component Analysis
Financial Sector

Mathematics Subject Classification:
62M10, 62P05, 91G70, 91B84,60G10

Important Dates:
Received: 26 January 2026
Revised: 17 February 2026
Accepted: 23 February 2026
Online: 27 February 2026

ABSTRACT

In developing equity market like Ghana, positive and negative shocks have different impacts on volatility. In this paper, the volatility of some financial equities is modeled using univariate GARCH family of models where the persistence and half-life measure are examined in details. Secondary data from the Ghana Stock Exchange spanning 2019 to 2024 is used. The principal component analysis is employed in selecting equities that best describe each sector. The selected equities are modeled using the GARCH family of models. The results showed that, the exponential GARCH with Gaussian innovations is the best model. Also, there is evidence of high volatility persistence and leverage effects, particularly for the threshold GARCH model. The half-life measure of the selected equities show that, volatility shocks tend to fade quickly giving an indication of short term memory.

1. Introduction

Efficient financial markets are fundamental to economic development, particularly in emerging and less endowed economies. Among these markets, stock exchanges serve as critical mechanisms for capital mobilization, allocation, and formation, attracting both domestic and foreign investment. Through the intermediation of surplus and deficit units, stock markets facilitate the internal and external generation of capital essential for productive investment and sustainable economic growth [7]. In the context of sub-Saharan Africa, the relevance of stock markets has surge over the past three decades. Faced with declining flows of foreign aid and significant cuts in donor funding, many African economies have increasingly turned to capital markets as alternative sources of development finance. Institutions such as the World Bank and the International Finance Corporation have actively promoted the development of domestic capital markets as part of broader financial liberalization strategies [16]. Consequently, the number of stock exchange markets in Africa have increased from eight in 1989 to nineteen by 2006, [11], reflecting both increased institutional interest and an evolving investment climate. Over the same period, market capitalization across African's stock markets more than doubled from US $113.4 billionin 1992 toUS\,244.7$ billion by 2002, indicating significant progress in capital market deepening [2]. However, a critical characteristic inherent in stock markets is the volatility of asset prices. Price volatility, defined as the rate and magnitude of fluctuations in asset values over time [5], is a key determinant of risk and return in equity investment. While moderate volatility can enhance market efficiency by allowing price discovery and risk-adjusted returns, excessive or unpredictable volatility may deter investment by increasing uncertainty and undermining investor confidence ([15], [20]). In empirical finance, volatility modeling has become a focal point of inquiry, especially within emerging markets where structural and informational inefficiencies are more pronounced. Numerous studies have demonstrated the presence of persistent and asymmetric volatility in equity returns, frequently employing the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) family of models. For instance, [3] analyzed stock return volatility in the Malaysian market using GARCH models, establishing that historical shocks significantly influence current volatility. Similarly, [4] reported high levels of volatility persistence and clustering in the Karachi Stock Exchange, while [24] found evidence of asymmetry and leverage effects in the Jordanian market using ARCH/GARCH specifications. In the Ghanaian context, [23] assessed the impact of COVID-19 on equity volatility and found a significant leverage effect, particularly during the pandemic period, with positive news having a stronger effect on market volatility than negative news. Ghana represents a small, open economy with an emerging stock market that is highly susceptible to both global and domestic shocks. As a price taker in the international economic system, Ghana's financial markets often respond passively to external developments, with volatility patterns influenced by global financial dynamics. Domestically, structural shocks such as the banking sector crisis between 2017 and 2019 further compounded volatility in the financial equities. The crisis, which led to the collapse, merger, or revocation of licenses of over 420 financial institutions, was enforced as a result of the new Bank and Specialized Deposit-Taking Institutions Act, 2016 (Act 930). This act introduced new regulatory requirements, including increased minimum capital thresholds and stricter corporate governance frameworks. These developments inevitably affected investor sentiment and asset pricing within the financial sub-sector. Despite the increasing importance of financial equities in Ghana's capital market, most existing empirical studies (see [12]) have focused on the Ghana Stock Exchange Composite Index (GSE-CI), with limited attention given to the behavior of sector-specific equities such as banking and insurance stocks. [1] considered the various sectors on the Ghana stock exchange using the Generalized Autoregressive Conditional Heteroscedasticity-in-mean (GARCH-M) family of models. This study aims to model the volatility of the returns of financial equities on the Ghana Stock Exchange using the univariate GARCH family of models.

2. Methods of Data Analysis

Historical data from the Ghana Stock Exchange spanning 1st January, 2019 to 31st December, 2024 was employed. The data consist of the daily closing prices of the financial equities listed on the GSE. These financial equities are: Cal Bank PLC (CAL), Ecobank Ghana PLC (EGH), Ecobank Transactional Inc.(ETI), and Standard Chartered Bank Ghana. PLC (SCB), Societe Generale Ghana PLC (SOGEGH), Trust Bank Gambia Ltd (TBL), GCB Bank PLC(GCB), Agricultural Development Bank PLC (ADB), Enterprise Group PLC (EGI), and State Insurance Company PLC (SIC).

The formula for the returns is given by,

$$X = \log \frac{P_t}{P_{t-1}}, \tag{1}$$

where X_t represents the continuous compound return at time, t, P_t represents the current closing stock price index at time t and P_{t-1} represents the previous closing stock price.

2.1. Principal Component Analysis

The Principal Component Analysis (PCA) is a technique that employs principles of mathematics to help reduce a large number of correlated variables to a smaller number of variables. It applies the vector space transform method to lessen the proportion of the data to a more concise set for easy manipulation. Thus, it helps select data that best describes the original data set. By performing PCA, it helps the user to be able to observe and spot outliers, patterns, and trends, which could have been missed when using the large data. Hence, this study employed the PCA to help select the equities that best describe each sector.

Assuming n-dimensional variable $x = (x_1, \dots, x_n)''$ has a covariance matrix x is related to using a few linear combinations of x_1 to describe the $\sum_x$ structure. If x is the daily returns of n stocks, then the PCA can be used in studying the origin of variation of these n stock returns. Applying covariance matrix, if $w_1 = w_{i1}, \dots, w'_{in}$ where $i = 1, \dots, n$. Then

$$X_i = w'_i x = \sum_{j=1}^{n} w_{ij} x_j, \tag{2}$$

where x comprises the returns of the stock and X_i is the portfolio return that assigns weight w_{ij} to the j^{th} stock.

2.2. Stationarity/ Unit Root Test

The Augmented Dickey-Fuller (ADF) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests were employed in testing for the stationarity of the series.

2.2.1. Augmented Dickey-Fuller (ADF) Test

The Augmented Dickey-Fuller (ADF) was used to test for the presence of a unit root in a time series. The ADF test extends the Dickey-Fuller test by including lagged differences of the time series to account for higher-order serial correlation.

Hypothesis:
$H_0 : P = 0$ (It is non-stationary)
$H_1 : P > 0$ (It is stationary).

