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Asymmetry and Persistence of Stock Returns: A Case of the Ghana Stock Exchange

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Abstract: Measuring and estimating volatility of asset return is bubbly for risk management, asset allocation, and option pricing. This paper investigated the asymmetry and persistence of the return of some stocks on the Ghana Stock Exchange using univariate TGARCH-M (1, 1) and half-life measure of the daily returns of eight stocks from 02/01/2004 to 20/12/2014. It was realized that, volatility was persistent (explosive process) in all the stocks. The persistence in volatility was extended in investigating the half-life measure of the stocks and it was realized that almost all the stocks had strong mean reversion and short half-life measure with the exception of Fan Milk Limited. Also all the returns series exhibited a positive leverage effect parameter indicating that bad news influenced volatility than good news of the same magnitude.

Keywords: Asymmetry, Persistent, Half-Life, Volatility, Leverage Effect

1. Introduction

Stock price volatility is an extremely important concept in finance for numerous reasons. The literature on stock price volatility agrees on one key phenomenon. There is evidence of several movements in stock prices. In other words, dynamic nature of stock price behaviour is an accepted phenomenon and all participants in stock markets including regulators, professionals and academics have consensus about it. But, what causes stock price volatility is a question that remains unsettled in finance field. This is because of the great number of complicated variables, which is not an easy task and up to now there is no consensus about it. However researchers in quest of answers to this question have investigated the stock price volatility from different angles. In this regards, from late twentieth century and particularly after introducing ARCH model by [8], as said by [3] and [27], a lot of studies accomplished in developed country and to some extent in developing countries has been done by researchers in this area using different methods.

[8] published a paper that measured the time-varying volatility. His model, ARCH, was based on the idea that a natural way to update a variance forecast is to average it with the most recent squared "surprise"(i.e. the squared deviation of the rate of return from its mean). While conventional time series and econometric models operate under an assumption of constant variance, the ARCH process allows the conditional variance to change over time as a function of past errors leaving the unconditional variance constant. [3] to overcome the ARCH limitations introduced his model, ARCH that generalized the ARCH model (GARCH) to allow for both a longer memory and a more flexible lag structure. As noted above, in the empirical application of the ARCH model, a relatively long lag in the conditional variance equation is often called for, and to avoid problems with negative variance parameters, a fixed lag structure is typically imposed. In the ARCH process the conditional variance is specified as a linear function of past sample variance only, whereas the GARCH process allows lagged conditional variances to enter in the model as well.

[9] 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. [24] 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 rigidness 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. [13] 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 (GJRGARCH) and the Threshold Generalized Autoregressive Conditional Heteroskedasticity (TGARCH) models. They concluded that there was 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.

[10] measured the impact of bad and good news on volatility and reported an asymmetry in stock market volatility towards good news as compared to bad news. More specifically, market volatility was assumed to be associated with the arrival of news. A sudden drop in price was associated with bad news on the other hand, a sudden increase in price was said to be due to good news. They found that bad news created more volatility than good news of equal importance. This asymmetric characteristic of market volatility has come to be known as the "leverage effect".

In stock market, negative shocks lead to higher volatility than positive shocks. In case of commodity and energy returns, asymmetry is observed in opposite direction. Energy return volatility reacts more to positive shocks than to negative shocks. For studying asymmetry in crude oil volatility, [23] used exponential GARCH model to evaluate varying effects of positive and negative shocks on oil return volatility. [5] also studied the asymmetry effect on two crude oil prices; West Texas Intermediaries (WTI) and Brent crude oil. He found that volatility reacts more to negative shocks than to positive shocks. However, it was evident only for Brent crude not for WTI crude oil. The literature on asymmetry of energy prices is limited to crude oil prices. Persistence or long memory plays a crucial role in volatility forecasting and it has immense influence in risk management, derivative pricing and portfolio management. Persistence implies that any shocks to volatility do not die quickly rather its effect endures. Among the studies, [17], [26], [29] and [30] examined persistence in oil return volatility. [26] estimated volatility persistence of crude oil and natural gas using GARCH and 'half-life' volatility measure and found the evidence of persistence in the volatility of crude oil and natural gas. However, his measure of persistence suggested that the fluctuations were short-lived than previously assumed. If there was a shock to crude oil or natural gas prices, it lasted up to 5 to 10 weeks.

