

Modelling Volatility and the Risk-Return Relationship of some Stocks on the Ghana Stock Exchange

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Abstract The volatility and the risk-return trade off of stocks or stock markets play essential role in investment decision making, financial stability among others. This paper modelled the volatility and the risk-return relationship of some stocks on the Ghana Stock Exchange using univariate GARCH-M (1,1) models with three distributional assumptions namely, the student-t, GED and Gaussian distributions. The results showed that, the market was bullish for investors of most of the stocks and that there was a high probability of gains than losses. All the stocks were extremely volatile. The results also indicated the existence of positive risk premium meaning investors were compensated for holding risky assets. The results also showed that, the asymmetry models gave a better fit than the symmetry model indicating the presence of leverage effect among the selected stocks. The TGARCH-M (1, 1) model with the student-t distribution was the appropriate model selected.

Keywords Risk-return, Volatility, Stocks, Risk premium, GARCH-M

1. Introduction

The stock market provides a framework within which capital formation takes place and where previously issued securities are traded among investors for productive investment. The Stock Exchange plays an integral role in the capital formation and wealth creation activities in any nation. One of the essential characteristics that need distinct consideration by any investor or policy maker is the volatility of stock returns. Volatility can be defined as a statistical measure of the dispersion of returns for a given security or market index and it can either be measured using the standard deviation or variance between returns from that same security or market index [23].

[8] introduced the ARCH-M model by extending the ARCH model to allow the conditional variance to be determinant of the mean. Whereas in its standard form, ARCH model expresses the conditional variance as a linear function of past squared innovations, in this new model they hypothesized that, changing conditional variance directly affect the expected return on a portfolio. Their results from applying this model to three different data sets of bond yields are quite promising. Consequently, they concluded that risk premia are not time invariant; rather they vary systematically with agent's perceptions of underlying uncertainty.

[20] extended the ARCH framework in order to better describe the behaviour of return volatilities. Nelson's study

was important because of the fact that it extended the ARCH methodology in a new direction, breaking the rigidity of the G/ARCH specification. The most important contribution was to propose a model (Exponential Autoregressive Conditional Heteroskedasticity (EARCH)) to test the hypothesis that the variance of return was influenced differently by positive and negative excess returns. His study found that not only was the statement true, but also that excess returns were negatively related to stock market variance. [10] modified the primary restrictions of Generalized Autoregressive Conditional Heteroskedasticity- in Mean (GARCH-M) model based upon the truth that GARCH model enforce a symmetric response of volatility to positive and negative shocks, introduced the Glosten-Jagannathan-Runkle Generalized Autoregressive Conditional Heteroskedasticity (GJR-GARCH) and the Threshold Generalized Autoregressive Conditional Heteroskedasticity (TGARCH) models. They conclude that there is a positive but significant relation between the conditional mean and conditional volatility of the excess return on stocks when the standard GARCH-M framework was used to model the stochastic volatility of stock returns.

[6] also investigated the behaviour of stock return volatility of the Nigerian Stock Exchange (NSE) returns using GARCH (1, 1) and the GJR-GARCH (1,1) models assuming the Generalized Error Distribution (GED) using data from the monthly all share indices of the NSE from January 1999 to December 2008. He sought to do this by examining the NSE return series for evidence of volatility clustering, fat-tails distribution and leverage effects, because they provided essential information about the riskiness of assets on the market. He discovered that there exists

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volatility clustering on the Nigeria Stock Exchange (NSE) and used GARCH (1,1) to model that. He captured the existence of leverage effects in the series with the GJR-GARCH (1,1) model. The GED shape test also revealed a leptokurtic returns distribution. The entire results revealed that there was evidence of volatility persistence, fat-tail distribution, and leverage effects present in the NSE. He concluded that the volatility of the stock returns was persistent in Nigeria and that the shape parameter estimated from GED revealed evidence of leptokurtosis in the NSE returns distribution. In modelling the volatility on the Johannesburg Stock Exchange (JSE) employing ARCH-type models, [18] found that volatility was symmetric and was not a commonly priced factor. This result was obtained by considering two portfolios (with data from 1973 to 2002): the All Share Index (ALSI) and a portfolio with 42 stocks. The portfolio of 42 stocks was used because the ALSI is dominated by resource stocks and thus it was essential to have a portfolio that was not improperly influenced by the dynamics of the resource stocks. This result was echoed by [3], who primarily studied returns and volatility linkages between South Africa (SA) and the world major equity markets. Using a GARCH-M methodology to test the risk-premium hypothesis the authors, like [18], found that volatility is not a commonly priced factor and found that volatility is asymmetric.

Using a GARCH-M model, [20] investigated stock market volatility in the East European emerging markets of Hungary and Poland. The study covered a period from 1994 to 1996 using daily data from the Bulgarian and Warsaw stock markets. A similar result was obtained by [27] using an extension to the GARCH model, the EGARCH model realized that, there was a significant positive risk-return relationship in Bahrain, Oman and Saudi Arabia, while in Egypt, Jordan, Morocco and Turkey volatility was not priced. Using the same model, [12] found evidence in support of a negative risk-return relationship on the Indian stock market using the S and P CNX (Console Energy Inc.) Nifty for the period 1990 to 2004. Similarly, using the EGARCH-M model [21] found that positive returns were matched with higher volatility on Pakistan's stock exchange (Karachi stock exchange). [1] investigated the relationship between risk, return and volume on the Bilbao stock exchange (1916 to 1936) using the augmented GARCH-M model that was modified to account for volume traded. They found that there was little evidence of a significantly positive risk-return trade-off. [22] found a significant relationship between risk and return in 20 emerging markets. They further stated that the existence of such a relationship is highly dependent on the sample period used. They concluded that the difference between emerging and developed equity premiums follows a cyclical pattern that resembles the global business cycle.

Also, using the GARCH, EGARCH, TGARCH and PGARCH models, [13] found a weak relationship between risk and return in the Macedonian Stock Exchange (MSE). The study used the MBI-10 index, which is the capitalization-weighted index consisting of up to 10 shares

listed on the official market of the MSE, covering a period from 2005 to 2007. [13] tested the result assuming three different distributions; the Gaussian, Student-t and GED test and found that the TARCh model with a Student-t distribution was the best model to accurately model the data. [16] used a similar approach by using GARCH models with a Student-t and a Gaussian distributional assumption in investigating the risk-return relationship in the West African Economic and Monetary Union, using weekly returns for the period 1999 to 2005. The study revealed that, expected stock return has a positive but statistically insignificant relationship with expected volatility. He also found that volatility is higher during market booms than when the market declines.

[25] studied the nature of stock market volatility and its relation to expected returns for ten industrialized countries (Australia, Belgium, Canada, France, Italy, Japan, Switzerland, the United Kingdom, the United States, West Germany). They used the GARCH-M specification and tested three different specifications for the conditional variance and expected market returns relationship, which are the linear, square root and log-linear specifications. The results of this study supported the findings of the preceding studies that did not find a significant relationship between conditional volatility and expected returns. [14] used a modified GARCH-M model in order to cater for skewness and kurtosis. The study used monthly US stock returns for the period from 1946 to 2002. They motivated this modification by arguing that the modified model was capable of modelling moderate skewness and kurtosis typically encountered in financial return series. The results of this study showed that there was a positive and significant relationship between risk and return.

The essence of this paper is to model volatility and the risk-return relationship of some stocks on the Ghana Stock Exchange using univariate GARCH-M family of models assuming three distributional assumptions namely the Student-t, Generalized Error Distribution (GED) and the Gaussian distribution and under which distributional assumption the model performs best. This will provide investors and policy makers first-hand information about the nature of uncertainty on the Ghana Stock Exchange. That is, it will help investors in their investment decision making processes and assist regulators of the exchange to monitor and implement rules that will cause more companies to list on the exchange.

2. Materials and Methods of Analysis

2.1. Source of Data

This paper employed secondary data of 8 equities (CAL Bank Limited, Produce Buying Company, Fan Milk Limited, Clydestone (Ghana) Limited, Enterprise Group Limited, Uniliver Ghana Limited, Tullow Oil Plc and Benso Oil Palm Plantation) from the Ghana Stock Exchange (GSE) and Annual Report Ghana databases comprising the daily closing

prices from the period 02/01/2004 to 16/01/2015, totalling 7616 observations.

2.2. Methods of Data Analysis

The daily index series were converted into compound returns given by;

$$X_t = \log\left(\frac{p_t}{p_{t-1}}\right) \quad (1)$$

where X_t is the continuous compound returns at time t , p_t is the current closing stock price index at time t and p_{t-1} is the previous closing stock price index.

2.2.1. Unit Root Test: ADF Test

The Augmented Dickey-Fuller (ADF) test was employed to determine whether the individual series studied have unit root or were covariance stationary. It was proposed [4] as an upgraded form of the Dickey-Fuller (DF) test. The ADF test assumes the hypothesis: $H_0: \Theta = 1$ (non-stationary) against $H_0: \Theta < 1$ (covariance stationary).

where Θ is the characteristics root of an AR polynomial and ε_t is an uncorrelated white noise series with zero mean and constant variance.

The ADF test statistic is given by;

$$F_\tau = \frac{\hat{\phi}}{SE(\hat{\phi})} \quad (2)$$

where $\hat{\phi}$ is the estimate of ϕ and $SE(\hat{\phi})$ is the standard error of the least square estimate of $\hat{\phi}$. The null hypothesis is rejected if the p -value $< \alpha$ significance level.

2.2.2. Jarque-Bera Test

[11] is a goodness-of-fit test which examines if the sample data have kurtosis and skewness similar to a normal distribution.

The test statistic is given by;

$$JB = T \cdot \left[\frac{S^2}{6} + \frac{(K-3)^2}{24} \right] \quad (3)$$

where S and K are the sample skewness and kurtosis respectively.

The Hypothesis is given by;

H_0 : normality

H_1 : non-normality

If the sample data comes from a normal distribution JB should, asymptotically, have a chi-squared distribution with two degrees of freedom.

2.2.3. Univariate Ljung-Box Test

The [17] was employed to test whether there exist autocorrelations (r_l) in the returns series. The statistic is given by;

$$Q(K) = T(T+2) \sum_{l=1}^k \frac{r_l^2}{T-l} \quad (4)$$

where r_l is the residual sample autocorrelation at lag l , T is the size of the series, k is the number of time lags included in the test. $Q(K)$ has an approximately chi-square distribution with k degree of freedom. The null hypothesis is rejected and

concluded at α -level of significance that, the residuals are free from serial correlation when the p -value is greater than the significance.