Test Statistic: The ADF test statistic is derived from the following regression model:

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta y_{t-i} + \epsilon_t, \tag{3}$$

where, Δy_t is the first difference of the series, t is a time trend, y_{t-1} is the lagged level of the series, Δy_{t-i} are the lagged differences of the series and ϵ_t is the error term. The test statistic for the ADF test is the t-statistic for the coefficient γ:

$$\text{ADF statistic} = \frac{y}{SE(y)}, \tag{4}$$

where, y is the estimated coefficient and $SE(y)$ is its standard error.

2.2.2. Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test

The Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test is another statistical test used to test for stationarity in a time series. Unlike the ADF test, the KPSS test has stationarity as the null hypothesis.

Hypothesis:
Null Hypothesis (H_0): The time series is stationary.
Alternative Hypothesis (H_1): The time series has a unit root (i.e., it is non-stationary).

The KPSS test statistic is based on the following model:

$$y_t = \mu + \beta t + u_t, \tag{5}$$

where, y_t is the time series, μ is a constant, βt is a deterministic trend and u_t is a stationary error term. The test statistic is computed as:

$$\text{KPSS statistic} = \frac{1}{T^2} \frac{\sum_{t=1}^{T} S_t^2}{\sigma_u^2}, \tag{6}$$

where T is the number of observations, S_t is the cumulative sum of the residuals u_t, and σ_u^2 is an estimate of the long-run variance of the residuals.

2.3. The Durbin-Watson Test

The Durbin-Watson (DW) test was used to test for autocorrelation of errors. The error term, which is represented as ϵ_t, needs to be distributed as represented by $N(0, \sigma^2)$ for the statistic to have an exact distribution. Therefore, the test statistic is expressed by,

$$d = \frac{\sum_{i=2}^{n} (e_i - e_{i-1})^2}{\sum_{i=1}^{n} e_i^2}, \tag{7}$$

where $e_i = y_i - \hat{y}_i$, y_i represents the observed values of the response whiles, $\hat{y}_i$ represents the predicted values of the response and i is the individual variable response. The more the serial correlation increases, the less d becomes and vice versa.

The hypothesis is given as:
$H_0 : P = 0$
$H_1 : P > 0.$

This implies that a positive autocorrelation exists if the values of d are less than 2, $p > 0$, a negative correlation exists when all the values of d are greater than 2, ($p < 0$); and when all the values of d are closer to 2, the results do not have first-order autocorrelation.

2.4. The Breush-Godfrey Test

The Breusch-Godfrey (B-G) test will be used to test for higher order-serial correlation in the disturbance. It is expressed as;

$$B - G = NR^2, \tag{8}$$

where; N denotes the number of observations and R^2 forms the regression;

$$u_t = \gamma_i u_{t-1} + \ldots \gamma_p u_{t-p} + \ldots \beta_1 x_{1t} \ldots \beta_k x_{kt} + \epsilon_t, \tag{9}$$

The hypothesis is stated as;
H_0; there is no correlation
H_1; there is autocorrelation. The test statistic is asymptotically χ^2_p distributed.

2.5. Testing for Normality

The Jarque-Bera Test (JB) is a test statistic used for testing a series to check whether it is either normally distributed or not [10]. The JB test was employed to determine the goodness-of-fit of the sample data on the null against the alternative hypothesis. The test statistic is expressed as below;

$$JB = T \cdot \left(\frac{S^2}{6} + \frac{(K-3)^2}{24} \right), \tag{10}$$

where T represents the total observation, S represents skewness and K represents kurtosis.

The null and Alternative hypothesis given as:
H_0: the series is normally distributed.
H_1: the series is not normally distributed. The test is asymptotically χ^2_p distributed.

2.6. Ljung-Box Test

It is used to examine the squared residuals by determining whether autocorrelation exists in the return series and the squared residuals of the model selected or not. The test statistic is given as;

$$Q_K = T(T+2) \sum_{i=1}^{K} \frac{\Upsilon_l^2}{T - l}, \tag{11}$$

where Υ_l denotes the sample autocorrelation at lag l function, T denotes the sample size, Q represents the parameter, which is distributed as a chi-square with q degrees of freedom. The null hypothesis is given as: there is no autocorrelation of residuals. This implies that the null hypothesis will be rejected if the value obtained from the estimation of the test statistic is greater than the critical value of the distribution with a given degree of freedom.

2.7. *Testing for ARCH Effects*

The presence of ARCH effect in the residuals was examined using the ARCH-LM test. If the ARCH effect is present, then the ARCH model will be estimated. The Lagrange Multiplier will be used to test for the presence of the ARCH effect. By representing i as the lag autocorrelation of the absolute and the square returns represented by ρ_i, the Ljung Box statistic is expressed as;

$$Q = T(T+2)\sum_{i=1}^{m}\frac{\rho_i^2}{T-i} \sim \chi_m^2. \tag{12}$$

The LM hypothesis is stated below as:
$H_0 : \alpha_1 = \alpha_2 = \ldots \alpha_i = 0$ (There is no existence of ARCH effect)
$H_1 : \alpha_1 \neq \alpha_2 \neq \ldots \alpha_i \neq 0$ (There is existence of ARCH effect). For at least $i = 1, 2, \ldots, q$. The Lagrange Multiplier (LM) test statistic is given as;

$$LM = T \cdot R^2 \sim \chi_q^2, \tag{13}$$

where T represents the total observation, R^2 denotes the regression whiles the number of restrictions placed on the model is represented by q.

2.8. *Symmetric Models*

2.8.1. Generalized Autoregressive Conditional Heteroscedasticity Model

The Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model was developed by Bollerslev in the year 1986. This was in response to the weakness of the ARCH model, which needed a large number of parameters to assess volatility [4]. However, the GARCH model needed fewer parameters and provided better estimates ([4]. According to [6], the GARCH model has a good interpretation of a range of volatility (1992). GARCH (p, q) is given as;

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p}\alpha_i\epsilon_{t-i}^2 + \sum_{j=1}^{q}\beta_j\sigma_{t-j}^2, \tag{14}$$

where $\alpha_0 > 0$ and $\alpha_i \geq 0, i = 1, \ldots, p$ and $\beta_j \geq 0, j = 1, \ldots, q$. σ_t^2 represents the squared volatility, α_0, α_i denotes the coefficient ARCH component, ϵ_{t-i}^2 denotes the lagged squared residual and β_j represents the coefficient of the GARCH component.

2.9. *Asymmetric Models*

Negative news tends to have a greater impact on volatility in the market than positive news [9]. This is termed the ‘leverage effect’. Hence, different models were developed to be able to assess the leverage effect, which was initially observed by Black in 1976 [20]. The asymmetric models include but are not limited to Exponential-GARCH (E-GARCH) and Threshold-GARCH (T-GARCH).