[1], estimated the daily returns of the Khartoum Stock Exchange using GARCH models. Their study showed that the conditional variance process was highly persistent and provided evidence on the existence of risk premium for the KSE index returns series. They also realised that, the asymmetric models provided better fit than the symmetric models which confirmed the existence of leverage effect. [28] also estimated persistence in crude oil and found the evidence of long memory even with structural break.

Also, [14] estimated and compared the asymmetry and persistence of volatility of crude oil, natural gas and coal. Their research revealed that, coal volatility exhibited strong mean reversion whereas crude oil and natural gas return volatility endured shocks for relatively higher periods. And that volatility of crude oil and gas increased after positive shocks in price.

[18] used Iterated Cumulative Sum of Squares (ICSS) to determine regime shifts and then applied in the asymmetric volatility models to study the impact of shocks on volatility persistence and asymmetry. Their results revealed that, the persistence and asymmetry in volatility were reduced considerably when regime shifts were taken into account in the models. [16] study in Nigeria obtained an evident of volatility clustering and volatility persistence and also asymmetric volatility effect in Nigeria.

Moreover, [25] examined the behaviour of stock return volatility in the Kenyan stock exchange phases for the NSE20 share index and the 10 sample stocks over 11 years. They employed the FIEGARCH (1,d,1) in fitting the asymmetry effect and volatility persistent. Their results revealed persistent bullish phases than bearish with bear phases much frequent. Also, there was non-systematic pattern across all the stocks though a higher degree dependence in both the level and volatility in the bull periods and that, the FIEGARCH models was capable of modelling volatility clustering and asymmetry in volatility.

The purpose of this paper is to investigate the asymmetry and persistence of some stocks on the Ghana Stock Exchange. This is to provide investors with information on how persistence some stocks are and their respective half-life measure so as make the right investment decisions.

2. Materials and Methods of Analysis

2.1. Source of Data

This paper used secondary data of 8 stocks (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 20/12/2014, totaling 7616 observations.

2.2. Methods of Data Analysis

The daily closing prices were converted into compound returns given by;

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

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.

2.3. Tests

2.3.1. Stationarity Test

It is very paramount to establish the existence or non-existence of unit root in the time series under study so as to be able to ascertain the nature of the process that produces the time series. This paper employed two quantitative unit root tests namely; the PhillipPerron (PP) unit root test and the Kwiatkowsky, Phillips, Schmidt and Shin (KPSS) test. The KPSS test was used to test the null hypothesis that the data generating process is stationary, H_o: $I(0)$ against the alternative that it is non-stationary, H_1: $I(1)$. This test was developed [19]. It assumes that there is no linear trend term and is given by;

$$Y_t = X_t + Z_t,\ Z_t\ \ I(0) \tag{2}$$

where X_t is a random walk, $X_t = X_{t-1} + v_t$; $v_t \sim N(0, \sigma_v^2)$ and Z_t is a white noise series. The previous pair of hypothesis is equivalent to;

$$H_o: \sigma_v^2 = 0$$

$$H_1: \sigma_v^2 > 0$$

If H_o is true, the model becomes $Y_t = constant + Z_t$; $Z_t I(0)$ hence Y_t is stationary. The test statistic is given by;

$$KPSS = \frac{1}{T^2}\sum_{t=1}^{T}\frac{s_t^2}{\hat{\sigma}_\infty^2} \tag{3}$$

where T is the number of observations, $\hat{\sigma}_\infty^2$ is an estimator of the long-run variance of the process Z_t.

The PP statistic test the hypothesis;

H_o: unit root against

H_1: stationary about deterministic trend

Under the H_o of $p = 0$, the PP test Z_p and Z_τ statistics have the same asymptotic distributions as the ADF t-statistic and normalized bias statistics. The PP test is categorized into two statistics known as Phillips Z_p and Z_τ tests given by;

$$Z_p = n(\hat{p}_n - 1) - \frac{1}{2}\frac{n^2\hat{\sigma}^2}{s_n^2}\left(\hat{\lambda}_n^2 - \hat{\gamma}_{0,n}\right) \tag{4}$$

$$Z_\tau = \sqrt{\frac{\hat{\gamma}_{0,n}}{\hat{\lambda}_n^2}}.\frac{\hat{p}_n - 1}{\hat{\sigma}} - \frac{1}{2}\left(\hat{\lambda}_n^2 - \hat{\gamma}_{0,n}\right)\frac{1}{\hat{\lambda}}.\frac{n\hat{\sigma}}{s_n} \tag{5}$$

