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VOLATILITY DYNAMICS IN EQUITY RETURNS: A MULTI-GARCH APPROACH

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ABSTRACT: *In this paper, volatility of stock returns in Ghana is modeled from July 4, 2011 to October 3, 2014 using both symmetric and asymmetric univariate Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models under the normal Gaussian distribution assumption. Results show that equity returns exhibit stylized characteristics such as volatility clustering, peakedness, and leverage effect found with most advanced stock markets. Further, results show that shocks to the Ghana equity market are usually transient with minimal instances of persistence. It is further confirmed that EGARCH (1, 1) is superior in modeling the volatility of returns on the equity market for the studied period.*

KEYWORDS: Ghana, Volatility, GARCH Models, Stock Market, EGARCH (1, 1)

INTRODUCTION

A common consensus in finance literature is that high frequency financial time series data exhibit characteristics of long-memory (persistence), leptokurtic innovations, volatility clustering, as well as, time-varying volatility. These have implications for optimal asset allocation decisions and risk management practices adopted by investors.

The theory of price-efficient capital markets relates to a financial market where asset prices rapidly reflect all available information. This means that all available information is already impounded into an asset's price, so investors should expect a return equal to the equilibrium, which is necessary to compensate them for their anticipated risk. In such a market, the prices of securities observed at any point in time are based on a "correct" evaluation of all information available at that time. An important implication of the efficient market theory is that stock prices should approximately follow a random walk (that is, normal distributions of returns); and under this assumption, the probabilities of potential gains or losses associated with each investment can be estimated. However, in reality, the distribution of returns is not normal as suggested by Grouard *et al* (2003) and Frimpong and Oteng-Abayie (2006). Mandelbrot (1963) also insists extreme events in financial data series are far too frequent for the normal distribution to hold. Since the interest of market participants lies in the losses/gains from the rise/fall of asset prices, investors devise practical measures to overcome the downside risk of losses. Investigating the dynamic behavior of asset price fluctuation and efficiency of markets is therefore essential to investors and policy makers.

Despite the obvious challenges such as low capitalization and liquidity, the Ghana equity market has made significant strides over the years. Evidence available suggests that Ghana

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came among the top 10 performing stock markets in Africa out of 25 for the year 2011. Additionally, the Ghana equity market in year 2013 experienced outstanding performance of listed firms since its establishment in 1990. The Ghana stock exchange (GSE) Composite Index (CI), which measures the performance of the market, went up by 78.8% between years 2010 and 2013. In U.S dollar ($) terms the GSE-CI went up by 55%, second to Malawi in Africa. In the midst of fears from the concomitant effects of the 2007 financial turmoil and the subsequent Eurozone debt crisis on capital flows, Ghana remains a dominant beneficiary of portfolio and cross-border bank flows to Sub-Saharan African markets. For such a promising market, the volatility dynamics and behavior of prices and returns ought to be examined in order to provide and in-depth understanding of the risk-return trade-off of assets. This paper therefore seeks to model the volatility of returns on the Ghana equity market with different types of GARCH models using a more current and new market-based capitalization index different from the index used in prior studies (such as Frimpong and Oteng-Abayie, 2006; Alagidede and Panagiotidis, 2006).

Our analysis involve examining the Ghana Stock Exchange Composite Index (GSE-CI) return series for evidence of volatility clustering, leptokurtic innovations, and leverage effects as they provide essential information about the riskiness of assets in the Ghanaian market. Correct modeling of extreme returns is essential to financial risk management since asset and risk managers are mostly interested in guarding against the risk of extreme gains/losses stemming from the surge/plummet in the prices of financial assets held by firms.

Empirical evidence suggests the inappropriateness of linear models such as the OLS and Random Walk (RW) in explaining volatility of returns, hence, the resort to different phenomenon in explaining the ‘peculiar characteristics’ of stocks returns. Common features investigated in related studies are: volatility clustering or volatility pooling and stability (see Mandelbrot, 1963); leptokurtosis (e.g. Fama, 1965); and leverage effect (e.g. Black, 1976). Among the models employed to capture these dynamic features are the autoregressive conditional heteroskedasticity (ARCH) range of models proposed by Engle (1982) and extended to generalized autoregressive conditional heteroscedasticity (GARCH) by Bollerslev (1986). According to Suliman, (2012), ARCH range of models successfully model and predict the time-varying conditional volatility of financial time series data by using past unpredictable changes in the returns of that series and is predominantly used in financial market research aside other fields.