2.9.1. Exponential-GARCH Model

This model was developed by [21]. The E-GARCH consists of a logarithm of conditional variance that has the primary function to ensure the positivity of the observed conditional variance. This implies that

E-GARCH does not take into account only the non-negativity of the conditional variance. E-GARCH (p, q) is given as;

$$\ln \sigma_t^2 = \alpha_0 + \beta \ln \sigma_{t-1}^2 + \alpha \frac{\epsilon_{t-1}}{\sigma_{t-1}} - \sqrt{\frac{2}{n}} \gamma_i \frac{\epsilon_{t-1}}{\sigma_{t-1}}, \tag{15}$$

where α_0 denotes a constant, α denotes the coefficient of the ARCH component, β represents the coefficient of the GARCH component and Υ denotes the leverage of the parameter.

If $\epsilon_{t-i} > 0$, the total effect of ϵ_{t-i} is $1 + \gamma\epsilon_{t-1}$; if $\epsilon_{t-1} < 0$, therefore its total effect of ϵ_{t-1} will be $1 + \gamma\epsilon_{t-1}$. This implies that the model is stationary and has a finite kurtosis if $|\beta_j| < 1$. Hence, there is no restriction on the leverage effect.

2.9.2. Threshold-GARCH Model

[13] and [25] introduced this model in the year 1994. The T-GARCH model has been modified to include a dummy variable, which takes account of the asymmetric effect. The TGARCH (p, q) model can be expressed as;

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} (\alpha_i + \gamma_1 d_{t=1}) \epsilon_{t-1}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2, \tag{16}$$

where α_0 represent the constant, the dummy variable is represented by d whiles, γ represents the asymmetric coefficient.

2.10. Distributional Assumption of Error Term

The parameters of the GARCH are modelled with distributional assumptions employing the maximum likelihood approach. There is enough evidence that most financial returns deviate from normal distribution ([22], [18], and [19]). Most financial time series data have fat tails, and their excess kurtoses in stock returns and other variables are not always accounted for by a normal distribution. This work considered three distributional assumptions, which include: Generalized Error Distribution (GED), Gaussian (Normal) distribution, and Student-t distribution.

The contribution to the likelihood for observation for the Student-t distribution is given by;

$$l_t = \frac{1}{2} \log \frac{\pi(\nu - 2)\Gamma(\frac{\nu}{2})^2}{\Gamma(\frac{\nu+1}{2})^2} - \frac{1}{2} \log \sigma_t^2 - \frac{\nu + 1}{2} \log \left(1 + \frac{(y_t - X_t'\theta)^2}{\sigma_t^2(\nu - 2)}\right), \tag{17}$$

where $\Gamma(.)$ represents the gamma function and $\nu > 2$ represents the shape parameter that directs the tail behavior. If $\nu \longrightarrow \infty$, then the distribution converges to the Gaussian distribution.

Most data of financial time series exhibits fat tails, and their excess kurtoses in equity returns and other variables are not always accounted for by a normal distribution. In order to take care of the weaknesses of normal distribution with reference to financial series data, the GED was introduced by [21]. GED is given as

$$l_t = -\frac{1}{2} \log \frac{\Gamma(\frac{1}{r})^3}{\Gamma(\frac{3}{r})(\frac{r}{2})^2} - \frac{1}{2} \log \sigma_t^2 - \frac{\Gamma(\frac{3}{r})(y_t - X_t'\theta)^2}{\sigma_t^2 \Gamma(\frac{1}{r})}, \tag{18}$$

where $r > 0$ signifies the tail parameter. If $r < 0$, then the distribution indicates a fat tail and becomes the Gaussian distribution, $r = 0$. The student-t distribution is expressed as;

$$l_t = \frac{1}{2} \log 2\pi - \frac{1}{2} \log \sigma_t^2 - \frac{(y_t - X_t'\theta)^2}{2\sigma_t^2}, \tag{19}$$

where terms are the same as defined earlier.

2.11. Model Selection Criterion

Bayesian Information Criterion and Akaike Information Criterion are employed in selecting the best model. The formulas of AIC and BIC are given by

$$AIC = \ln \sigma^2 + \frac{2k}{T}, \tag{20}$$

and

$$BIC = \ln \sigma^2 + \frac{k \ln T}{T}, \tag{21}$$

respectively, where σ^2 represents the residuals of the variance, T represents the sample size and k represents the total number of parameters. With the general GARCH (p, q) model, $k = p + q + 1$. The model that exhibits the least AIC and BIC values is deemed to be the best model.

2.12. Volatility Persistence

2.12.1. Half-Life

It refers to the time it takes for the impact of a volatility shock to decay by half. Half-life is mostly used in modeling time series data in GARCH models to measure how persistent volatility shocks are in the financial market. The formula for half-life of a GARCH (p, q) model is expressed as;

$$\sigma_t^2 = \omega + \alpha \cdot \epsilon_{t-1}^2 + \beta \cdot \sigma_{t-1}^2, \tag{22}$$

where Half-Life Volatility decay is expressed as;

$$t_{\frac{1}{2}} = \frac{\ln(0.5)}{\ln \beta}, \tag{23}$$

where β represents the persistence of volatility and ln(0.5) is the natural logarithm of 0.5. With the interpretation that, if β is close to 1, volatility shocks are highly persistent, and the half-life is long, but if it is small, volatility dissipates quickly.

2.13. Long-term trend in volatility

The study examined the long-term trend volatility. The conditional variance is regressed on a constant time variable to be able to determine how volatility changes over time. The model is expressed as;

$$\sigma_i^2 = \sigma_i + \sigma_2 T, \tag{24}$$

where σ_i^2 represents the conditional variance of each financial equity, σ_t represents the constant term and T represents the number of days. If σ_2 is statistically significant and shows a positive, it implies that volatility is increasing over time, but if σ_2 shows a negative and it is significant, volatility is decreasing over time.

3. Results ad Discussions

3.1. Descriptive Statistics

The equities of local banks (specifically GCB and ADB) recorded positive average returns, indicating overall gains for investors. GCB exhibited negative skewness, suggesting a higher likelihood of negative returns, whereas ADB showed positive skewness, indicating a higher probability of gains. Both equities had low standard deviations, reflecting low investment risk, with GCB being more stable in its volatility pattern. However, both equities displayed high kurtosis values, pointing to leptokurtic distributions with extreme values and fat tails.

Most foreign bank equities reported positive mean returns, suggesting modest investor gains. However, CAL and TBL showed negative skewness, implying a potential for losses despite their average positive returns. Volatility levels across the sector were moderate, with standard deviations generally low to moderate, except for ETI, which showed the highest standard deviation, making it the most volatile equity in this group. All foreign bank equities had excess kurtosis, indicating non-normal, peaked distributions with fat tails.

Among the insurance equities, EGL recorded a negative mean (implying losses), while SIC had a positive mean, indicating gains. Correspondingly, EGL showed negative skewness (higher risk of loss), and SIC showed positive skewness (higher probability of gains). Both equities exhibited moderate standard deviations, suggesting moderate volatility. Like other sectors, they displayed high kurtosis, reflecting leptokurtic distributions.