2.2.4. Testing for ARCH Effects

In applying GARCH methodology, it is very essential to examine the residuals for evidence of ARCH effects. The ARCH-LM test was employed. [15] documented that the Lagrange Multiplier (LM) test can be used to test the ARCH effect in a series. By representing the i lag autocorrelation of the squared or absolute returns by \hat{p}_i , the Ljung-Box statistic is given by;

$$Q = T(T+2) \sum_{i=1}^m \frac{\hat{p}_i^2}{T-i} \sim \chi^2(m) \quad (5)$$

The LM hypothesis is given by;

$H_0: \alpha_1 = \alpha_2 = \dots = \alpha_i = 0$ (no ARCH effect) against

$H_1: \alpha_1 \neq \alpha_2 \neq \dots \neq \alpha_i \neq 0$ (ARCH effect)

for at least $i = 1, 2, \dots, q$

The statistic of the LM test is given by;

$$LM = T \cdot R^2 \sim \chi^2(q) \quad (6)$$

where q is the number of restrictions placed on the model, T is the total observations and R^2 forms the regression.

2.2.5. The Durbin-Watson Test

[5] was employed to determine whether the error term in the mean equation follows an AR (1) process. The test requires the error term ε_t to be distributed $N(0, \sigma^2)$ for the statistic to have an exact distribution. The test statistic is given as;

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

where $e_i = y_i - \hat{y}_i$ and y_i and \hat{y}_i are the observed and predicted values of the response variable for individual i respectively. d becomes smaller as the serial correlations increases.

The hypothesis is given by;

$H_0: \rho = 0$

$H_1: \rho > 0$

Also, the d statistic can take on values between 0 and 4 and under the null hypothesis d is equal 2. Values of d less than 2 suggest positive autocorrelation ($\rho > 0$), whereas values of d greater than 2 suggest negative autocorrelation ($\rho < 0$). When d is closer to 2, it suggest that there is no first order autocorrelation in the residuals.

2.2.6. The Breusch-Godfrey Test

This is an LM test which is used to test for higher-order serial correlation in the disturbance.

The test statistic is given by;

$$B - G = NR^2 \quad (8)$$

where N is the number of observations and R^2 is the simple R^2 from the regression

$$\hat{u}_t = \gamma_1 \hat{u}_{t-1} + \dots + \gamma_p \hat{u}_{t-p} + \beta_1 x_{1t} + \dots + \beta_k x_{kt} + \varepsilon_t \quad (9)$$

The hypothesis is given by;

H_0 : no autocorrelation

H_1 : autocorrelation

The test is asymptotically $\chi^2(p)$ distributed.

2.2.7. The Mean Equation

In modelling volatility, it is very essential to specify an appropriate mean equation. The mean equation should be white noise series, that is it should have a finite mean and variance; constant mean and variance, zero autocovariance, except at lag zero. Comparatively following [24] and [3], this paper employed the mean equation given by:

$$X_t = \mu + \lambda X_{t-1} + \varepsilon_t \quad (10)$$

where X_t is the returns for each equity in each sector, μ and λ are constants and ε_t is the innovation.

The Univariate GARCH-in Mean (GARCH-M) Model

Mostly, the return of a security may depend on its volatility. In other for such a phenomenon to be modelled, there is the need to consider the GARCH-M model of [8].

It is an extension of the basic GARCH model which allows the conditional mean of a sequence to depend on its conditional variance or standard deviation. The general form of the GARCH (p,q) model is given by;

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^p \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^q \beta_j \sigma_{t-j}^2 \quad (11)$$

where $\alpha_0 > 0$ and $\alpha_i \geq 0, i = 1, \dots, p$ and $\beta_j \geq 0, j = 1, \dots, q$. σ_t^2 is the squared volatility, α_0 is a constant, α_i is the coefficient of the lagged squared residuals, ε_{t-i}^2 is the lagged squared residual and β_j is the coefficient for the GARCH component.

The simplest GARCH-M model is the GARCH-M (1, 1) given by;

$$\text{Mean equation: } X_t = \mu + \lambda \sigma_t^2 + \varepsilon_t, \quad \varepsilon_t \sim N(0, \sigma_t^2) \quad (12)$$

$$\text{Variance equation: } \sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad (13)$$

where μ and α_0 are constants. X_t is the returns on an equity or sector, σ_t^2 is the squared volatility, λ is the coefficient of the standard deviation (risk premium parameter), α_1 is the coefficient of the lagged squared residuals, ε_{t-1}^2 is the lagged squared residual from the mean equation and β_1 is the coefficient for the GARCH component (lagged conditional variance). To satisfy the stationary condition, $\alpha + \beta < 1$.

If λ is positive or negative and statistically significant, then increased risk given by an increase in conditional variance, leads to a rise or fall in the mean return, that is λ can be said to be time-varying risk premium. A statistically positive relationship will indicate that investors are compensated for assuming greater risk. But a negative relationship will indicate that investors react to factor(s) other than the standard deviation of equities from their historical mean.

[8] also assumed that risk premium is an increasing function of the conditional variance of ε_t . That is, the greater the conditional variance of the return, the greater the

compensation necessary to induce an investor to hold an asset for a long period [7]. This model will be tested for ARCH effects, and if the ARCH LM test reveals evidence of ARCH effects, the EGARCH-M will be employed.

2.2.8. The Exponential GARCH-M (EGARCH-M)

This model captures asymmetric responses of time-varying variance to shocks and at the same time ensures the variance is always positive. It was developed by [20], the generalized form can be specified as EGARCH (p, q) given by;

$$\ln(\sigma_t^2) = \alpha_0 + \sum_{j=1}^q \beta_j \ln(\sigma_{t-j}^2) + \sum_{i=1}^p \alpha_i \left[\left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}^2} \right| - \sqrt{\frac{2}{\pi}} \right] + \gamma_i \frac{\varepsilon_{t-i}}{\sigma_{t-i}^2} \quad (14)$$

where α_0 is a constant, α and β are the same as in GARCH-M and γ is the asymmetric response parameter (leverage parameter).

If $\varepsilon_{t-i} > 0$ or there is arrival of good news, the total effect of ε_{t-i} is $(1 + \gamma) |\varepsilon_{t-1}|$; if $\varepsilon_{t-i} < 0$ (arrival of bad news), the total effect of ε_{t-i} is $(1 - \gamma) |\varepsilon_{t-1}|$. The model is stationary and has a finite kurtosis if $|\beta_j| < 1$. That is there is no restriction on the leverage effect. There is no leverage effect if γ is negative.

The sign of γ is expected to be positive in most empirical case so that a negative shock increases future volatility whereas a positive shock reduces the effect on future uncertainty. Also if $\gamma < 0$ and statistically significant, then negative shocks imply a higher next period conditional variance than positive shocks of the same magnitude.

Assuming the mean equation in Equation (10), the simplest form of EGARCH-M is the EGARCH-M (1, 1), the variance equation is given by;

$$\ln(\sigma_t^2) = \alpha_0 + \beta_1 \ln(\sigma_{t-1}^2) + \alpha_1 \left[\left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}^2} \right| - \sqrt{\frac{2}{\pi}} \right] + \gamma_1 \frac{\varepsilon_{t-1}}{\sigma_{t-1}^2} \quad (15)$$

$\alpha + \beta < 1, \gamma < 0$, if volatility is asymmetric.

In the original specification of the model, [20] assumed GED (Generalized Error Distribution) for the errors. If the distributional assumption of the errors are altered from the original, the model specification will leave the estimates the same except for α_0 . The TARCH-M will also be explored if the EGARCH-M does not fully eliminate the ARCH effects. Like the EGARCH-M model, the TARCH-M is an asymmetric model. However, the specification and interpretation differs from the EGARCH-M.

2.2.9. The Threshold GARCH-M (TGARCH-M)

This model was proposed by [10] and [27]. It is simply a respecification of the GARCH-M model with an additional term to account for asymmetry (leverage effect). In the general specification of this model, the TGARCH (p, q) model is given by;

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^p (\alpha_i + \gamma_i d_{t-i}) \varepsilon_{t-i}^2 + \sum_{j=1}^q \beta_j \sigma_{t-j}^2 \quad (16)$$

where α_0 is a constant, d is the asymmetric component and γ is the asymmetric coefficient. α_i, γ_i and β_j are

non-negative. Assuming the mean equation in equation (10), the variance equation for TGARCH-M (1, 1) is given by;

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \gamma_1 d_{t-1} \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad (17)$$

$$d_{t-1} = \begin{cases} 1 & \text{if } \varepsilon_{t-1} < 0, \text{ bad news} \\ 0 & \text{if } \varepsilon_{t-1} \geq 0, \text{ good news} \end{cases} \quad (18)$$

If $\gamma > 0$, then leverage effects exist in stock markets and if $\gamma \neq 0$ then the impact of news is asymmetric [9]. Also when $\gamma = 0$, the model collapses to the standard GARCH form. Nevertheless, when the shock is positive (good news), the volatility is α_1 , whereas if the news is negative (bad news), the effect on volatility is $\alpha_1 + \gamma_1$. Similarly, if γ is positive and statistically significant then negative shocks will have a larger effect on σ_t^2 than positive shocks [2]. Also, since the conditional variance must be positive, the constraints of the parameters are $\alpha_0 > 0$, $\alpha_1 \geq 0$, $\beta_1 \geq 0$ and $\alpha_1 + \gamma_1 \geq 0$. The model is stationary if $\gamma_1 < 2(1 - \alpha_1 - \beta_1)$.