$\hat{\gamma}_{j,n} = \frac{1}{n}\sum_{i=j+1}^{n}\hat{\varepsilon}_i.\hat{\varepsilon}_{i-j}$, for $j = 0$, then $\hat{\gamma}_{j,n}$ is a maximum likelihood estimate of the error terms whiles $\hat{\gamma}_{j,n}$ is the covariance between the error terms j-periods apart *for* $j > 0$.

$\hat{\lambda}_n^2 = \hat{\gamma}_{0,n} + 2\sum_{j=1}^{q}\left(1 - \frac{j}{q+1}\right)\hat{\gamma}_{j,n}$, when there exist no autocorrelation between the error terms, $\hat{\gamma}_{j,n} = 0$ for $j > 0$, then $\hat{\lambda}^2{}_n = \hat{\gamma}_{0,n}$.

2.3.2. Jarque-Bera Test

[15] 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;

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

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

The Hypothesis is given by;

H_o: normality

H_1: non-normality

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

2.3.3. Univariate Ljung-Box Test

The [21] was employed to test whether there exist autocorrelation r_l in the returns series. It is of the assumption that, the returns series and standardized residuals contain no serial correlation up to a given lag k.

The statistic is given by;

$$Q(K) = T(T+2)\sum_{l=1}^{k}\frac{r_l^2}{T-l} \tag{7}$$

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 level.

2.3.4. Testing for ARCH Effects

In fitting GARCH models, it is very essential to examine the residuals for evidence of ARCH effects. The observation that the magnitude of current residuals for any financial time series tends to be non-linearly related to the magnitude of their past residuals form the reasoning for ARCH test. This paper employed the ARCH-LM test as it is the most widely used method to test for ARCH effects in empirical studies ([6] and [22]).

By representing the i lag autocorrelation of the squared or absolute returns by $\hat{p}_i$, the Ljung-Box statistic is given by;

$$Q = T(T+2)\sum_{i=1}^{m}\frac{\hat{p}_i^2}{T-i} \sim \chi^2(m) \tag{8}$$

The LM hypothesis is given by;

$H_o: \alpha_1 = \alpha_2 = \cdots = \alpha_i = 0$ (no ARCH effect) against

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

for at least $i = 1,2,..,q$

The statistic of the LM test is given by;

$$LM = T.R^2 \sim \chi^2(q) \tag{9}$$

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

2.3.5. The Durbin-Watson Test

The [7] 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;

$$d = \frac{\sum_{i=2}^{n}(e_i - e_{i-1})^2}{\sum_{i=1}^{n} e_i^2} \tag{10}$$

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;

$$H_o: \rho = 0$$

$$H_1: \rho > 0$$

Also, the d statistic can take on values between 0 and 4 and under the null hypothesis d is equal 2.

2.3.6. The Breusch-Godfrey Test

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

The test statistic is given by;

$$B - G = NR^2 \tag{11}$$

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

$$\hat{u}_t = \gamma_1 \hat{u}_{t-1} + \cdots + \gamma_p \hat{u}_{t-p} + \beta_1 x_{1t} + \cdots + \beta_k x_{kt} + \varepsilon_t \tag{12}$$

The hypothesis is given by;

$$H_o: no\ autocorrelation$$

$$H_1: autocorrelation$$

The test is asymptotically χ^2(p) distributed.

2.4. 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 [31] and [6], this paper employed the mean equation given by:

$$X_t = \mu + \lambda X_{t-1} + \varepsilon_t \tag{13}$$

where X_t is the returns for each stock, μ is a constant, λ is the coefficient of X_{t-1} and ε_t is the innovation.