Across all three sectors, returns were generally mild, with non-normal distributions due to high kurtosis in all equities. The insurance sector was the least volatile and least risky, while the foreign banks sector showed higher volatility, especially due to equities like ETI. The local banks, though relatively stable, also displayed signs of extreme value risk due to high kurtosis.

Table 1. Descriptive Statistics of the Return Series

Sector	Mean	SD	Min	Max	Skew.	Kurt.
Local Banks						
GCB	0.0061	0.0061	-0.2767	0.2767	-0.6400	428.1000
ADB	0.0012	0.0025	-0.0703	0.0603	0.6000	507.7800
Foreign Banks						
CAL	0.0001	0.0108	-0.1317	0.1317	-0.3189	31.6000
EGH	-0.0001	0.0542	-2.0007	2.0007	-0.0001	953.0006
ETI	0.0002	0.0477	-0.9030	1.0000	1.1161	285.5500
SOGEGH	0.0001	0.0001	-0.1959	0.1959	0.0100	185.4200
SCB	0.0001	0.0085	-0.1543	0.1543	0.0100	157.1200
TBL	0.0002	0.0090	0.0739	0.0739	0.2545	37.2400
Insurance						
EGL	0.0001	0.0079	-0.1267	0.1267	-52.0000	37.2400
SIC	0.0001	0.0122	-0.1111	0.1111	50.1400	21.7000

Figures 1, 2, 3, 4, 5, 6, 7, and 8 are the time series plots of the return series for each equity: GCB, ADB, CAL, EGH, ETI, SOGEGH, SCB, TBL, EGL, and SIC, respectively. From the plot, there is a high level of fluctuation in our return series, which does not suggest stationarity clearly. Also, these plots exhibit high density and light density at certain points of the graphs, indicating volatility clustering. Thus, high volatility levels tend to be followed by high values, and low volatility tends to follow low values.