2.2.10. Distributional Assumptions of Error Term

In GARCH model specification, it is more appropriate to consider the choice on the distributional assumption of the error term. Following [13], this study assumed three distributional assumptions; Student-t distribution, Generalized Error Distribution (GED) and Gaussian (Normal) distribution in order to account for fat tails that are common in most financial data. The ARCH models are estimated using the maximum likelihood approach given a distributional assumption. The contribution to the likelihood for observation t for the Student-t distribution is given by;

$$l_t = -\frac{1}{2} \log \left(\frac{\pi(v-2) \Gamma(\frac{v}{2})}{\Gamma(\frac{v+1}{2})^2} \right) - \frac{1}{2} \log \sigma_t^2 - \frac{v+1}{2} \log \left(1 + \frac{(y_t - X'_t \theta)^2}{\sigma_t^2(v-2)} \right) \quad (19)$$

where $\Gamma(\cdot)$ is the gamma function and $v > 2$ is a shape parameter which controls the tail behaviour. When $v \rightarrow \infty$ the distribution converges to Gaussian distribution. [20] proposed the use of the GED in order to account for fat-tails observed commonly in financial time series. It is given by;

$$l_t = -\frac{1}{2} \log \left(\frac{\Gamma(\frac{3}{r})}{\Gamma(\frac{3}{r}) \Gamma(\frac{r}{2})^2} \right) - \frac{1}{2} \log \sigma_t^2 - \left(\frac{\Gamma(\frac{3}{r}) (y_t - X'_t \theta)^2}{\sigma_t^2 \Gamma(\frac{r}{2})} \right)^{\frac{1}{2}} \quad (20)$$

where $r > 0$ is the tail parameter. The distribution becomes Gaussian distribution if $r = 2$ and fat tailed if $r < 2$.

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

$$l_t = -\frac{1}{2} \log(2\pi) - \frac{1}{2} \log \sigma_t^2 - \frac{(y_t - X'_t \theta)^2}{2\sigma_t^2} \quad (21)$$

2.2.11. Model Selection Criterion

This study employed two information criteria namely,

Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) in selecting the best model. Their respective estimations are given by;

$$AIC = \ln(\hat{\sigma}^2) + \frac{2k}{T} \quad (22)$$

$$BIC = \ln(\hat{\sigma}^2) + \frac{k}{T} \ln T \quad (23)$$

where $\hat{\sigma}^2$ is the variance of the residuals, T is the sample size, k is the total number parameters. For a GARCH (p, q) model, $k = p + q + 1$. The best model is the model that has least AIC, SBIC and HQIC values.

2.2.12. Model Diagnostic

It is very essential to perform a diagnostic checks on the model after determining the best model and its corresponding distribution for the error term so as to establish whether the model and distribution are correctly specified. This study will employ the Ljung-Box test and Lagrange Multiplier (LM) test to test for the presence of autocorrelation and ARCH effects. The presence of autocorrelation and ARCH effects for both the raw series and the standardized residuals of the selected model will be tested.

2.2.13. Cross Validation of GARCH-M (1,1) Family of Models

The fitted model was cross validated with an out-sample forecast from 5th January, 2015 to 16th January, 2015. The chi-square goodness of fit test was employed. This is a statistical test that examines the level to which a set of observed sample data deviates from the corresponding set of expected values of the sample. The test statistic is given by;

$$\chi^2 = \sum_{i=1}^k \frac{(o_i - e_i)^2}{e_i} \quad (24)$$

With $k-1$ degree of freedom, where o_i is the observed returns series and e_i is the expected returns series.

3. Results and Discussion

3.1. Descriptive Statistics

The summary statistics of the returns series as reported in Table 1 reveals that most of the equities had positive mean returns ranging from 0.0002 to 0.0020 and negative mean returns ranging from -0.0019 to -0.0002. The highest mean return was recorded in Benso Oil Palm Plantation and the lowest mean return recorded in Produce Buying Company. A positive mean return indicates that investors of such equities made gains whereas those with negative mean return shows that investors made losses. The standard deviation as a measure of risk was high in Tullow Oil Plc (0.0527) and low in Uniliver Ghana Limited (0.0187) indicating the risk levels across the equities. The variability between risk and return as a measure of coefficient of variation ranges from -24856.2300 (Clydestone (Ghana) Limited) to 16299.1900 (Enterprise Group Limited). Also, most of the mean returns were positively skewed ranging from 0.5900 to 28.7400.

This indicates that, the upper tail of the distribution of the return were ticker than the lower tail and that there were higher chances of gains than losses. That is, there was greater probability of making gains by investors in such equities. Nevertheless, Enterprise Group Limited recorded a negative skewness (-16.8800) indicating that there was a high probability of making loss than gain by investors. The excess kurtosis ranged from 32.8200 to 866.0000 which are greater than 3. This means that the underlying distribution of the returns leptokurtic in nature and heavy tailed and that there was more frequently extremely large deviations from the mean returns than a Normal distribution making the equities

highly volatile.

From Figure (1), (2), (3), (4), (5), (6), (7) and (8) which shows the time series plots of CAL Bank Limited, Produce Buying Company, Fan Milk Limited, Clydestone (Ghana) Limited, Enterprise Group Limited, Uniliver Ghana Limited, Tullow Oil Plc and Benso Oil Palm Plantation respectively, it is evident that the returns series did not clearly indicate any trend but there is evidence of volatility clustering an indication that low values of volatility tends to be followed by low values and high values of volatility tends to be followed by high values.

Table 1. Descriptive Statistics of the Returns Series

Equity	Mean	St. Dev	CV	Skewness	Kurtosis
CAL Bank Limited	0.0013	0.0425	338.3000	4.6600	220.3900
Produce Buying Company	-0.0019	0.0223	2309.6400	1.9100	132.8100
Fan Milk Limited	0.0012	0.0216	1800.6600	0.7200	41.0800
Clydestone (Ghana) Limited	-0.0002	0.0460	-24856.2300	0.5900	32.8200
Enterprise Group Limited	0.0002	0.0380	16299.1900	-16.8800	347.1800
Uniliver Ghana Limited	0.0009	0.0187	2031.5300	2.2300	92.5900
Tullow Oil Plc	0.0017	0.0527	3058.0600	28.7400	866.0000
Benso Oil Palm Plantation	0.0020	0.0420	2154.5100	14.5100	346.4800