Several literature abound on volatility modeling and forecasting in advanced, emerging and African markets, however, few of such studies are available in Ghana. A quick scan reveals, among others; Frimpong and Oteng-Abayie (2006) who modeled and forecasted volatility (conditional variance) on the Ghana Stock Exchange using a random walk (RW), GARCH(1,1), EGARCH(1,1), and TGARCH(1,1) models. Their results indicate that the Data Bank Stock Index (DSI) used to represent market returns in Ghana exhibits stylized characteristics such as volatility clustering, leptokurtosis and asymmetric effects associated with stock market returns. In their estimations, the GARCH (1, 1) model outperformed the other models under the assumption that the innovations follow a normal distribution. The other paper on Ghana is that of Alagidede and Panagiotidis (2006). The authors used both daily and monthly stock data to examine calendar anomalies (day of the week and month of the year effects) in the GSE. They employed non-linear models from the GARCH family in a rolling framework to investigate the role of asymmetric behavior in equity returns. Their conclusion was that TGARCH better models the volatility of the Ghana equity market than the OLS,

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GARCH, and EGARCH models in terms of both information criteria and the log likelihood function value for anomalies in rolling windows.

Examples of some extant literature on other African markets are: Piesse and Hearn (2002), Jayasuriya (2002), Eskandar (2005), Ogun *et al.,* (2005), Okpara and Nwezeaku (2009), Kalu (2010), Iyiegbuniwe *et al.* (2012), Mckerrow (2013), Sigaukea *et al.*, (2014), etc. The related studies on Ghana and other African economies provide inconsistent results which need to be rectified.

The rest of the paper is structured as follows: Section 2 outlines the data and methodologies used; Section 3 presents and discusses the results; and Section 4 concludes the paper.

DATA AND METHODOLOGY

Data Description

Data used in the study is the daily volume weighted average prices (VWAP) of equities, herewith referred to as Composite Index (CI) of the Ghana Stock Exchange (GSE) from July 4, 2011 to October 3, 2014 making a total of 776 observations excluding non-trading days. The data were gleaned from the Ghana Stock Exchange official CD-ROM. GSE Composite Index (GSE-CI) is a market-based capitalization index introduced in January, 2011. Its computation is based on the VWAP of all listed equities, except those in the international register. It has a base date of December 31, 2010 and base index value of 1000.The returns series of the GSE-CI data is generated as follows:

$$r_t = ln\left(\frac{P_t}{P_{t-1}}\right) \tag{1}$$

where r_t is the return of the index at time t; P_t and P_{t-1} denote the closing market index of GSE-CI at the current day and previous day, respectively; and *ln* denote natural logarithm.

Methodology

The study applies Autoregressive conditional heteroscedasticity (ARCH) and its generalization (GARCH) models in estimating the volatility of the Ghana stock market. The GARCH models are used to capture the main characteristics (such as peakedness, leverage effects and volatility clustering) of the data used. In this paper, both the symmetric [GARCH (1, 1), GARCH-M (1, 1)] and asymmetric [EGARCH (1, 1), TGARCH (1, 1) and PGARCH (1, 1)] univariate GARCH specifications are employed to model stock returns volatility in the Ghana. In addition, diagnostics tests (ARCH-LM test and Q-statistics) are performed to preview the econometric attributes of the underlying data in order to ascertain the level of confidence to repose on the model estimates. A combination of information criteria such as Akaike Information Criteria (AIC), Schwarz Criterion (SC) and the maximum Log-likelihood (LL) values are employed to choose the volatility model that best models the conditional variance of the GSE-CI.

GARCH

The basic GARCH (1, 1) model by Bollerslev (1986) is based on the assumption that conditional variance is influenced by its own lags and previous unexpected increase or decrease in returns at time *t*. The starting point of GARCH (1, 1) can be expressed as:

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$$r_t = \mu + \varepsilon_t \tag{2}$$

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} \tag{3}$$

where ω > 0, α ≥ 0, β ≥ 0.

r_t = the return of the index at time t

ε_t = the error term

h_t = conditional variance of the index

ω = a constant term

ε_{t-1}^2 = the news about volatility from the previous period (the ARCH term)

h_{t-1}= the conditional variance which is the last period forecast variance (the GARCH term) must be non-negative.