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

This model was proposed by [13] and [32]. It is simply a re-specification 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;

$$\sigma_t^2 = \alpha_o + \sum_{i=1}^{p}(\alpha_i + \gamma_i d_{t-i})\varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \tag{14}$$

where α_o 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 (13), the variance equation for TGARCH-M (1, 1) is given by;

$$\sigma_t^2 = \alpha_o + \alpha_1 \varepsilon_{t-1}^2 + \gamma_1 d_{t-1} \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{15}$$

$$d_{t-1} = \begin{cases} 1 & if\ \varepsilon_{t-1} < 0, \quad bad\ news \\ 0 & if\ \varepsilon_{t-1} \geq 0, \quad good\ news \end{cases} \tag{16}$$

If $\gamma > 0$, then leverage effects exist in stock markets and if $\gamma \neq 0$ then the impact of news is asymmetric [12]. 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 [4]. Also, since the conditional variance must be positive, the constraints of the parameters are $\alpha_o > 0$, $\alpha_1 \geq 0$, $\beta_1 \geq 0$ and $\alpha_1 + \gamma_1 \geq 0$. The model is stationary if $\gamma_1 < 2(1 - \alpha_1 - \beta_1)$.

2.6. Student-t Distributional Assumption

The student-t distributional assumption was employed to account for fat tails that are common in most financial data. The ARCH models were 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;

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

where $\Gamma(.)$ 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.

2.7. Mean Reversion

Mean reversion implies that current information have no influence on the long run forecast of the volatility. Persistence dynamics in volatility is generally captured in the GARCH coefficient(s) of a stationary GARCH model. In stationary GARCH models, the volatility mean reverts to its long run level, at a rate given by the sum of ARCH and GARCH coefficients, which is usually close to one (1) for financial time series. The average number of time periods for the volatility to revert to its long run level is measured by the half-life of the volatility shock. The mean reverting form of the basic GARCH (1, 1) model is given by;

$$(\varepsilon_t^2 - \bar{\sigma}^2) = (\alpha_1 + \beta_1)(\varepsilon_{t-1}^2 - \bar{\sigma}^2) + X_t + \beta_1 X_{t-1} \quad (18)$$

where $\bar{\sigma}^2 = \frac{\alpha_o}{1-\alpha_1-\beta_1}$, the unconditional long run level of volatility and $X_t = (\varepsilon_t^2 - \bar{\sigma}^2)$. The magnitude of the mean reverting rate $\alpha_1 + \beta_1$ controls the speed of the mean reversion.

2.8. Half-Life

One measure of volatility persistence is the volatility half-life τ, [11] defined half-life as the time required for the volatility to move half way back towards its unconditional mean. More precisely, τ is the smallest k such that

$$\left|\sigma_{t+k|t} - \bar{\sigma}^2\right| = \frac{1}{2}\left|\sigma_{t+1|t} - \bar{\sigma}^2\right| \quad (19)$$

where k is the number of days, $\sigma_{t+k|t}$ is the conditional expected value of volatility k days into the future and $\bar{\sigma}^2$ is the unconditional long run level of volatility (the mean level to which the unconditional variance eventually reverts).

Also, the GARCH (1, 1) process is mean reverting if $(\alpha_1 + \beta_1) < 1$ since if this condition is satisfied, $\sigma_{t+k|t} \rightarrow \bar{\sigma}^2$ as $k \rightarrow \infty$. Thus, the forecast conditional variance reverts to the unconditional variance as the forecast horizon increases.

For $k \geq 2$ and a GARCH (1, 1) process, the value of $\sigma_{t+k|t}$ is given by;

$$\sigma_{t+k|t} = \bar{\sigma}^2 + (\alpha_1 + \beta_1)^{k-1}(\sigma_{t+1} - \bar{\sigma}^2),\ k \geq 2 \quad (20)$$

From Equation (19) and Equation (20), the number of days k for a GARCH (1, 1) process is given by;

$$|\bar{\sigma}^2 + (\alpha_1 + \beta_1)^{k-1}(\sigma_{t+1} - \bar{\sigma}^2) - \bar{\sigma}^2| = \frac{1}{2}\left|\sigma_{t+1|t} - \bar{\sigma}^2\right| \quad (21)$$