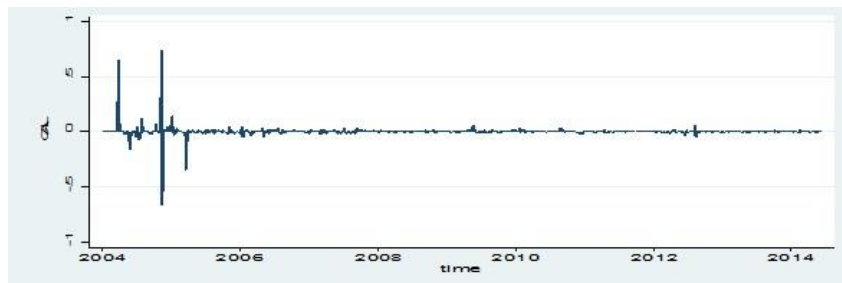


Figure 1. Time Series plot of CAL Bank Limited Returns Series

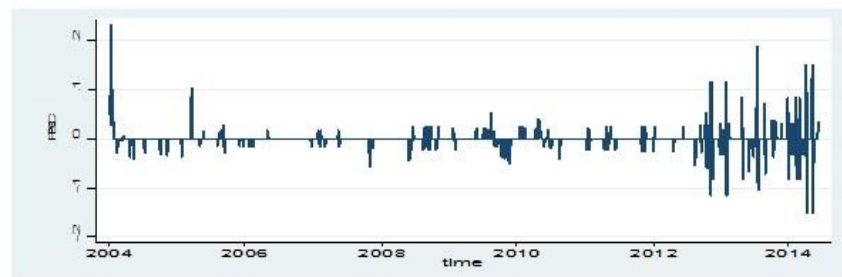


Figure 2. Time Series plot of Produce Buying Company Returns Series

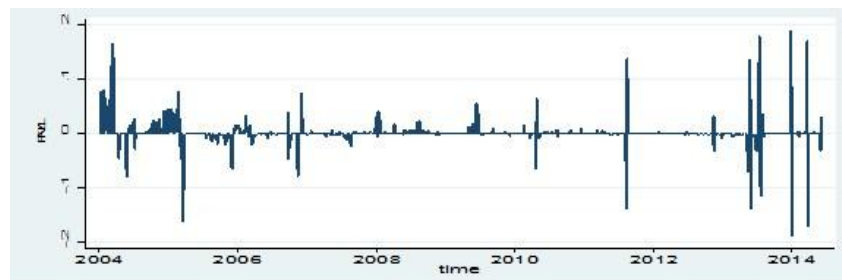


Figure 3. Time Series plot of Fan Milk Limited Returns Series

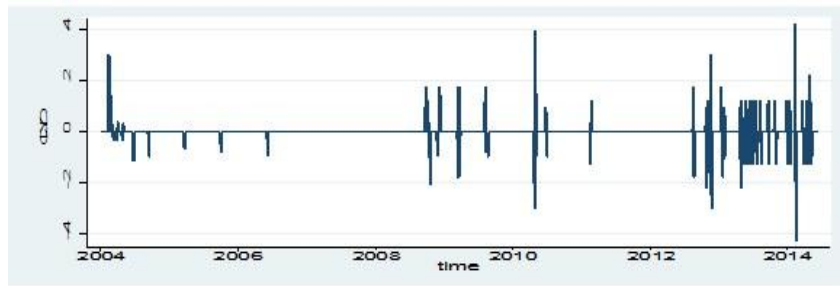


Figure 4. Time Series Plot of Clydestone (Ghana) Limited Returns Series

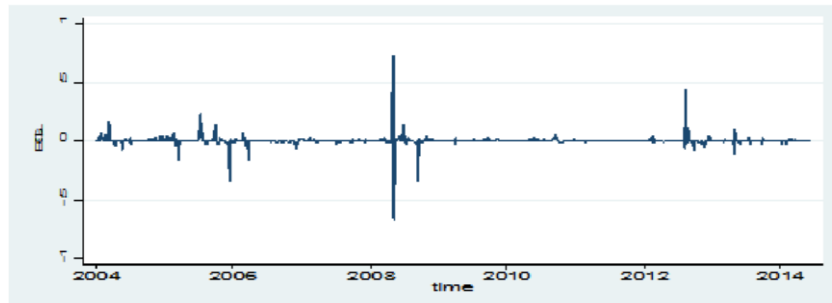


Figure 5. Time Series Plot of Enterprise Group Limited Returns Series

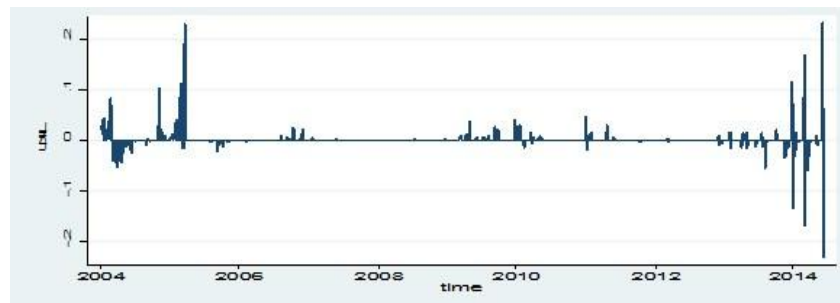


Figure 6. Time Series plot of Uniliver Ghana Limited Returns Series

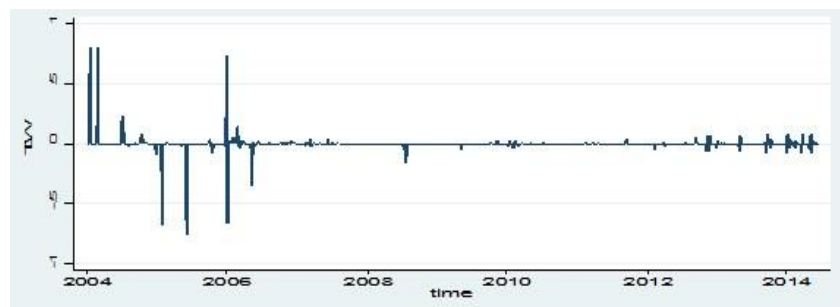


Figure 7. Time Series plot of Tullow Oil Plc Returns Series

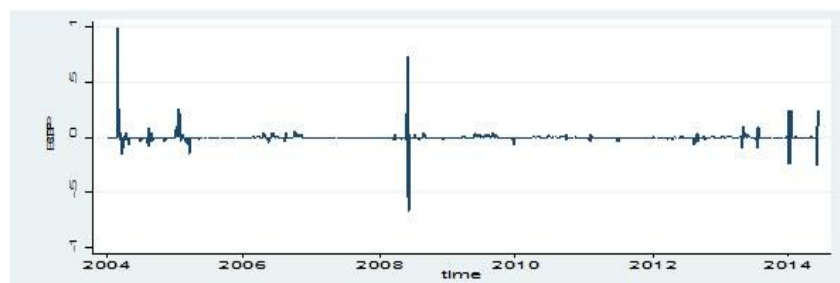


Figure 8. Time Series plot of Benso Oil Palm Plantation Returns Series

From Figure (9), (10), (11), (12), (13), (14), (15), (16) and (17), (18), (19), (20), (21), (22), (23), (24), it is also evident that the ACF and PACF plots of the returns series and squared returns series of CAL Bank Limited, Produce Buying Company, Fan Milk Limited, Clydestone (Ghana) Limited, Enterprise Group Limited, Uniliver Ghana Limited, Tullow Oil Plc and Benso Oil Palm Plantation respectively did not clearly showed stationarity. Also the ACF and PACF

plots of CAL Bank Limited, Produce Buying Company, Fan Milk Limited, Clydestone (Ghana) Limited, Enterprise Group Limited, Uniliver Ghana Limited, Tullow Oil Plc and Benso Oil Palm Plantation did not vividly indicate whether the returns series were serially correlated except at lag (1) and the ACF plots does not decay slowly, an indication of long memory behaviour.