Equation (2) is the mean equation and equation (3) represents the variance equation. GARCH (1, 1) refers to the presence of a first-order autoregressive GARCH term and a first-order moving average ARCH term. The GARCH model can be interpreted as predicting thecurrent period's variance by forming a weighted average of a long term (the constant), the forecast variance from last period (the GARCH term), and information about volatility observed in the previous period (the ARCH term).Usually investors will increase the estimate of the variance for the next period, if the asset return is unexpectedly large in either the upward or the downward direction. This model is also consistent with the volatility clustering often seen in financial returns data, where large changes in returns are likely to be followed by further large changes.

Higher order GARCH models, denoted GARCH (p, q) are required to arrive at reasonable estimates of the parameters (Roberto *et al.*, 2000). The general specification of GARCH (*p*, *q*) process is given by:

$$h_t = \omega + \sum_{j=1}^{p} \beta_j h_{t-j} + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 \tag{4}$$

where h_t is the conditional variance, which is a linear function of q lags of the squares of the error terms ε_t^2 or the ARCH terms and p lags of the past value of the conditional variance or the GARCH terms, and $\omega, \beta_{j,} \alpha_i$ are parameters.

GARCH-M

If conditional variance or standard deviation is introduced into the mean equation, we get the GARCH-in-Mean (GARCH-M) model as proposed by Engle, Lilien and Robins (1987). GARCH-M model follows the utility theory that an increase in variance (risk proxy) will result in a higher expected returns. In the GARCH-M model; the conditional mean is an explicit function of the conditional variance. This model is often used in financial applications where the expected return on an asset is related to the expected risk. A simple GARCH-M (1, 1) model can be written as:

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$$r_t = \mu + \lambda h_t + \varepsilon_t \tag{5}$$

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} \tag{6}$$

In this model, the estimated coefficient λ on the expected risk is a measure of the risk-return tradeoff in financial assets and is also known as the risk premium parameter. In this paper, λ shows dependence of the conditional mean on the conditional standard deviation obtained from Equation (5).

Two variants of GARCH-M specification use the conditional standard deviation or the log of the conditional variance in place of the variance in Equation (5). These are represented as:

$$r_t = \mu + \lambda\sqrt{h_t} + \varepsilon_t \tag{7}$$

$$r_t = \mu + \lambda\log(h_t) + \varepsilon_t \tag{8}$$

GARCH and GARCH-M are symmetric models that successfully capture thick tailed returns, and volatility clustering, and can readily be modified to allow for several other stylized facts, such as non-trading periods and predictable information releases (Bollerslev, Engle, and Nelson: 1993). It does not however, capture the asymmetric effect that is inherent in most stock markets return data also known as the "leverage effect".

EGARCH

In the Exponential GARCH (EGARCH) model proposed by Nelson (1991), natural logarithm of the conditional variance is allowed to vary over time as a function of the lagged error terms rather than lagged squared errors. The specification for EGARCH (1, 1) model can be written as:

$$r_t = \mu + \varepsilon_t \tag{9}$$

$$lnh_t^2 = \omega + \alpha\left|\frac{\varepsilon_{t-1}}{h_{t-1}}\right| + \gamma\left|\frac{\varepsilon_{t-1}}{h_{t-1}}\right| + \beta lnh_{t-1}^2 \tag{10}$$

The exponential nature of the EGARCH ensures that the conditional variance is always positive even if the parameter values are negative; thus there is no need for parameter restrictions to impose non negativity. The asymmetric effect is captured by γ. The presence of leverage effects can be tested by the hypothesis that $\gamma < 0$; and the impact is asymmetric if $\gamma \neq 0$.

The general specification of EGARCH (p, q) models can be specified as follows:

$$\ln h_t^2 = \omega + \sum_{j=1}^{p}\beta_j \ln h_{t-j}^2 + \sum_{i=1}^{q}\left[\alpha_i\left\{\left|\frac{\varepsilon_{t-i}}{h_{t-i}}\right| - \sqrt{\frac{2}{\pi}}\right\} - \gamma_i\left|\frac{\varepsilon_{t-i}}{h_{t-i}}\right|\right] \tag{11}$$

TGARCH

The next volatility model commonly used to handle leverage effects is the Threshold GARCH (or TGARCH) introduced independently by Zakoïan (1994) and Glosten, Jaganathan, and Runkle (1993).TGARCH also known as GJR model modifies the original GARCH specification using a dummy variable. This model is based on the assumption that unexpected changes in the market returns have different effects on the conditional variance of the returns.