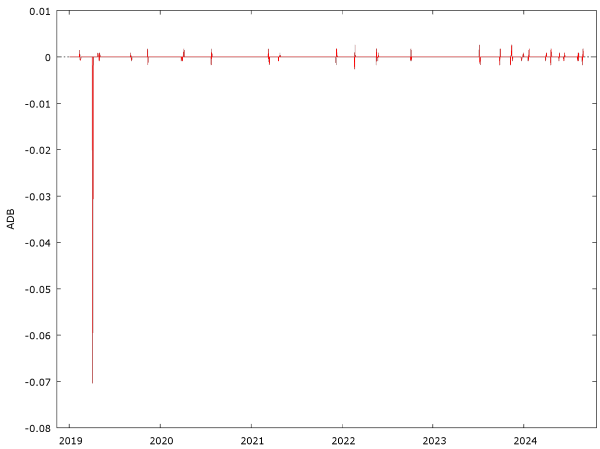

Figure 1. Time Series Plot of GCB Return Series

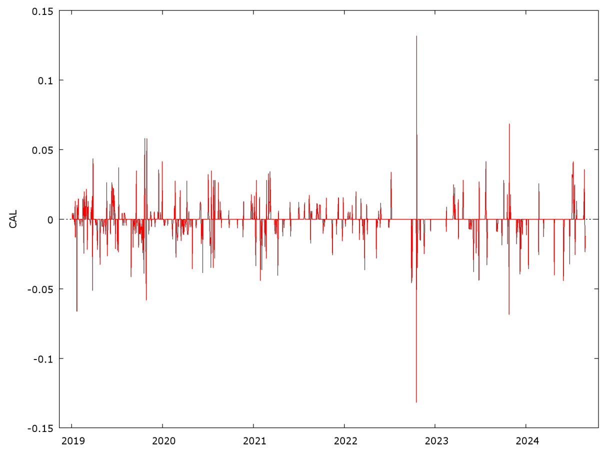

Figure 2. Time Series Plot of CAL Return Series

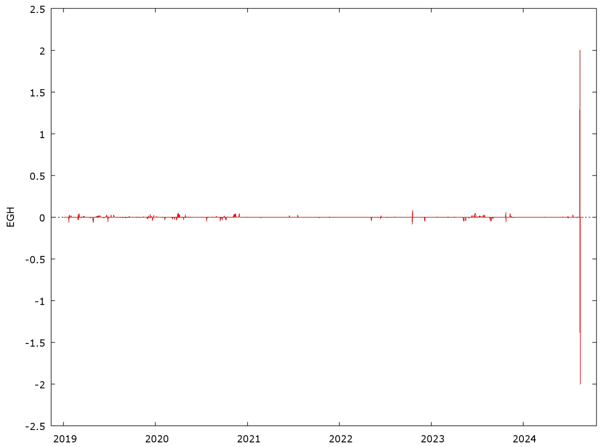

Figure 3. Time Series Plot of EGH Return Series

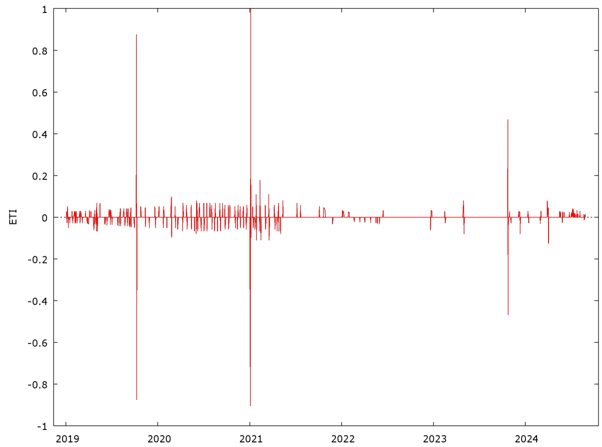

Figure 4. Time Series Plot of ETI Return Series

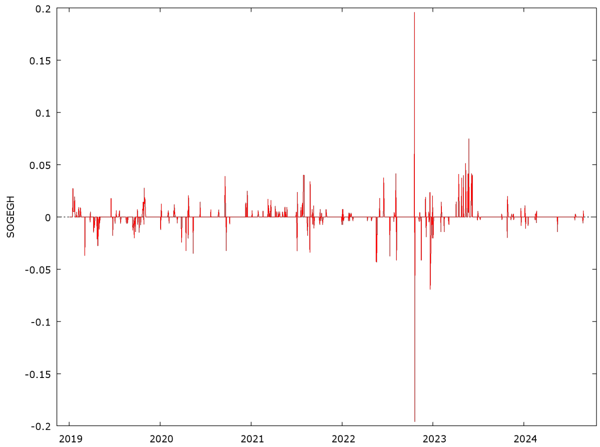

Figure 5. Time Series Plot of SOGEGH Return Series

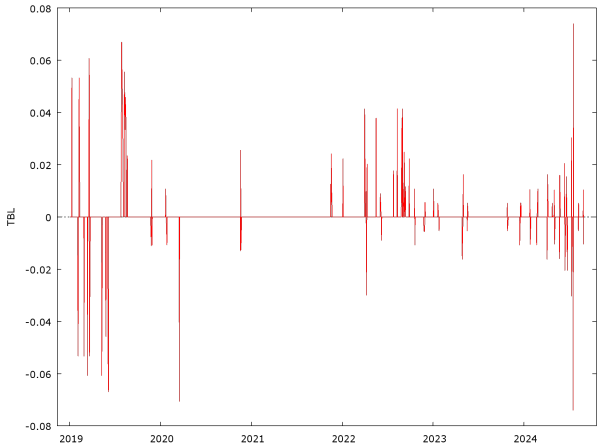

Figure 6. Time Series Plot of TBL Return Series

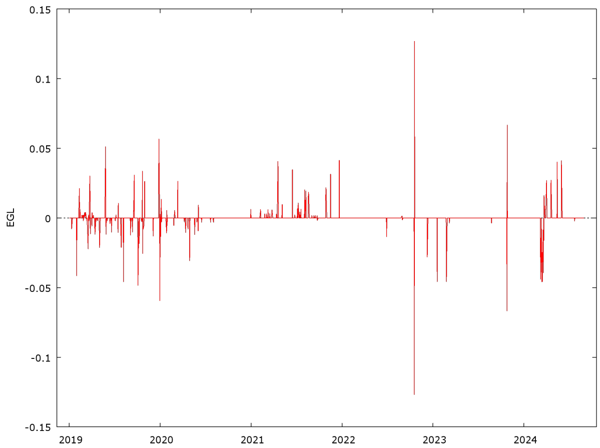

Figure 7. Time Series Plot of EGL Return Series

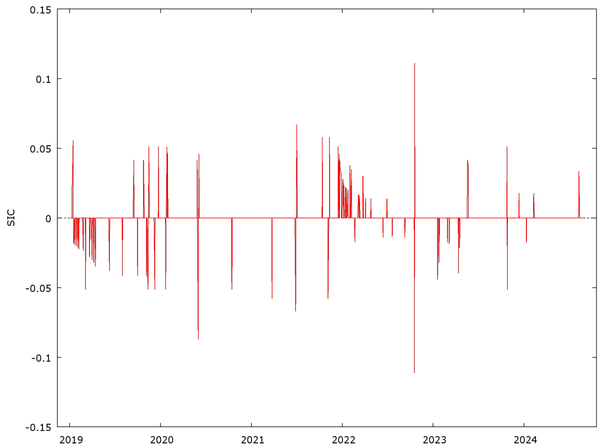

Figure 8. Time Series Plot of SIC Return Series

3.2. Test for Stationarity

The ADF test was used to test the stationarity of the return series of the various equities at 5% significance level. Based on the results in Table 2, the null hypothesis of non-stationarity of the data was rejected. This is because all p-values for each equity are less than 0.05, an indication that the return series of each equity of each sector appears stationary at a 5% significance level. Table 3 shows the KPSS test results of the return series. From the results, we fail to reject the null hypothesis of stationarity of the return series, as all the test statistics for all the equities were not significant at 5% significance level. Even though the visual inspection of the return series did not clearly suggest stationarity, the unit root tests provided more reliable inference. Thus, both ADF and KPSS tests confirmed stationarity at the 5% level, and therefore the GARCH modeling was conducted on a stationary return series.

Table 2. ADF Test of the Return Series

Variable	Sector	Constant Only	P-Value	Constant and Trend	P-Value
GCB	Local Banks	-15.4673	0.0000**	-15.4650	0.0000**
ADB	Local Banks	-14.6838	0.0000**	-14.7289	0.0000**
CAL	Foreign Banks	-11.5103	0.0000**	-11.5660	0.0000**
EGH	Foreign Banks	-17.3560	0.0000**	-17.3355	0.0000**
ETI	Foreign Banks	-18.4100	0.0000**	-18.4100	0.0000**
SOGEGH	Foreign Banks	-10.3258	0.0000**	-10.3258	0.0000**
SCB	Foreign Banks	-14.3680	0.0000**	-14.3680	0.0000**
TBL	Foreign Banks	-10.9625	0.0000**	-10.9625	0.0000**
EGL	Insurance	-13.3054	0.0000**	-13.3054	0.0000**
SIC	Insurance	-15.5459	0.0000**	-15.5459	0.0000**

**Significant at 5% significance

Table 3. KPSS Test of the Return Series

Sector	Variable	Test Statistic	Critical Value (5%)
Local Banks	GCB	0.1181	0.4612
	ADB	0.2412	0.4612
Foreign Banks	CAL	0.1892	0.4612
	EGH	0.0091	0.4612
	ETI	0.0930	0.4612
	SOGEGH	0.1101	0.4612
	SCB	0.1372	0.4612
Insurance	EGL	0.1242	0.4612
	SIC	0.1104	0.4612

3.3. Test for ARCH Effect

The PCA was used to select equities that best characterized each sector, and the eigenvalue criterion was used. The rule of Thumb was that all equities that had an eigenvalue greater than 0.95 and an absolute component loading greater than 0.65 were selected. Following [17], component selection was guided by eigenvalues and loading thresholds. Although the Kaiser criterion suggests eigenvalues greater than one, alternative cut-offs (0.90–1.00) are commonly used in financial PCA applications to retain sufficient variance while avoiding excessive dimensionality ([17]; [14]). A loading threshold of 0.65 was adopted to ensure strong variable representation of latent factors. So based on this rule, ADB and GCB, and EGL and SIC of the Local Banks and the Insurance equities respectively were retained, while SOGEGH and SCB of the Foreign Banks were selected. These selected equities were subjected to an ARCH test using the Arch-LM test. This was very important because, to be able to fit the GARCH models, the return series of the selected equities must show evidence of ARCH effect. Hence, GCB of the Local Banks, SCB of the Foreign Banks, and the two Insurance equities (EGL and SIC) showed the presence of the ARCH effect. Therefore, these equities were selected to be fitted into the GARCH models as shown in Table 4. Also, the selected equities were tested for normality as shown in Table 5 and autocorrelation and heteroscedasticity, also result shown in Table 6. The Jarque-Bera (JB) test was employed for the normality test, and the outcome of the test was significant at 5% significance level. Therefore, the null hypothesis of non-normal distribution was rejected.

Also, Table 6 shows the results of the Ljung Box (LB) at lag 14, which was used to test for autocorrelation in the return series. The outcome of the test was statistically significant at a 5% of significance. So, the null hypothesis of no autocorrelation was rejected. The Ljung Box square (LB2) was used to test for hetereoscedacitity and the outcome of the test was statistically significant at 5% level of significance. [cite: 60] This indicated the existence of an ARCH effect on the return series of the selected equities. The outcome of the LB2 test also meant that no investor could gain more than the average gains based on the utilization of historical information of equities on the market. The DW was used to test for first-order correlation; the d statistic for all the equities was greater than two (2) as observed in Table 6. Thus, the null hypothesis was rejected.