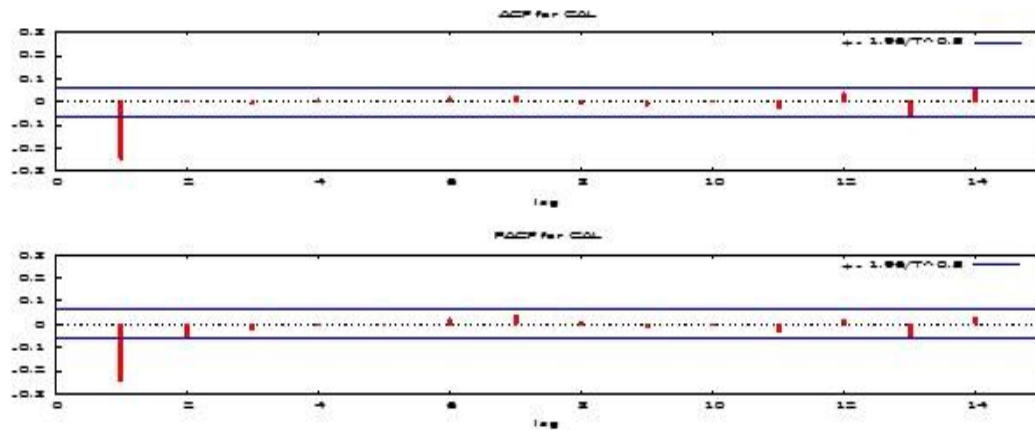


Figure 9. ACF and PACF plot of CAL Bank Limited Returns Series

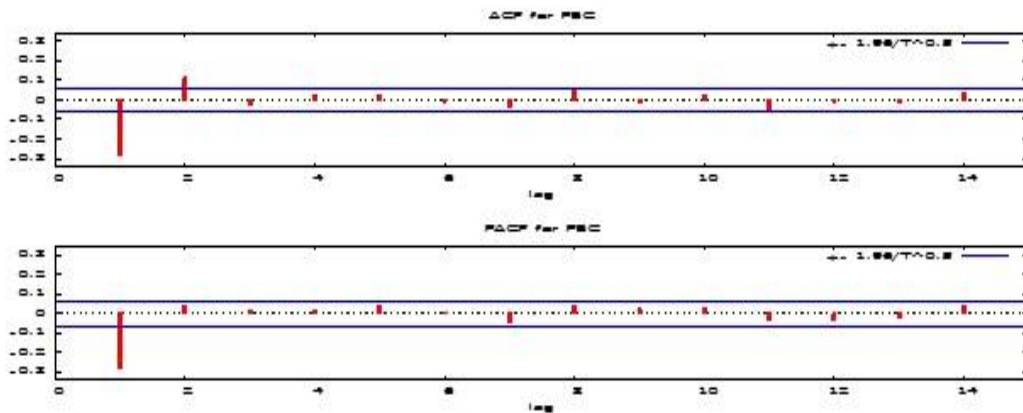


Figure 10. ACF and PACF plot of Produce Buying Company Returns Series

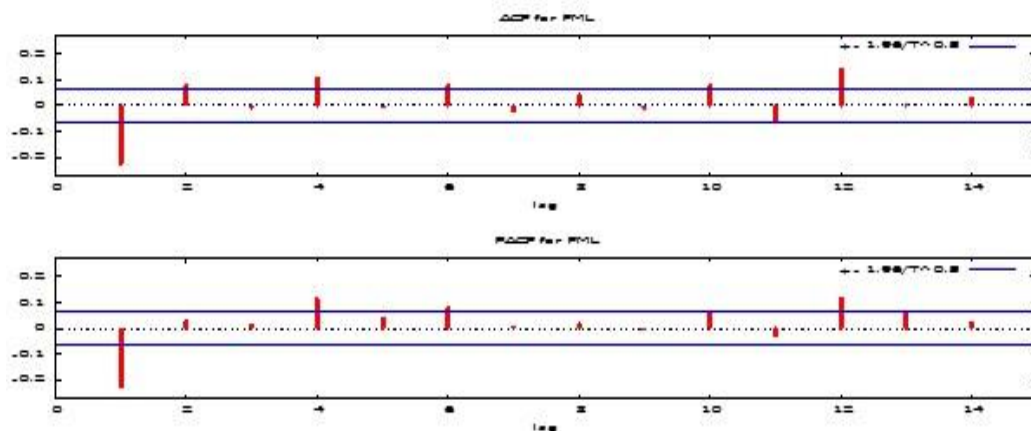


Figure 11. ACF and PACF plot of Fan Milk Limited Returns Series

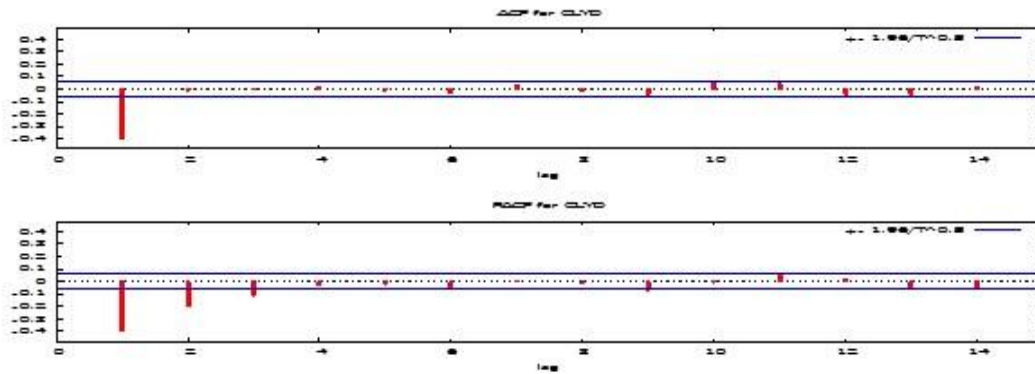


Figure 12. ACF and PACF plot of Clydestone (Ghana) Limited Returns Series

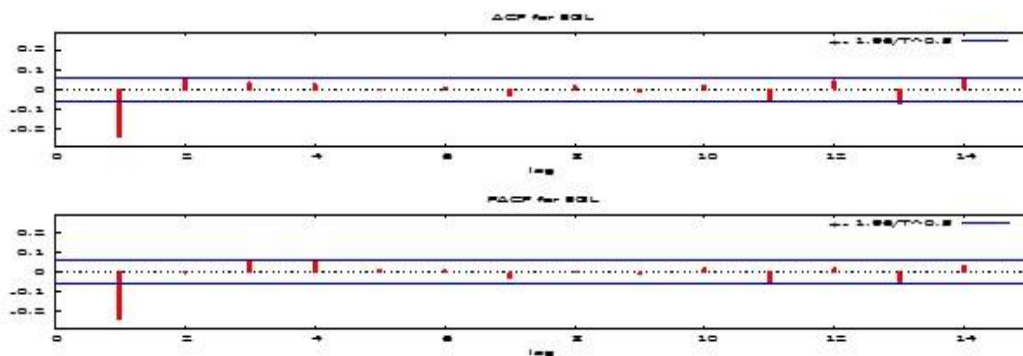


Figure 13. ACF and PACF plot of Enterprise Group Limited Returns Series

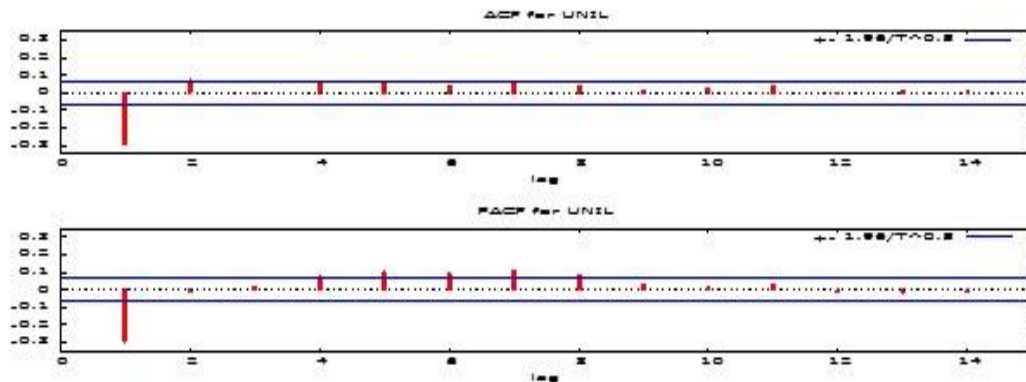


Figure 14. ACF and PACF plot of Uniliver Ghana Limited Returns Series

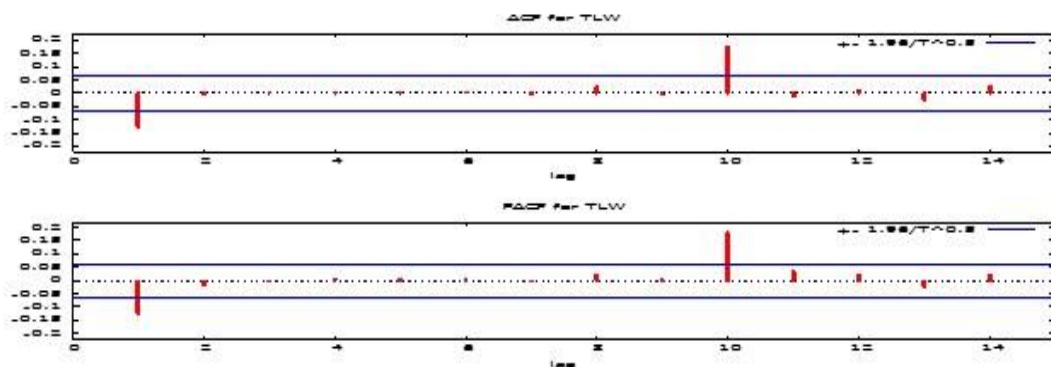


Figure 15. ACF and PACF plot of Tullow Oil Plc Returns Series

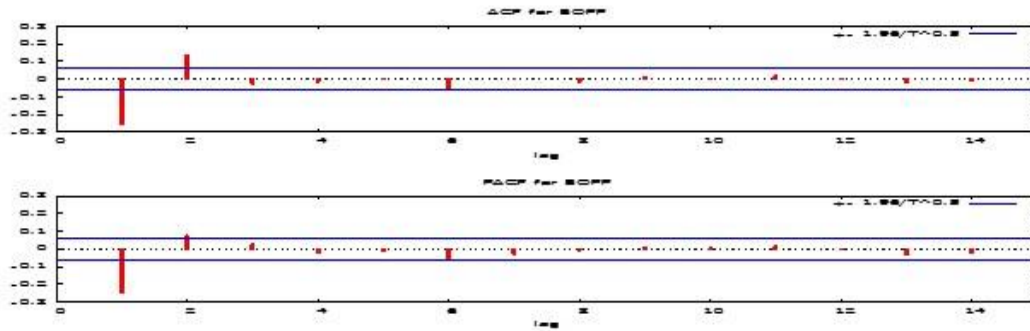


Figure 16. ACF and PACF plot of Benso Oil Palm Plantation Returns Series

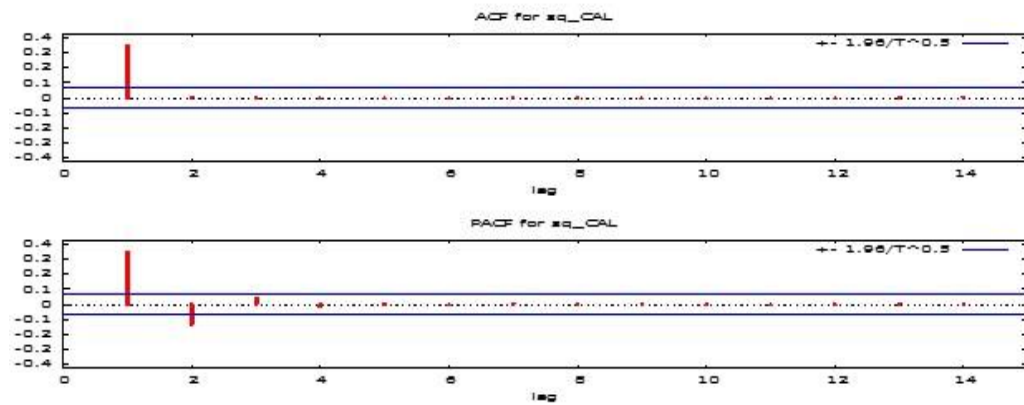


Figure 17. ACF and PACF plot of the squared Returns Series of CAL Bank Limited

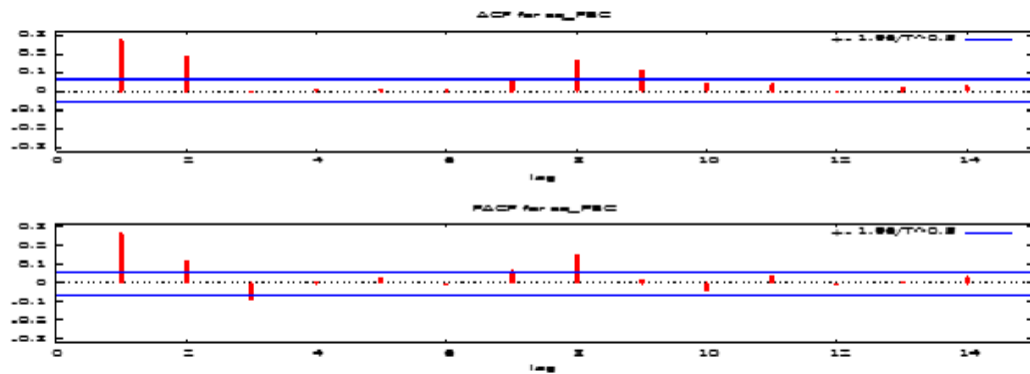


Figure 18. ACF and PACF plot of the squared Returns Series of Produce Buying Company

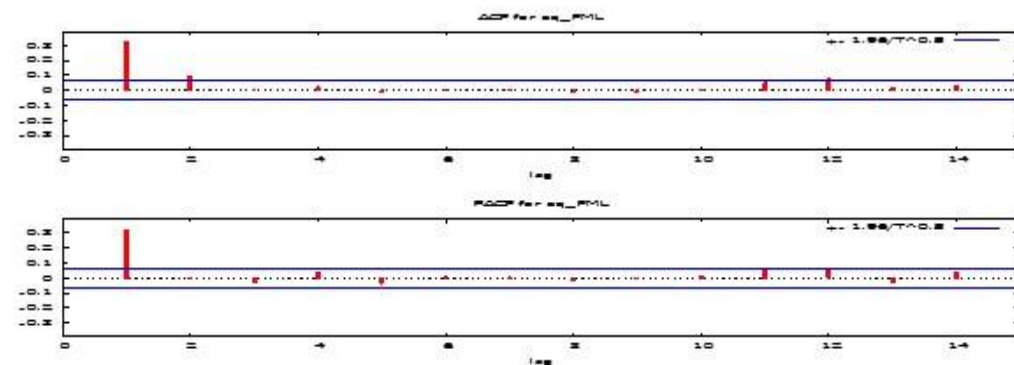


Figure 19. ACF and PACF plot of the squared Returns Series of Fan Milk Limited

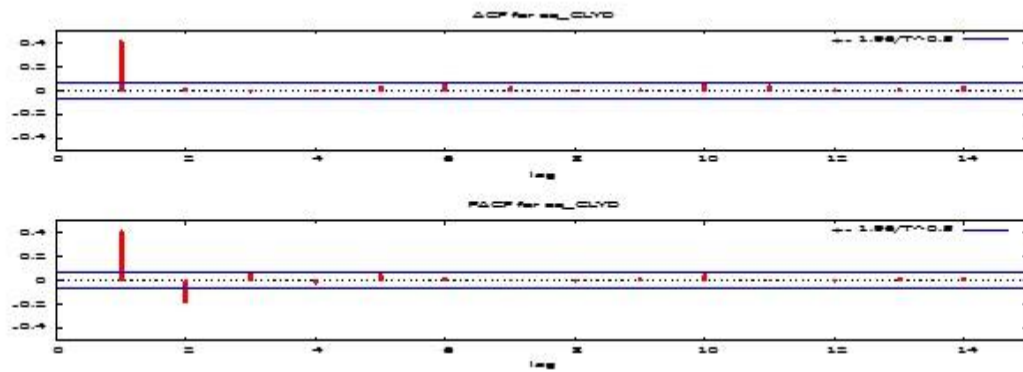


Figure 20. ACF and PACF plot of the squared Returns Series of Clydestone (Ghana) Limited

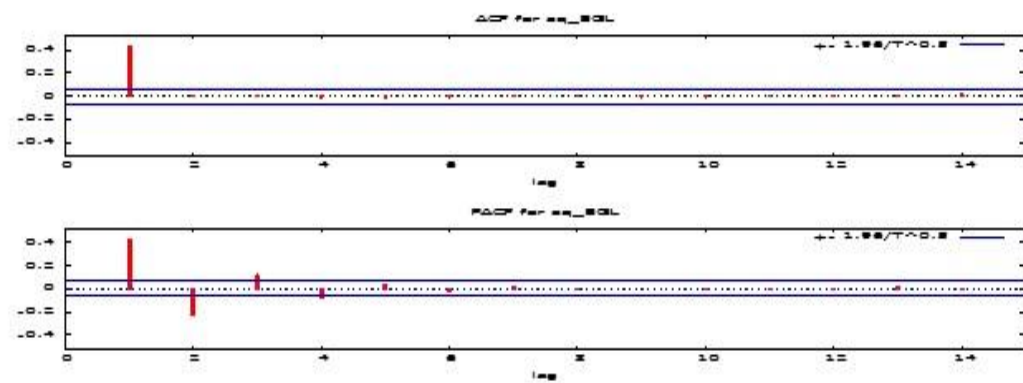


Figure 21. ACF and PACF plot of the squared Returns Series of Enterprise Group Limited