Good news goes with an unforeseen increase and hence will contribute to the variance through the coefficient β instead of an unexpected decrease which is presented as a bad news and contributes to the variance with the coefficient $\alpha + \gamma$. If $\gamma > 0$, the leverage effect exists and news impact is asymmetric if $\gamma \neq 0$. The basic TGARCH (1, 1) model is written as:

$$r_t = \mu + \varepsilon_t \tag{12}$$

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \gamma\varepsilon_{t-1}^2\eta_{t-1} + \beta h_{t-1} \tag{13}$$

Where $\eta_{t-1} = 1$ if $\varepsilon_{t-1} < 0$ and $\eta_{t-1} = 0$ if $\varepsilon_{t-1} > 0$

Note that GARCH is a special case of the TGARCH model where the threshold term is set to zero. To estimate the TGARCH model, GARCH model is specified with ARCH and GARCH order with the threshold order altered to the desired value. The general specification of TGARCH (p, q) conditional variance is specified as follows:

$$h_t = \omega + \sum_{i=1}^{q}(\alpha_i + \gamma_i\eta_{t-i})\varepsilon_{t-i}^2 + \sum_{j=1}^{p}\beta_j h_{t-j} \tag{14}$$

PGARCH

Taylor (1986) and Schwert (1989) introduced the standard deviation GARCH model, where the standard deviation is modeled rather than the variance as in most of the GARCH-family. This model, along with several other models, is generalized in Ding, Granger and Engle (1993) with the Power GARCH (PGARCH) specification. In the PGARCH model, the power parameter of the standard deviation can be estimated rather than imposed, and the optional parameters are added to capture asymmetric effects of up to order r. In the general specification of PGARCH (p,q) model, the conditional variance equation is specified as follows:

$$h_t^{\delta} = \omega + \sum_{j=1}^{p}\beta_j h_{t-i}^{\delta} + \sum_{i=1}^{q}\alpha_i\left(\left|\varepsilon_{t-i}\right| - \gamma_i\varepsilon_{t-i}\right)^{\delta} \tag{15}$$

Where $\delta > 0$, $|\gamma_i| \leq 1$ for $i = 1, \ldots, r$, $\gamma_i = 0$ for all $i > r$, and $r \leq p$.α_i and β_j are ARCH and GARCH parameters. The symmetric model sets $\gamma_i = 0$ for all i. Note that if $\delta = 2$and $\gamma_i = 0$ for all i, the PGARCH model is simply a usual GARCH specification. As in the previous models, asymmetric effects are present if $\gamma \neq 0$.

Preliminary Results

We present time plots of the GSE-CI in the level and returns series in Fig. *1a* and *1b* respectively. Fig.*1a* provides a diagrammatic representation of the fluctuations of returns on the Ghana equity market over time. It is observed here that prices exhibited short but frequent fluctuations with minimal incidence of structural breaks during the sample period. Overall, the index assumes upward trend over time after some few months in 2011.The mean-reverting characteristic depicted by the returns series in Fig.*1b* is indicative of the possibility of volatility clustering of the GSE-CI returns. Further, Table 1 shows the descriptive statistics and unit root tests of the sample.

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From Table 1, the mean daily GSE-CI returns series range from -0.201407 to 0.205101. As expected, the mean of the returns is close to zero. The high standard deviation is indicative of high volatility in the market returns and the risky nature of the market. There is also a positive skewness suggesting that the data distribution has a long right tail indicating that returns are asymmetric. Also, GSE-CI shows kurtosis that is very large; greater than the normal value of 3 indicating a leptokurtic distribution. The skewness and kurtosis shows how the equity returns deviate from the normality assumption. The Jarque-Bera statistic and corresponding *p*-value in Table 1 reject the hypothesis of normality at 1% significance level.

Panel B reports the test for possible unit roots in the returns series using the Augmented Dickey-Fuller (ADF) and Phillips-Peron (PP) tests. The high absolute ADF and PP test statistics above the critical values suggest stationarity at the 1% level of significance.

Table 2 presents the autocorrelation coefficients of the returns. The low p-values of the autocorrelation coefficients up to lag 36 signify evidence of ARCH effect and thus prove the presence of volatility clustering.