Table 4. ARCH LM Test Results for Selected Return Series from PCA

Sector	Variable	Lag	Test Statistic	P-value
Local Banks	GCB	14	848.210	0.000**
	ADB	14	0.0174	1.000
Foreign Banks	CAL	14	0.015	1.000
	SOGEGH	14	0.012	1.000
	SCB	14	575.190	0.000**
Insurance	EGL	14	400.410	0.000**
	SIC	14	144.640	0.000**

**Significant at 5% significance level

Table 5. Test for Normality of the Return Series

Sector	Variable	Jarque-Bera
Local Banks	GCB	21057100**
Foreign Banks	SCB	1084840**
Insurance	EGL	580237**
	SIC	38446.2**

**Significant at 5% significance level

Table 6. Test for Autocorrelation and Hetereoscedacity of the Return Series

Sector	Variable	LB (14)	LB2 (14)	DW	B-G
Local Banks	GCB	221.7470**	483.25**	2.7721**	0.0000**
Foreign Banks	SCB	86.2104**	417.99**	2.4139**	0.0000**
Insurance	EGL	49.4995**	345.64**	2.3023**	0.0000**
	SIC	21.0813**	208.43**	1.9776**	0.2080**

**Significant at 5% significance level

3.4. The GARCH models and Model Selection

The GARCH family of models (asymmetric and symmetric) was estimated and the best selected. The GARCH models estimation was carried out with the Student-t, Gaussian, and GED distributions (results on Table 6, 7, and 8). The EGARCH with Gaussian was best among the models estimated, hence, it was selected. Despite the presence of extreme leptokurtosis in the return series, the EGARCH model with Gaussian innovations provided the lowest AIC and BIC values. This is because of the ability of the EGARCH specification to capture volatility clustering and asymmetry, which absorbs excess kurtosis effects even under Gaussian assumptions [21]. Moreover, emerging market data often exhibit structural breaks and thin trading, which can distort kurtosis measures, leading to Student-t and GED distributions to over-penalize tail behavior [8]. Furthermore, its outcomes were very consistent throughout, coupled with the robust parameter values of α and β, and its ability to capture asymmetric volatility. Also, the equities under study are from a developing market, which often have "asymmetric volatility" as a common feature among developing markets.

The parameter, α is the coefficient that reflects the ARCH effect in a GARCH model and it is often used to assess the impact of news (positive or negative shocks) on volatility behavior in the equity market whiles, while the parameter, β is the parameter that reflects the GARCH effect is used to assess volatility persistence. Therefore, the low positive values reported for both α and β in the GARCH model in meant any form of news had a direct impact on volatility, and previous pattern behavior of volatility could impact the outcome of future volatility. Also, the parameters with largely positive values indicated high volatility persistence. Thus, the occurrence of shocks in the market that are driven by volatility will stay in the market for a long time before they dissipate. Also, the EGARCH model results in Table 7 reported very low values for the ARCH parameter and very high values for the GARCH parameter. This pattern showed that it could capture sudden extreme shocks in the market, but its response to changes in volatility is gradual. This was an indication that shocks did not immediately have an impact on volatility, and there was strong volatility persistence. The low value for α parameter indicates that the immediate impact of news or shocks on volatility is limited, and the high value for the β parameter shows a very strong volatility persistence, which implies that, when volatility increases, it takes a longer period to subside.

The asymmetric GARCH model was also investigated for the leverage effect. When negative news has more influence on volatility than positive news, it is termed the leverage effect. The EGARCH model produced mixed signs for the leverage parameter, suggesting symmetric responses to shocks. However, the TGARCH model detected significant positive asymmetry coefficients, indicating that negative shocks exert a larger effect on volatility. This discrepancy may arise from differences in model specification and the sensitivity of TGARCH to threshold effects, suggesting that leverage effects in Ghanaian equities are model-dependent. Therefore, the equitable distribution of the signage of the leverage effect of the EGARCH model in Table 7 meant there was evidence of the leverage effect. The outcome of six models out of the twelve models estimated under EGARCH reported negative values, and the rest of the models were positive. This implies both positive and negative news have a greater impact on the volatility of equal measure. Hence, the asymmetric effect was null and void in the equity market for these equities. Also on Table 8, the TGARCH had very high positive values with a few outcomes of negative values, an indication of the presence of the leverage effect. EGL, SCB, and GCB with student-t distribution recorded very high values. This implies that the market response to shocks was very strong, swift, and fast. As reported in Table 9, EGARCH with Gaussian was the best model selected, which was fitted in the return series to become equations 25, 26, 27, and 28.

Table 7. Estimated GARCH (1, 1) Model

Sector	Distribution	α	β	BIC	AIC	
GCB	Gaussian	-0.0002	0.0573	0.8928	-9250.4160	-9230.0560
	Student-t	0.1474	2.3526	0.2860	21597.300	21617.3900
	GED	-0.0002	0.6072	0.8926	-7520.9713	-7938.0761
SCB	Gaussian	-0.0005	0.1346	0.2349	8793.6340	-8773.2730
	Student-t	0.0107	2.6977	0.2466	24677.3100	24697.6700
	GED	-0.0005	0.5346	0.5049	-8793.6340	-8773.2730
EGL	Gaussian	-0.0006	0.1033	0.2294	-8539.7860	-8519.4260
	Student-t	-0.0397	3.1027	0.2180	28513.6500	28534.0200
	GED	-0.0006	0.3033	0.7294	8539.7860	-8519.4260
SIC	Gaussian	-0.0013	0.1930	0.5295	-7752.4740	-7732.1130
	Student-t	-0.0219	1.0620	0.5461	14057.300	14077.6600
	GED	-0.0013	0.4930	0.5295	-7752.4740	-7732.1130

Table 8. Estimated EGARCH (1, 1)Model

Sector	Dist.	λ	α	β	γ	BIC	AIC
GCB	Gauss	-0.0003	0.4470	-0.9495	-0.0183	-9284.6200	-9259.1700
	Stu-t	0.1118	0.3920	0.9859	-0.2657	21666.0300	21691.4800
	GED	-0.0013	0.5472	0.6337	-0.0183	-6389.7205	-5329.1340
SCB	Gauss	-0.0019	0.0607	0.5590	0.0654	-8788.7350	-8763.2850
	Stu-t	0.0999	0.3534	-0.0731	-0.8222	24797.0400	24797.0400
	GED	-0.0023	0.2965	0.8731	0.7612	-5799.6520	-3906.3650
EGL	Gauss	-0.0009	0.1316	0.3401	0.0247	-8540.4900	-8515.0400
	Stu-t	0.0127	0.0634	0.0898	0.0523	28513.6500	14247.3040
	GED	-0.0009	0.4316	0.5632	0.0145	-7843.0065	-2923.5432
SIC	Gauss	-0.0007	0.0192	0.7230	-0.0157	-7744.3910	-7718.9410
	Stu-t	-0.0214	0.0302	0.9956	0.0134	14049.7500	14075.2000
	GED	-0.0007	0.0826	0.9223	-0.0220	-5534.4021	-6723.6412