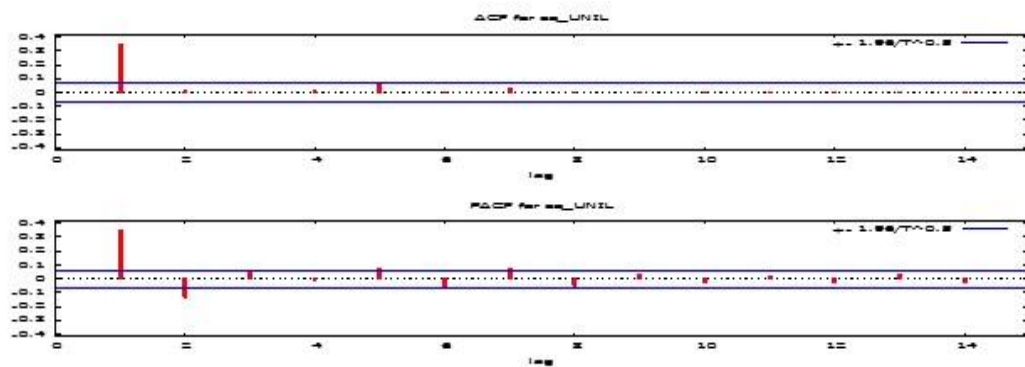


Figure 22. ACF and PACF plot of the squared Returns Series of Uniliver Ghana Limited

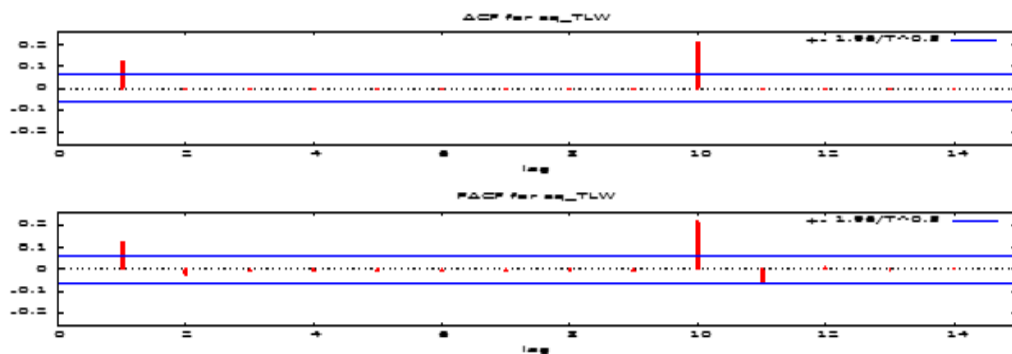


Figure 23. ACF and PACF plot of the squared Returns Series of Tullow Oil Plc

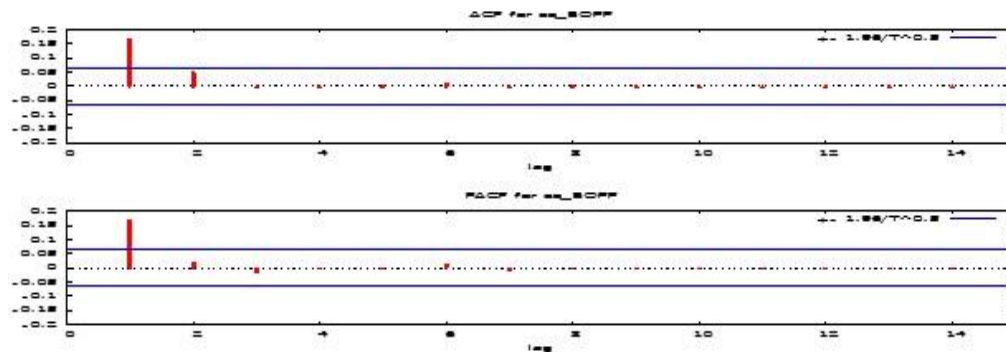


Figure 24. ACF and PACF plot of the squared Returns Series of Benso Oil Palm Plantation

3.2. Further Analysis

As is reported of the ADF test in Table 2, it is evident that all the eight returns series were stationary since the p-value were significant at the 5% significance level and the null hypothesis of non-stationary was rejected.

The residuals of the individual equations were examined for the presence or absence of conditional heteroskedasticity. The ARCH-LM test was conducted at lags 1, 7 and 14. It is evident from Table 3 that all the returns series exhibited ARCH effects at the 5 % significance level. Hence making GARCH modelling applicable.

The returns series were tested for normality, autocorrelation and heteroskedasticity using the Jarque-Bera and Ljung Box tests respectively. It is evident from Table 4 that, the Jarque-Bera test for normality was significant at the 5% significance level, therefore we conclude that the returns series are not normally distributed. The $LB(14)$ and $LB^2(14)$ are all significant at the 5% level of significance. We therefore reject the null hypothesis of no autocorrelation in the levels of the returns series. The significance of $LB^2(14)$ statistic suggest the presence of ARCH effects and hence making an AR(1) conditional mean model more suitable for GARCH specification and it also indicates the presence of volatility clustering.

From Table 5, it is evident that the DW-AR(1) had indications of autocorrelation but the B-G AR(1) indicated no evidence of autocorrelation since it was not significant at the 5% level of significance across the entire return series, therefore, we fail to reject the null hypothesis of no autocorrelation. This indicates that the mean equation follows an AR(1) process.

As is reported in Table 6, the GARCH-M (1,1) model was tested for stationarity by summing the ARCH and GARCH coefficients. It is evident that most of the models with a given distribution were non-stationary since the summation of α and β were greater than one (1). Since most of the models for GARCH-M (1,1) was non-stationary, the EGARCH (1,1) and TGARCH (1,1) were employed. It also evident from Table 7 and 8 of the EGARCH-M (1,1) and TAGARCH-M (1,1) that the TGARCH-M (1,1) had most of its models being stationary as compared to the EGARCH-M (1,1).

In establishing the relationship between risk and return for the three models, λ was employed as the coefficient in estimating this relationship. As it is reported in Table 6, 7 and 8 of the GARCH-M (1, 1), EGARCH-M (1, 1) and the TGARCH-M (1, 1) models respectively. The risk-return coefficient of the GARCH-M (1, 1) model had most of the models showing a positive and a significant relationship (positive risk premium). The EGARCH-M (1, 1) model also had most of the coefficients positive and significant as in the GARCH-M (1, 1). Also, the TGARCH-M (1, 1) model had the risk-return coefficients mostly positive and significant. Again, the risk-return coefficient for the GARCH-M (1, 1) model showed that 17 out of the 24 models were positive and significant (positive risk premium). For the EGARCH-M (1, 1), 18 out of the 24 models estimated were positive and significant whereas 17 out of the 24 models of the TGARCH-M (1, 1) were positive and significant. In essence, 52 out of the 72 models estimated showed evident of positive risk premium under the various distribution assumptions with the exception of a few. All the three models showed a positive relationship between risk and return. This results is in line with the findings of [19] and [21], who also found a positive relationship between risk and returns on other markets. The results also supports the usual view in financial market that high risk suggests higher returns. The presence of a positive relationship between risk and return means that, investors had the required returns for holding risky assets. This is also in conformity with the predictions of many asset pricing models like the APT and CAPM. In the event of risk neutral investors on the market, they will decide to invest in equities that have a risk-return coefficient which are closer to one (1) since they have a linear risk-return relationship and would not therefore like to take a lot of risk. Therefore, for a positive risk-return relationship, if an investor is a risk lover, an increase in risk will lead to an increase in the demand for that equity leading to an increase in share price but for a negative relationship between risk and return, risk averse investors will sell off their shares in anticipation of volatility leading to a decline in share price. The two asymmetry models (EGARCH and TGARCH) were investigated further for leverage effects by reporting on the leverage effect coefficient γ . As it is reported from Table 7, the leverage

effects coefficient for the EGARCH model were mostly negative and significant at the 5% significance level indicating the presence of leverage effect. The TGARCH-M (1, 1) model as reported in Table 8, showed that most of the leverage effects coefficient were positive and significant at the 5% significance level indicating the existence of leverage effect. The presence of leverage effects indicates that negative shocks (bad news) have higher impact on next level volatility of the returns series than positive shock (good news) of the same magnitude. This is supported by the results of [6] who captured leverage effects on the NSE using TGARCH (1,1); evidence of volatility persistence and leverage effects. For equities that had the expected sign under a given distribution, the asymmetry effect takes place when an unexpected decline in price (bad news) tends to increase

volatility more than an unexpected increase in price (good news) of the same magnitude. In an event of an anticipated increase in volatility, expected returns tends to decrease, leading to a decline in the share price. The ARCHLM test which shows whether a model fully captured ARCH effects shows that the GARCH-M (1, 1) model was able to capture some of the ARCH effects at the 5% significance level. Therefore the null hypothesis of no ARCH effects was rejected. The EGARCH- M (1, 1) also captured some of the ARCH effects at the 5% significance level. Hence, the null hypothesis of no ARCH effects was also rejected. Nevertheless, the TGARCH- M (1, 1) model eliminated most of the ARCH effects. Therefore, we failed to reject the null hypothesis of no ARCH effects.