Therefore the half-life of a GARCH (1, 1) process is given by;

$$\tau = \frac{log[(\alpha_1+\beta_1))/2]}{log(\alpha_1+\beta_1)} \quad (22)$$

3. Results and Discussion

3.1. Descriptive Statistics

Table 1 shows the summary statistics of the returns series. Most of the stocks had positive mean returns (CAL Bnak Limited, Fan Milk Limited,Enterprise Group Limited, Uniliver Ghana Limited, Tullow Oil Plc and Benso Oil Palm Plantation) ranging from 0.0002 to 0.0020. The rest of the stocks (Produce Buying Company and Clydestone (Ghana) Limited) had negative mean returns ranging from -0.0019 to -0.0002. The highest mean return was recorded in Benso Oil Palm Plantation (0.0020) and the lowest mean return recorded in Produce Buying Company (-0.0019). A positive mean return indicates that investors of such stocks 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 stocks. 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 stocks. 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 are leptokurtic (highly peaked) in nature and heavy tailed and that there was more frequently extremely large deviations from the mean returns than a Gaussian distribution and hence making the stocks highly volatile.

Table 1. *Descriptive Statistics of the Returns Series.*

Stock	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

3.2. Further Analysis

The PP and KPSS was employed in testing and confirming stationarity of the returns series. From Table 2, it is evident that for the PP tests, $p - values$ were very significant at 5% significance level and therefore the null hypothesis of non-stationary or unit root was rejected. In the case of the KPSS test, we failed to reject the null hypothesis of stationary since the test was significant at the 5% significance level. Therefore, the returns series were all stationary at the 5% level of significance.

Table 2. *PP Test and KPSS Test of the Returns Series.*

	PP Test		KPSS Test	
Stock	Test Statistic	P-value	Test Statistic	Critical value (5%)
CAL Bank Limited	-40.2780	0.0000**	0.0423	0.1480
Produce Buying Company	-41.6420	0.0000**	0.0615	0.1480
Fan Milk Limited	-38.4000	0.0000**	0.0167	0.1480
Clydestone (Ghana) Limited	-54.0670	0.0000**	0.0230	0.1480
Enterprise Group Limited	-30.3310	0.0000**	0.0497	0.1480
Uniliver Ghana Limited	-39.8050	0.0000**	0.0734	0.1480
Tullow Oil Plc	-31.5120	0.0000**	0.0511	0.1480
Benso Oil Palm Plantation	-35.0780	0.0000**	0.0678	0.1480

** Significant at 5% significance level.

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.

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

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

** Significant at 5% significance level

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 concluded 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.

Table 4. *Test for Normality, Autocorrelation and Heteroscedascitity 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.

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 returns series, therefore, we fail to reject the null hypothesis of no autocorrelation. Thus, making the choice of mean equation more appropriate for the GARCH estimation.

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.

The TGARCH was investigated for stationarity by summing the ARCH (α) and GARCH (β) coefficients. As it was reported in Table 6, all the estimated models were stationary indicating that the TGARCH was appropriate for asymmetric modelling of volatility. Again, the summation of the ARCH and GARCH coefficients was extended in measuring the level of persistence. It was evident that, the summation of α and β were all closer to one (1) indicating their persistence levels. Fan Milk Limited exhibited the highest level of persistence (0.9622) with the least persistence (0.7580) level recorded in Produce Buying Company. Also, the TGARCH was extended in examining the leverage effect parameter γ, it was evident the leverage effect parameter across all the returns series were positive and significant at the 5% significance level. This means that there was the probability of bad news influencing volatility than good news of the same magnitude hence making volatility across the stocks to be asymmetric in nature. All the models were tested for ARCH effects and it was clear that the ARCH-LM test was not significant at the 5% level of significance hence there was no further ARCH effects.

Table 6. *Estimated TGARCH-M (1,1) Model.*

Stock	$\alpha+\beta$	γ	ARCHLM
CAL Bank Limited	0.8712	0.0816*	0.6183
Produce Buying Company	0.7580	0.0974*	0.6103
Fan Milk Limited	0.9622	0.2940*	0.0925
Clydestone (Ghana) Limited	0.8275	0.0063*	0.8461
Enterprise Group Limited	0.8927	0.1546*	0.0572
Uniliver Ghana Limited	0.8149	0.4105*	0.5812
Tullow Oil Plc	0.8301	0.3827*	0.3086
Benso Oil Palm Plantation	0.7789	0.3030*	0.7154

* Significant at 5% significance level.