Table 9. Estimated TGARCH (1, 1) Model

Sector	Dist.	λ	α	β	γ	BIC	AIC
GCB	Gauss	-0.0001	0.1167	0.8845	-0.1530	-9276.3970	-9250.9460
	Stu-t	0.0225	2.4930	0.2847	1.1157	21598.6000	21624.0500
	GED	-0.0001	0.3113	0.9745	-0.6552	-8205.1600	-8723.5012
SCB	Gauss	0.0607	0.1000	0.2636	0.3008	-8792.9240	-8767.4740
	Stu-t	-0.0731	2.1959	0.3400	1.1379	24991.0600	25016.5100
	GED	0.0607	0.9953	0.0523	0.4790	-72.0245	-7927.0027
EGL	Gauss	-0.0008	0.0951	-0.0534	0.2824	-8509.9520	-8489.5920
	Stu-t	0.1027	2.1674	0.2462	1.0042	22116.7040	23075.6250
	GED	-0.0008	0.0924	-0.0021	0.1090	-7502.3410	-7817.0910
SIC	Gauss	-0.0004	0.2020	0.5282	0.3572	-7750.5660	-7725.1160
	Stu-t	-0.0137	1.0556	0.5461	0.7797	14059.3000	14084.25
	GED	-0.0004	0.6510	0.4223	0.4973	-4000.7320	-3421.1125

Table 10. Model Selection via Information Criterion

Model	BIC	AIC
GARCH (1, 1) with Gaussian	-9250.4160	-9230.0560
EGARCH (1, 1) with Gaussian*	**-9284.6200***	**-9259.1700***
TGARCH (1, 1) with Gaussian	-9276.3970	-9250.9460

*Model selected with least BIC and AIC

The selected EGARCH models for GCB, SCB, EGL, and SIC are presented in Equations 25–28, respectively.

$$\text{GCB;}\ \ln\sigma_t^2 = -0.1530 + 0.4470\ln\sigma_{t-1}^2 - 0.9495\frac{\varepsilon_{t-1}}{\sigma_{t-1}} - 2n - 0.0183\frac{\varepsilon_{t-1}}{\sigma_{t-1}} \tag{25}$$

$$\text{SCB;}\ \ln\sigma_t^2 = 0.3008 + 0.5590\ln\sigma_{t-1}^2 - 0.0607\frac{\varepsilon_{t-1}}{\sigma_{t-1}} - 2n + 0.0654\frac{\varepsilon_{t-1}}{\sigma_{t-1}} \tag{26}$$

$$\text{EGL;}\ \ln\sigma_t^2 = 0.2824 + \ln\sigma_{t-1}^2 - 0.6316\frac{\varepsilon_{t-1}}{\sigma_{t-1}} - 2n + 0.0247\frac{\varepsilon_{t-1}}{\sigma_{t-1}} \tag{27}$$

$$\text{SIC;}\ \ln\sigma_t^2 = 0.3572 + 0.7230\ln\sigma_{t-1}^2 - 0.0192\frac{\varepsilon_{t-1}}{\sigma_{t-1}} - 2n - 0.0157\frac{\varepsilon_{t-1}}{\sigma_{t-1}} \tag{28}$$

3.5. Diagnostic Test for the Selected Model

The EGARCH model was tested for its appropriateness and suitability in terms of its specification. From Table 11, all the standardized standard deviation values for the specified model were all less than the values for the return series of the raw returns. The LB and LB2 were deployed to test for autocorrelation and hetereoscedacitity respectively. All the standardized values for the selected model for both LB and LB2 were all statistically insignificant, indicating the non-existence of ARCH effect and heteroscedasticity, respectively whiles the raw returns had all the values for LB and LB2 been statistically significant at 5% significance level, showing the presence of autocorrelation, hence ARCH effect and heteroscedasticity in the series. Also, the standardized values for the selected model for both skewness and kurtosis were all lower than the raw return series. It is evident that EGARCH (1, 1) with a Gaussian distribution is well specified for the estimated return series.

Table 11. Diagnostic Test EGARCH (1, 1) with Gaussian Distribution

Sector	Type	Mean	St. Dv	JB	SK	K	LB	LB2
GCB	Raw returns	0.0001	0.1080	21057100	-0.1400	428.1000	221.7470	483.2500
	EGARCH	0.0188	0.0066	19821.2002	0.0678	2.5223	0.2833	0.0543
SCB	Raw returns	0.0001	0.0085	1084840	0.1000	157.1200	86.2107	417.9900
	EGARCH	0.0694	0.0161	19321.0471	0.0595	0.5254	0.7690	0.5913
EGL	Raw returns	-0.0001	0.0079	580237	52.0000	37.2400	49.4995	345.6400
	EGARCH	0.0065	0.0027	6322.0595	0.1680	1.7654	0.4137	0.1711
SIC	Raw returns	0.0001	0.0122	38446.200	50.1400	21.700	21.0813	208.4320
	EGARCH	0.0168	0.0049	2987.1004	0.2268	2.1442	0.3423	0.1171

3.6. Volatility Persistence and Half-Life Measure

Table 11 shows the summation of α and β of the EGARCH model, which were used to determine the volatility persistence and half-life measure of the selected equities. The results showed that all the equities had high volatility persistence. However, GCB had the longest mean reversion of 14 days, while SCB, EGL, and SIC had short mean reversion periods. This meant that GCB exhibited the longest half-life (14 days), suggesting more persistent volatility shocks relative to other equities. This reflects GCB's dominant market capitalization, systemic importance, and higher investor attention. But based on Table 1.1, on average, volatility shocks tend to fade quickly, giving an indication of short-term memory in market volatility. The β coefficients indicate statistically significant volatility persistence, meaning past volatility significantly influences current volatility. However, the calculated half-life measures show that shocks decay relatively quickly, indicating short memory in practical terms. Thus, persistence refers to statistical dependence, whereas half-life reflects the economic speed of mean reversion. This outcome implies that the risk involved in investing in these equities was moderate, as any imbalances in the market tend to be stabilized in the short run. Hence, the market was very conducive for investors as it could guarantee consistent returns.

The study also investigated the volatility trends of the selected equities using the α parameter as shown in Table 12, which reflects the sensitivity of volatility to new information or shocks. All the α parameters of the equities were positive and small, showing that new information had an impact on volatility. But, the impact on volatility was a gradual and stable manner, and these volatility spikes can also be observed in Figures 1 to 8, around 2019 coincide with Ghana's banking sector restructuring and license revocations, while the sharp spikes in 2020 align with the COVID-19 pandemic-induced market disruptions. Thus, this indicates a steady upward movement of the trend in-terms of equity performance. This trend of movement are business friendly, which boosts the confidence of the market, thereby attracting more capital and investment to the market, leading to the overall growth of the economy. The short volatility half-life implies rapid information absorption, an indication of an improvement in market efficiency in Ghana's financial sector. Policymakers should also enhance transparency and liquidity to further reduce volatility persistence. Investors should be very circumspect when investing in the GSE, as some of the equities showed moderate volatility with short volatility persistence. This indicates that these equities offer lower risk in the short run. Also, some of the equities exhibited high volatility persistence, and investors with long-term interest and also risk-averse can invest in these equities because of the stability of the volatility trend. Investors and portfolio managers should spread their investment across sectors of the equity market as a result of the different sectoral volatility behaviors of the equities. This will enable them mitigate risk and enhance their potential of making gains in terms of imbalances in the market. Also, risk management strategies should be adopted to stem the flow of negative news in the market. This is because most of the equities exhibit the leverage effect, which could potentially have a greater impact on volatility in the market, hence affecting the returns of investors. Policies, guidelines, laws, and other regulatory frameworks should be enhanced and reinforced to guide the activities of the market, so as to minimize system shocks and reduce volatility persistence in the market.