Table 2. ADF Test of the Returns Series

Stock	Constant only		Constant and Trend	
	Test Statistic	P-value	Test Statistic	P-value
CAL Bank Limited	-25.8229	0.0000**	-25.8425	0.0000**
Produce Buying Company	-41.5265	0.0000**	-41.5408	0.0000**
Fan Milk Limited	-10.7141	0.0000**	-10.8630	0.0000**
Clydestone (Ghana) Limited	-24.5964	0.0000**	-24.5907	0.0000**
Enterprise Group Limited	-16.8608	0.0000**	-16.8858	0.0000**
Uniliver Ghana Limited	-10.0682	0.0000**	-10.1852	0.0000**
Tullow Oil Plc	-31.4693	0.0000**	-31.5073	0.0000**
Benso Oil Palm Plantation	-13.3981	0.0000**	-13.5204	0.0000**

** Significant at 5% significance level

Table 3. ARCH-LM Test of the Selected Returns Series

Stock	Lag	Test Statistic	P-value
CAL Bank Limited	1	125.1810	0.0000**
	7	148.5370	0.0000**
	14	186.9760	0.0000**
Produce Buying Company	1	6.8591	0.0088**
	7	21.8946	0.0026**
	14	40.7375	0.0002**
Fan Milk Limited	1	73.3761	0.0000**
	7	77.4349	0.0000**
	14	80.9421	0.0000**
Clydestone (Ghana) Limited	1	130.3180	0.0000**
	7	133.4630	0.0000**
	14	138.8120	0.0000**
Enterprise Group Limited	1	26.6978	0.0000**
	7	36.6906	0.0000**
	14	36.4258	0.0000**
Uniliver Ghana Limited	1	59.7481	0.0000**
	7	61.2771	0.0000**
	14	60.9034	0.0000**
Tullow Oil Plc	1	15.1319	0.0000**
	7	24.9135	0.0008**
	14	40.8408	0.0002**
Benso Oil Palm Plantation	1	23.8970	0.0003**
	7	56.0000	0.0001**
	14	163.8830	0.0000**

** Significant at 5% significance level

Table 4. Test for Normality, Autocorrelation and Heteroscedasticity of Return Series

Stock	Jarque-Bera	LB(14)	LB ² (14)
CAL Bank Limited	1.9098*	30.5740*	52.7909*
Produce Buying Company	42803.6000*	22.3281*	32.7670*
Fan Milk Limited	66302.5000*	51.9865*	38.6640*
Clydestone (Ghana) Limited	42308.9000*	68.4155*	42.4638*
Enterprise Group Limited	987916.0000*	33.8373*	56.0461*
Uniliver Ghana Limited	337264.0000*	58.9513*	46.8042*
Tullow Oil Plc	634210.0000*	34.5074*	49.7469*
Benso Oil Palm Plantation	1.5759*	38.7833*	32.8956*

* Significant at 5% significance level.

Table 5. Mean Equation Results for the Returns Series

Stock	DW-AR(1)	B-G(1)	ARCHLM AR(1)
CAL Bank Limited	2.0300	0.0609	0.0000*
Produce Buying Company	1.9930	0.9129	0.0000*
Fan Milk Limited	1.9856	0.3787	0.0000*
Clydestone (Ghana) limited	2.1602	0.5620	0.0000*
Enterprise Group Limited	2.0019	0.9014	0.0000*
Uniliver Ghana Limited	1.9043	0.3965	0.0000*
Tullow Oil Plc	2.0043	0.5908	0.0000*
Benso Oil Palm Plantation	2.9043	0.2899	0.0000*

* Significant at 5% significance level.

Table 6. Estimated GARCH-M (1,1) Model

Sector	λ	$\alpha + \beta$	ARCHLM	BIC	AIC
<i>Finance</i>					
CAL					
Gaussian Distribution	-0.0743	1.1880	0.0652	-3966.1520	-3990.4450
Student-t Distribution	0.2046*	0.8221	0.0000*	-6252.4630	6276.7560
GED	0.0070*	0.6979	0.0308*	-6365.8690	-6390.1620
<i>Distribution</i>					
PBC					
Gaussian Distribution	0.0240*	0.9944	0.0080*	5330.3940	-5349.8290
Student-t Distribution	0.0013*	0.6807	0.0010*	-3540.2450	-3825.1450
GED	0.0001*	1.0807	0.1400	-4592.1960	-4611.6310
<i>Food and Beverage</i>					
FML					
Gaussian Distribution	0.0340*	0.9964	0.0730	-5135.8460	-5155.2800
Student-t Distribution	0.3102*	0.8183	0.0000*	-7350.1910	-7369.6260
GED	0.0004	0.9026	0.0206*	-7244.4100	-7263.8440
<i>Info. Technology</i>					
CLYD					
Gaussian Distribution	-0.0722*	0.9848	0.0582	-3773.1100	-3767.4030
Student-t Distribution	0.3050*	0.6752	0.0000*	-3284.1671	-3520.8141
GED	0.0970*	1.0780	0.0000*	-2767.8720	-2792.1640
<i>Insurance</i>					
EGL					
Gaussian Distribution	0.0067*	1.0601	0.0000*	-4810.7930	-4835.0860
Student-t Distribution	0.0475*	1.1032	0.0640	-6127.2900	-6151.5830
GED	0.0075*	0.8420	0.1805	-3986.8510	-4011.1440
<i>Manufacturing</i>					
UNIL					
Gaussian Distribution	0.5958*	0.9470	0.0000*	-6487.0910	-6511.3840
Student-t Distribution	0.0002*	0.9354	0.0940	-8848.4440	-8872.7370
GED	0.0072*	0.6281	0.0000*	-6183.8450	-6201.3520
<i>Mining</i>					
TLW					
Gaussian Distribution	0.0043	0.8736	0.0173*	-6379.0014	-6438.3106
Student-t Distribution	0.0309*	0.7082	0.0000*	-7300.0170	-7324.3090
GED	-0.0285	0.8503	0.0000*	-5241.2710	-5328.7240
<i>Agriculture</i>					
BOPP					
Gaussian Distribution	0.0561	0.9021	0.1364	-3341.4040	-3365.6970
Student-t Distribution	0.2134*	0.6513	0.0348*	-6814.1500	-6838.4430
GED	0.0008*	0.7360	0.0013*	-6430.9500	-6723.2436

* Significant at 5% significance level

Table 7. Estimated EGARCH-M (1,1) Model

Sector	λ	$\alpha + \beta$	γ	ARCHLM	BIC	AIC
<i>Finance</i>						
CAL						
Gaussian Dist.	-0.0314*	0.8128	0.0712*	0.0000*	-4071.0230	-4095.3160
Student-t Dist.	0.7149*	1.0610	-0.0151*	0.0000*	-6184.5320	-6213.6830
GED	0.0532*	0.6979	-0.5879*	0.0840	-2533.7700	-2558.0620
<i>Distribution</i>						
PBC						
Gaussian Dist.	0.0214*	0.7243	-0.1800*	0.2160	-3452.8700	-3830.2102
Student-t Dist.	-0.0813	1.2908	-0.1301*	0.0030*	-6445.2830	-6469.5760
GED	-0.3418*	0.7634	-0.0401*	0.0574	-4375.6010	-4736.6720
<i>Food and Beverage</i>						
FML						
Gaussian Dist.	0.0901*	1.2673	-0.2450*	0.0000*	-5099.3920	-5123.6850
Student-t Dist.	0.0045*	1.0173	-0.0810*	0.0000*	-7131.7480	-7156.0401
GED	0.0310*	0.9977	-0.3171*	0.1040	-4187.5670	-4211.8600
<i>Info. Technology</i>						
CLYD						
Gaussian Dist.	0.0184	0.9938	-0.2796*	0.1502	-3769.1350	-3793.4280
Student-t Dist.	0.5914*	0.7750	-0.0658*	0.0201*	-3257.1230	-3406.3086
GED	0.8301*	1.0660	-0.1773	0.0000*	-2516.9550	-2641.2480
<i>Insurance</i>						
EGL						
Gaussian Dist.	0.6104*	0.9864	-0.2949*	0.0000*	-3589.1590	-3613.4510
Student-t Dist.	0.0850*	1.1341	-0.0515*	0.2600	-6868.6860	-6892.9790
GED	-0.0432	1.3927	-1.4550	0.0000*	-3922.5290	-3946.8210
<i>Manufacturing</i>						
UNIL						
Gaussian Dist.	0.8013*	1.5590	0.2480*	0.0000*	-4780.1680	-4903.8000
Student-t Dist.	-0.0018*	0.9680	-0.6075*	0.0000*	-3010.7100	-3208.1802
GED	0.5096*	1.0860	-1.0222*	0.0735	-5321.4101	-5452.7120
<i>Mining</i>						
TLW						
Gaussian Dist.	0.4728*	0.7928	-0.0214*	0.0000*	-7345.8120	-7532.2100
Student-t Dist.	0.0842*	1.0435	-0.1630*	0.0000*	-5492.1210	-5664.4200
GED	-0.0083	0.0846	-0.0294*	0.0000*	-4612.7130	-4930.0901
<i>Agriculture</i>						
BOPP						
Gaussian Dist.	-0.4120	0.8903	-1.2232*	0.1350	-1786.4730	-1810.7660
Student-t Dist.	-0.0702*	1.0823	-0.0912*	0.0017*	-6627.9850	-6652.2780
GED	0.5016*	1.4267	-0.7390	0.0082*	-3334.3690	-3358.6610

* Significant at 5% significance level

Table 8. Estimated TGARCH-M (1,1) Model

Sector	λ	$\alpha + \beta$	γ	ARCHLM	BIC	AIC
<i>Finance</i>						
CAL						
Gaussian Dist.	-0.0082*	0.9507	0.0650*	0.0000*	-5488.1230	-5512.4160
Student-t Dist.	0.0729*	0.8712	0.0816*	0.6183	-6092.7070**	-6117.0000
GED	0.2856	0.9780	0.1212*	0.5052	-4970.8690	-4995.1610
<i>Distribution</i>						
PBC						
Gaussian Dist.	-0.9000*	0.5926	-0.5941*	0.0000*	-4946.9410	-4976.0920
Student-t Dist.	1.0824*	0.7580	0.0974*	0.6103	-3201.8921	-3481.5401
GED	0.9516*	1.1017	0.0464*	0.0558	-4592.6530	4621.8040
<i>Food and Beverage</i>						
FML						
Gaussian Dist.	0.0431*	0.6346	0.0085	0.0896	-5129.2620	-5153.5550
Student-t Dist.	0.2580*	0.9622	0.2940*	0.0925	-4354.25900	-4378.5510
GED	-0.0017	1.0406	0.0293*	0.0264*	-4179.1490	-4203.4420
<i>Info. Technology</i>						
CLYD						
Gaussian Dist.	-0.0373	0.9520	-0.0705*	0.7105	-3742.5000	-3771.6510
Student-t Dist.	0.5081*	0.8275	0.0063*	0.8461	-4258.3920**	-4529.1124
GED	0.4230	0.9737	0.2552*	0.0020*	-2773.5910	-2797.8840
<i>Insurance</i>						
EGL						
Gaussian Dist.	0.0506*	0.6680	0.0319*	0.0003*	-5601.8400	-5828.3200
Student-t Dist.	0.0239*	0.8927	0.1546*	0.0572	-6121.6860**	-6150.8380
GED	-0.6342	1.0235	0.0845*	0.0626	-4273.4501	-4602.6210
<i>Manufacturing</i>						
UNIL						
Gaussian Dist.	0.1435*	0.5970	0.0814*	0.0604	-6502.1120	-6531.2630
Student-t Dist.	0.6107*	0.8149	0.4105*	0.5812	-4860.3210	-4884.0680
GED	-0.3840*	0.6466	-0.2063*	0.2075	-5544.0270	-5568.3190
<i>Mining</i>						
TLW						
Gaussian Dist.	0.2813*	0.6938	1.4145*	0.0402*	-3879.0100	-3893.8000
Student-t Dist.	-0.3024*	0.8301	0.3827*	0.3086	-5480.1720**	-5802.3210
GED	0.0832	0.6810	0.4210*	0.0104*	-4325.8307	-4538.7512
<i>Agriculture</i>						
BOPP						
Gaussian Dist.	-0.0872	0.5138	-0.4382*	0.0063*	-3360.4710	-3384.7640
Student-t Dist.	0.1820*	0.7789	0.3030*	0.7154	-4829.9430**	-4857.0940
GED	0.3058*	1.0250	1.8793*	0.1520	-1804.2300	-1828.5200

* Significant at 5% significance level. ** Selected error distribution.