The persistence and half-life measure of volatility of the returns series were investigated from the TGARCH-M (1,1) model. The summation of α and β was used and it is evident from Table 7, all the 8 returns series were persistent exhibiting long-memory since their summation of α and β were closer to one (1). Also, in terms of mean reversion, almost all the returns series have strong mean reversion with the exception of Fan Milk Limited. Fan Milk Limited exhibited the highest persistence level. The half-life measure of volatility also revealed the same trend. The half-life of most of returns series were short (CAL Bank Limited (6 days), Produce Buying Company (4 days), Clydeston (Ghana) Limited (5 days), Enterprise Group Limited (7 days), Uniliver Ghana Limited (4 days), Tullow Oil Limited (5 days) and Benso Oil Palm Plantation (4 days)) with the exception of Fan Milk Limited (19 days). It was also clear that, once the returns series were less persistent, their half-life measure of volatility tends to be short. The persistence and half-life in volatility showed that all the eight returns series exhibited some level of volatility persistence. This degree of persistence was extended in measuring the half-life in volatility. Stocks that exhibited high degree of persistence imply their volatility will not move quickly to their long-run volatility levels whereas those with less degree of persistence will have their volatility moving very quickly to their long-run volatility levels. That is, there is the expectation that stocks with high degree of persistence will have high half-life and weak mean reversion whereas those with low persistence will have low half-life and strong mean reversion. The implication of weak and strong mean reversion is that, for stocks with strong mean reversion means that, the returns of those stocks approaches their average volatility very quickly whereas for stocks with weak mean reversion, their returns takes a long period to return towards their average volatility. Therefore, the results showed that, Produce Buying Company, Uniliver Ghana Limited and Benso Oil Palm Plantation had strong mean reversion since they all had their half-life measure been four (4 days). This means that, any shock to any of these stocks take 4 days to return half-way back without any further volatility (i.e. a shock takes 4 days to return half-way back to its volatility). Also, CAL Bank Limited, Clydestone, Enterprise Group and Tullow Oil Plc have strong mean reversion since the half-life measure were 6 days, 5 days, 7 days and 5 days respectively. This implies that a shock to CAL Bank Limited will take 6 days to return half-way back to its volatility, a shock to Clydestone (Ghana) Limited will take 5 days to revert, any shock to Enterprise Group Limited and Tullow will take 7 days and 5 days respectively to return half-way back without any further volatility. The half-life measure of Fan Milk Limited was 19 days indicating that any shock to Fan Milk Limited will take 19 days to mean revert. This implies that, investors will prefer stocks that have strong mean reversion since their volatility does not stay for a long time. But in the situation where positive shocks increases volatility, investors will prefer to invest in stocks that have high persistence measure of volatility and weak mean reversion. Also in a market where risk is priced, investors will prefer investing in stocks with high half-life measure since at the end of the day their returns will match the risk taken.

Table 7. *Persistence and Half-life Volatility measure of the Returns Series.*

Stock	$\alpha+\beta$	Half-life volatility measure (days)
CAL Bank Limited	0.8712	6
Produce Buying Company	0.7580	4
Fan Milk Limited	0.9622	19
Clydestone (Ghana) Limited	0.8275	5
Enterprise Group Limited	0.8927	7
Uniliver Ghana Limited	0.8149	4
Tullow Oil Plc	0.8301	5
Benso Oil Palm Plantation	0.7789	4

4. Conclusion

This paper examined the asymmetry and persistence in stock returns using univariate TGARCH-M (1,1) with the student-t distributional assumption and half-life measure. From the results, it was evident that volatility was persistent across all the stocks since the summation of ARCH and GARCH coefficients were all very close to one (1). The persistence and half-life measure revealed that, all the stocks exhibited some level of persistence in them and strong mean reversion. Fan Milk Limited was highly persistent with a weak mean reversion and a half-life of 19 days as compared to CAL Bank Limited, Produce Buying Company, Enterprise Group Limited, Uniliver Ghana Limited, Tullow Oil Plc and Benso Oil Palm Plantation which had 5 days, 7 days, 4 days, 5 days and 4 days respectively. Also all the returns series exhibited positive leverage effect parameter indicating that bad news influenced volatility than good news of the same magnitude and hence making volatility asymmetric.

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