Table 12. Half-Life Measure

Sector	Variable	α	β	$\alpha + \beta$	Half-Life Measure(day(s))
Local Bank	GCB	0.4470	-0.9495	-0.5025	14
Foreign Banks	SCB	0.0607	0.5590	0.6197	1
Insurance	EGL	0.1316	0.3401	0.4717	1
	SIC	0.0192	0.7230	0.7422	2

Table 13. Trends in Volatility of the Return Series

Sector	Variable	α	P value
Local Banks	GCB	0.4470	0.0000**
Foreign Banks	SCB	0.0607	0.0000**
Insurance	EGL	0.1316	0.0000**
	SIC	0.0192	0.0000**

**Significant at 5% significance level

4. Conclusion

In this paper, the volatility of some financial equities on the Ghana stock exchange are modeled using univariate GARCH family of models. The principal component analysis was used in selecting the equities for each sector. The volatility of the selected equities was examined using the GARCH family of models. The EGARCH model with Gaussian distribution emerged as the best-performing model based on the lowest AIC and BIC values. In the EGARCH models, the leverage parameter had an equal signage of both negative and positive values reported. This suggests an even distribution of leverage effects, implying that asymmetric effects were statistically insignificant for these equities. The TGARCH models, however, revealed predominantly high positive values, suggesting a stronger presence of leverage effects. EGL, SCB, and GCB using the Student-t distribution exhibited particularly high responsiveness to shocks, indicating swift market reactions. Volatility persistence and half-life were examined from the EGARCH model parameters. GCB exhibited the highest mean reversion time of 14 days, indicating more prolonged volatility, whereas SCB, EGL, and SIC had shorter mean reversion periods. This implies that, on average, there is a short memory in volatility pertaining to the equities, suggesting that the risks associated with these equities were moderate and that the market corrected itself relatively quickly. Estimates of the EGARCH model with Gaussian (selected model) showed that they were all positive and small across equities. This suggests that equity return trends were gradually and steadily increasing.

Conflict of Interest

The authors declare there is no existing conflict of interest.

References

1.Abonongo, J., Oduro, F. T., and Ackora-Prah, J. (2016). *Modelling volatility and the risk-return relationship of some stocks on the Ghana stock exchange*. PhD thesis, American Journal of Economics.

2.Adjasi, C. K. and Biekpe, N. B. (2006). Stock market development and economic growth: The case of selected african countries. *African Development Review*, 18(1):144–161.

3.Ahmed, R. A. and Shabri, A. B. (2014). Daily crude oil price forecasting model using arima, generalized autoregressive conditional heteroscedastic and support vector machines. *American Journal of Applied Sciences*, 11(3):425.

4.Arshad, I., Rani, H., and Shaikh, A. (2012). Volatility modeling of karachi stock exchange. *Sindh University Research Journal-SURJ (Science Series)*, 44(1).

5.Baskin, J. (1989). Dividend policy and the volatility of common stocks. *Journal of portfolio Management*, 15(3):19.

6.Bollerslev, T., Chou, R. Y., and Kroner, K. F. (1992). Arch modeling in finance: A review of the theory and empirical evidence. *Journal of econometrics*, 52(1-2):5–59.

7.Dailami, M. and Atkin, M. (1990). Stock markets in developing countries: key issues and a research agenda.

8.Du Preez, M., Dicken, M., and Hosking, S. G. (2012). The value of tiger shark diving within the aliwal shoal marine protected area: A travel cost analysis. *South African Journal of Economics*, 80(3):387–399.

9.Engle, R. F. and Ng, V. K. (1993). Measuring and testing the impact of news on volatility. *The journal of finance*, 48(5):1749–1778.

10.Fama, E. F. (1965). The behavior of stock-market prices. *The journal of Business*, 38(1):34–105.

11.Frimpong, S. (2011). Speed of adjustment of stock prices to macroeconomic information. *International Business and Management*, 2(1):151–156.

12.Gbeda, J. M. and Peprah, J. A. (2018). Day of the week effect and stock market volatility in ghana and nairobi stock exchanges. *Journal of Economics and Finance*, 42(4):727–745.

13.Glosten, L. R., Jagannathan, R., and Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *The journal of finance*, 48(5):1779–1801.

14.Hair, J. F., Black, W. C., Babin, B. J., and Anderson, R. E. (2010). *Multivariate Data Analysis: A Global Perspective*, volume 7. Pearson Education, Upper Saddle River, NJ.

15.Hameed, A. and Ashraf, H. (2009). Stock market volatility and weak-form efficiency: evidence from an emerging market. *International Journal of Business and Emerging Markets*, 1(3):249–263.

16.Jefferis, K. and Smith, G. (2005). The changing efficiency of african stock markets. *South African journal of economics*, 73(1):54–67.

17.Jolliffe, I. (2002). *Principal Component Analysis, Springer Series in Statistics. Springer, New York*. Springer.

18.Lux, T. (1998). The socio-economic dynamics of speculative markets: interacting agents, chaos, and the fat tails of return distributions. *Journal of Economic Behavior & Organization*, 33(2):143–165.

19.Mandelbrot, B. B. and Hudson, R. L. (2010). *The (mis) behaviour of markets: a fractal view of risk, ruin and reward*. Profile books.

20.Mittal, A. K., Arora, D., and Goyal, N. (2012). Modeling the volatility of indian stock market. *International Journal of Research in IT & Management*, 2(1):1–23.

21.Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica: Journal of the econometric society*, pages 347–370.

22.Peiro, A. (1999). Skewness in financial returns. *Journal of Banking & Finance*, 23(6):847–862.

23.Prempeh, K. B., Frimpong, J. M., and Amaning, N. (2022). Determining the return volatility of the ghana stock exchange before and during the covid-19 pandemic using the exponential garch model. *SN Business & Economics*, 3(1):21.

24.Rousan, R. and Al-Khouri, R. (2005). Modeling market volatility in emerging markets: The case of daily data in amman stock exchange 1992-2004. *International Journal of Applied Econometrics and Quantitative Studies*, 2(4):99–118.

25.Zakoian, J.-M. (1994). Threshold heteroskedastic models. *Journal of Economic Dynamics and control*, 18(5):931–955.