The next step in executing the ARCH models is to examine the residuals for evidence of heteroscedasticity. Here, the Engle (1982) Lagrange Multiplier (LM) test for detecting autoregressive conditional heteroskedasticity (ARCH) in the residuals is used. The ARCH-LM test the null hypothesis that there is no ARCH effect up to order q lags in the residuals as against the alternate hypothesis of ARCH effect in the residual. From the results in Table 3, the null hypothesis can successfully be rejected; indicating the existence of ARCH effects in the residuals in mean equation indicating a non-constant variance of returns.

Results and Discussion

The results of estimation and statistical verification of the various GARCH models [GARCH (1,1), GARCH-M(1,1), EGARCH(1,1),TGARCH(1,1), and PGARCH(1,1)] are presented in Table 4. The models are estimated using maximum likelihood method under the assumption of Gaussian distribution to search for optimal parameters. Next, we use a combination of information criteria and a set of model diagnostic tests (ARCH-LM test and Q-statistics test) to choose the volatility model that best estimates the conditional variance of the GSE-CI for the studied period.

Parameter estimates of the GARCH (1, 1) model are reported in column 2 of Table4. The results suggest that the coefficients of the conditional variance equation, ω, α and β, are significant at 1% level of significance indicating a strong support for the ARCH and GARCH effects. The significant α implies that information about volatility observed in the previous period has an explanatory power on current volatility. Similarly, the significant β shows the presence of volatility clustering in GSE-CI return series.

Results of GARCH-M model indicate that the risk premium parameter (λ) is positively related to the stock returns. This indicates that the mean of the returns sequence depends on past

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innovations and past conditional variance. This is in line with the theory which suggests that the higher the stock market volatility, the higher the expected rate of return.

From the results of EGARCH (1, 1), leverage effect of Ghana stock market is confirmed by the parameter γ being significant with negative sign. Leverage effect, which is the ratio of debt/equity signifies the negative correlation between the past return and future volatility of returns. Thus, positive news has less effect on the conditional variance compared to negative news on the Ghana stock market. Even though results from the TGARCH (1, 1) and PGARCH (1, 1) possess the right sign, leverage effects were not statistically significant.

The sum of ARCH (α) and the GARCH (β) of the models are low suggesting that the covariance stationarity of the model does not exhibit a high degree of persistence or long memory in the conditional variance. This reveals the ephemeral nature of shocks registered on the equity market. For this reason, investors' decision based on recent information may be more valuable than past information since information decays very quickly. Contrary to the above, the $\alpha + \beta$ in EGARCH (1, 1) model, is above unity contradicting other GARCH models. Thus, volatility persistence is very long and explosive indicating an integrated process as opined by Alagidede and Panagiotidis (2006).

Based on the minimum AIC, minimum SIC and maximum LL values, the EGARCH (1, 1) emerges as the preferable model to the other four specifications in modeling the volatility of the Ghana equity market. Results of the diagnostic tests show that the GARCH models pass the ARCH-LM and serial correlation tests. This indicates that the GARCH models are correctly specified.

CONCLUSIONS

The study models volatility of the GSE composite index (GSE-CI returns) from July 4 2011, to October 3, 2014 using five different GARCH models. Results revealed that the GSE-CI exhibits stylized characteristics such as volatility clustering, leptokurtosis and leverage effect found with most advanced stock markets. Some of the foremost conclusions drawn from the above models are that: there is a strong evidence of heteroscedasticity in the residuals of the series, the risk premium parameter in GARCH-M model is positively related to the stock returns. This is in line with the fact that barring market imperfection and disturbances an increase in expected risk is accompanied by higher expected returns. The study established leverage effect in EGARCH (1, 1) model but the other version of asymmetric models; TGARCH (1, 1) and PGARCH (1, 1) failed to confirm leverage effect. Also, all the models revealed that volatility of stock returns have low persistence except in EGARCH (1, 1) where the persistence in volatility is noted to be elongated and explosive. All the selection criteria used are in favor of EGARCH (1, 1) model; and that its conclusions will significantly reflect GSE-CI returns over the studied period.

Recommendation for Future Research

We recommend that future research must focus on the volatility dynamics of individual stocks listed on the stock exchange other than the aggregate stocks. It is our considered opinion that this will help investors to ascertain for sure how their investments should be diversified across different equities bearing in mind their risk characteristics.

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