Table 9. Diagnostic Checks of the TGARCH-M (1,1) (student-t distribution)

Sector	Mean	St. Dev.	Jarque-Bera	Skewness	Kurtosis	LB(14)	LB ² (14)
<i>Finance</i>							
CAL							
Raw returns	0.0013	0.0425	1.9098*	4.6600	220.3900	30.5740*	52.7909*
TGARCH-M	0.0006	0.0247	1.8609*	4.3509	212.2387	18.8130	19.1500
<i>Distribution</i>							
PBC							
Raw returns	-0.0019	0.0223	42803.6000*	132.8100	1.9100	22.3281*	32.7670*
TGARCH-M	-0.0026	0.0218	50460.9000*	34.9070	3.6615	14.0286	56.0643*
<i>Food and Beverage</i>							
FML							
Raw returns	0.0012	0.0216	66302.5000*	0.7200	41.0800	51.9865*	38.6640*
TGARCH-M	0.0215	0.0375	50460.5000*	0.7381	40.8590	51.9865*	11.0000
<i>Info. Technology</i>							
CLYD							
Raw returns	-0.0002	0.0460	42308.9000*	0.5900	32.8200	68.4155*	42.4638*
TGARCH-M	-0.0007	0.8275	42249.4000*	0.5975	32.6140	22.3249	41.9848*
<i>Insurance</i>							
EGL							
Raw returns	0.0002	0.0380	987916.0000*	-16.8800	347.1800	33.8373*	56.0461*
TGARCH-M	0.0321	0.0438	945696.0000*	1.5114	157.7900	10.4620	17.0643
<i>Manufacturing</i>							
UNIL							
Raw returns	0.0009	0.0187	337264.0000*	2.2300	92.5900	58.9513*	46.8042*
TGARCH-M	0.0004	0.0148	336613.0000*	0.0412	92.0180	58.1395*	16.8994
<i>Mining</i>							
TLW							
Raw returns	0.0017	0.0527	634210.0000*	28.7400	866.0000	34.5074*	49.7469*
TGARCH-M	0.0119	0.0653	5237.8400*	24.7321	506.2420	11.0150	13.0965
<i>Agriculture</i>							
BOPP							
Raw returns	0.0020	0.0420	1.5759*	14.5100	346.4800	38.7833*	32.8956*
TGARCH-M	0.1820	0.7789	1.5367*	7.8850	198.7000	16.0830	0.8940

* Significant at 5% significance level.

The suitable model and the distribution under which it performs best was selected by taking into account the summation of α and β to be less than one (1) for the stationarity of the model, capturing asymmetry in the returns series and been able to eliminate much of the ARCH effects in the returns series. When the above criterion are met, the information criteria (BIC and AIC) were employed in selecting the appropriate distribution assumption. Since BIC places a much stiffer penalty term compared to AIC, it was the information criterion that was employed even though the AIC as reported in Table 6, 7 and 8 does not contradict the

BIC. As is reported of the three models in Table 6, 7 and 8 of the GARCH-M (1, 1), EGARCH-M (1, 1) and TGARCH-M (1, 1) respectively, the TGARCH-M (1, 1) met the model selection criteria compared to the other two models. The BIC selected the student-t distribution assumption for the TGARCH-M (1, 1) since 5 out of the 8 returns series selected the student-t distribution.

Thus, the fitted TGARCH-M (1,1) with student-t distributional assumption models of the returns series becomes:

$$\text{CAL; } \sigma_t^2 = 0.0002 + 0.2508X_{t-1}^2 + 0.6204\sigma_{t-1}^2 + 0.6183d_{t-1}X_{t-1}^2 \quad (25)$$

$$\text{PBC; } \sigma_t^2 = 0.0017 + 0.2527X_{t-1}^2 + 0.5053\sigma_{t-1}^2 + 0.0974d_{t-1}X_{t-1}^2 \quad (26)$$

$$\text{FML; } \sigma_t^2 = 0.0001 + 0.4562X_{t-1}^2 + 0.5060\sigma_{t-1}^2 + 0.2940d_{t-1}X_{t-1}^2 \quad (27)$$

$$\text{CLYD}; \quad \sigma_t^2 = 0.0064 + 0.3592X_{t-1}^2 + 0.4683\sigma_{t-1}^2 + 0.0063d_{t-1}X_{t-1}^2 \quad (28)$$

$$\text{EGL}; \quad \sigma_t^2 = 0.0001 + 0.2841X_{t-1}^2 + 0.6086\sigma_{t-1}^2 + 0.1546d_{t-1}X_{t-1}^2 \quad (29)$$

$$\text{UNIL}; \quad \sigma_t^2 = 0.0024 + 0.3417X_{t-1}^2 + 0.4732\sigma_{t-1}^2 + 0.4105d_{t-1}X_{t-1}^2 \quad (30)$$

$$\text{TLW}; \quad \sigma_t^2 = 0.0002 + 0.2842X_{t-1}^2 + 0.5459\sigma_{t-1}^2 + 0.3827d_{t-1}X_{t-1}^2 \quad (31)$$

$$\text{BOPP}; \quad \sigma_t^2 = 0.0001 + 0.1022X_{t-1}^2 + 0.6767\sigma_{t-1}^2 + 0.3030d_{t-1}X_{t-1}^2 \quad (32)$$

A diagnostic checks was performed on the selected model (TGARCH-M (1, 1)) to ascertain whether it was well specified. Table 9 reveals the descriptive statistics of the returns series and the standardized residuals of the TGARCH-M (1, 1) model with the student-t distributional assumption. The standard deviation was lower for the selected model with the exception of FML, CLYD, TLW and BOPP. Also, the Jarque-Bera test for normality was significant at the 5% significance level for both the returns series and the standardized residuals of the TGARCH-M (1, 1). Therefore, the null hypothesis of normality was rejected for the returns series and the standardized residuals and that both were not normally distributed. The selected model had most of the skewness been lower than that of the returns series. Also, the kurtosis for the selected model were mostly lower. Moreover, the $LB(14)$ statistic which test for the absence of autocorrelation in the return series was statistically significant at all levels of the returns series indicating the presence of ARCH effects whereas the same statistic for the standardized residuals of the selected model were mostly insignificant at the 5% significance level indicating that most of the returns series have no further ARCH effects. Also, the $LB^2(14)$ statistic which test for the absence of heteroscedacity in the returns series and the standardized residuals, revealed that, for the returns series, there was evident of heteroscedacity since the test was statistically significant at the 5% significance level. In the case of the standardized residuals, it was revealed that the test was mostly insignificant with the indicating the absence of heteroscedacity. The above details indicates that the selected model was well specified for most of the estimated returns series.

The TGARCH-M (1, 1) model fitted was cross validated by employing the chi-square goodness of fit statistic with an out-of-sample. As it is reported in Table 10 of the chi-square test, the results reveals that there is no significant difference between the observed returns series and the predicted (forecasted) returns series for all the variables. This is supported by an insignificant chi-square obtained for all the models. It also evident that, the fitted model produce returns that are similar to the nature of the returns series even though the returns series of the observed and expected may differ.

4. Conclusions

This paper modelled volatility and the risk-return relationship of some equities on the Ghana Stock Exchange

using univariate GARCH models. The results revealed that, the market was good for investors since most of the equities recorded positive mean returns (gains) than negative mean returns (losses). There was high probability of making gains than losses by investors. Investing in any of the equities has its associate risk level and are highly volatile. Also, all the three models indicated that there exist a positive relationship between risk and return that is, investors were compensated for the risk assumed. The TGARCH-M (1,1) and EGARCH-M (1,1) indicated the existence of leverage effect on the market implying bad news have much effect on next period volatility than good news of the same magnitude. The TGARCH-M (1, 1) was the appropriate model since it was able to meet the model selection criterion of having the ARCH and GARCH summations mostly less than one i.e. ensuring stationairty of the model, been able to capture leverage effect and its ability in eliminate ARCH effects. It was then subjected to BIC in selecting the distributional assumption. The student-t distributional assumption was selected by the BIC. The model was then diagnosed to ascertain whether it was well specified for the returns series estimated. It was realized that, the skewness and kurtosis for the model was low for most of the returns series. Also the $LB^2(14)$ statistic was able to eliminate any further ARCH effect in the returns series. This makes the TGARCH-M (1, 1) well specified for most of the estimated returns series.

Table 10. Chi-square Goodness of Test for the TGARCH-M (1,1) Model

Model	Chi-square χ^2 Statistic	Critical value
<i>Finance</i>		
CAL	12.3727	16.9200
<i>Distribution</i>		
PBC	-14.1981	16.9200
<i>Food and Beverage</i>		
FML	0.0579	16.9200
<i>Info. Technology</i>		
CLYD	-11.8958	16.9200
<i>Insurance</i>		
EGL	-0.8820	16.9200
<i>Manufacturing</i>		
UNIL	5.51776	16.9200
<i>Mining</i>		
TLW	0.0236	16.9200
<i>Agriculture</i>		
BOPP	1.7710	16.9200

Reject if χ^2 Statistic > critical value

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