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Modeling Stock Market Volatility Using GARCH Approach on the Ghana Stock Exchange

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Abstract

The study examined and modeled stock market volatility of financial return series for three listed equities on the Ghana Stock Exchange (GSE). A historical data from 25th June 2007 to 31st October 2014 was considered for the analysis. The series for each of the three equities were tested for stationarity using the KPSS test. Series found to be non-stationary were transformed to be stationary. The study fitted a GARCH (p, q) model for volatility. GARCH (1, 1), GARCH (1, 2), GARCH (2, 1) and the GARCH (2, 2) models were fitted to residual series of some three equities. Results revealed the presence of volatilities in all three equities and also showed that volatility though present was not persistent in the three equities. For each of the companies under study, the GARCH (1, 1) model was found to outperform the other three models based on the comparison of the AICc for each model. The study recommended the use and comparison of other variants of the GARCH model in estimation of volatility.

Keywords: GARCH, heteroscedasticity, residuals, volatility

1. Introduction

One of the main problems of the stock market is the risk associated with high fluctuations in stock prices which are much beyond the probable changes in the real value of companies representing the stock. Fluctuations in the GSE over the years have led to decreased investor confidence in the stock market. A hedging technique such as portfolio insurance is directly affected by volatility level. This is because the prices of insurance increase with volatility. Volatility makes investing in stocks more risky. The stock market is among the most volatile financial institution in business. If one can predict the direction of the stock market, the investor has a good idea of what to expect of the economy.

According to Hamadu (2010), volatility modelling and forecasting have attracted much attention in recent years in emerging stock markets. However, modelling volatility and forecasting has not attracted much attention in some West African countries like Nigeria for the simple reason that the stock market is largely under developed (Hamadu, 2010). Ghana shares a similar condition.

Chen, Roll, & Ross (1986) attempted to explain stock price volatility by referring only to the changes in economic data. Their study investigated the reaction of the stock market to innovations in some macroeconomic variables. Then, Schwert (1989) analyzed the relation of stock volatility with real and nominal macroeconomic volatility, economic activity, financial leverage, and stock trading activity to evaluate why the stock market volatility changes over time.

This research is aimed at modelling volatility of three (3) equity returns using the GARCH (p, q) model.

2. Related Works

After the ARCH model of Engle (1982), a large number of models have been developed to address the conditional variance of financial time series when pricing derivatives, measuring risk and hedging against portfolio risk. Corhay and Rad (1994) explored and found that the autoregressive conditional heteroscedastic ARCH models could sufficiently describe stock price behaviour in European capital markets.

Furthermore, Bollerslev (1986) proposed the Generalized ARCH model as an extension to the ARCH model. Some relevant application of the GARCH was conducted by Hansen and Lund (2001), where they compared volatility models using intra-day estimated measures of volatility. By comparing with the first "species" of volatility models, they investigated whether the evolution of volatility models has led to better forecasts of volatility.

An extension of the GARCH model led to the development of the Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) model. Reyes (2001) examined volatility transfers between size-based stock indexes from the Tokyo Stock Exchange using a bivariate EGARCH model to test for volatility spillover effects between large-and small-cap stock indexes. Adjasi, Harvey and Agyapong (2008) applied the EGARCH to investigate the relationship between Stock markets and foreign exchange market and further ascertained whether movements in exchange rates have an effect on stock market in Ghana.

According to Ali and Mhmoud (2013), Vee and Gonpot (2011) evaluated volatility forecasts for the US Dollar/Mauritian Rupee exchange rate which was obtained through a GARCH (1, 1) model by assuming two distributions namely: the Generalized Error Distribution (GED) and the Student's-t distribution.

Ahmed and Shabri (2013) applied GARCH model in forecasting crude oil prices. They did that to illustrate the advantages of the models by assuming that the errors followed three distributions, thus normal, student's t and generalized error distribution. They subsequently fitted GARCH-N, GARCH-t and GARCH-G.

A lot of empirical studies have been done worldwide in modelling using the ARCH and GARCH models.

Basel, Awartani, and Corradi (2005), in their paper on predicting the volatility of the S&P-500 stock index via GARCH models examined the relative out-of-sample predictive ability of different GARCH models, with particular emphasis on the predictive content of the asymmetric component.

Kang, Cho, and Yoon (2009) found that controlling sudden changes effectively reduces the long memory property in the Korean and Japanese stock markets using a fractionally integrated GARCH (FIGARCH) model. They identified that sudden change is generally associated with major economic and political events. Their study suggested that incorporating information regarding sudden changes in variances improves the accuracy of estimating volatility dynamics.

Joshi (2010) investigated the stock market volatility in the emerging stock markets of India and China using closing prices. The results detected the presence of non-linearity using BDSL and conditional heteroscedasticity identified using the ARCH-LM test.

Ahmed and Suliman (2011) used GARCH models to estimate volatility in the daily returns of Khartoum Stock Exchange (KSE), Sudan.

Sattayatham, Sopipan, and Premanode (2012) forecast return and volatility of the Stock Exchange of Thailand (SET) index.

Bala and Asemota (2013) used monthly exchange rate return series for Naira/US dollar return and Naira/British pounds and Naira/Euro returns to critically look at the exchange rate volatility using GARCH models. Aziz and Uddin (2014) study the volatility of the Dhaka Stock Exchange (DSE). The study uses the GARCH models to estimate the presence of volatility.

Bhardwaj, Ranjit, Singh, and Singh (2014), studied time series with models which were non-structural-mechanical in nature. They studied the Box-Jenkins autoregressive integrated moving average (ARIMA) and the Generalized Autoregressive Conditional Heteroscedastic (GARCH) models and applied them for modelling and forecasting of spot prices of Gram at Delhi market.

Onwukwe, Samson and Lipcsey (2014) modelled and forecasted volatility of fifteen banks in Nigeria using three symmetric models; ARCH (1), ARCH (2) and GARCH (1, 1) as well as two non-symmetric models; EGARCH (1, 1) and TARCH (1, 1).

3. Methodology

The study fitted models for forecasting stock return volatility with the GARCH model using R (Software version 3.0.2). Data for this research was the Ghana Stock Exchange (GSE) daily closing price data from 25TH June 2007 to 31ST October 2014 obtained from the GSE website (www.gse.com.gh). The log return (continuously compounded return) was used throughout the work.

The GARCH model as proposed by Bollerslev (1986) requires that the conditional variance be dependent on previous lags. The GARCH model uses the lagged conditional variance terms as autoregressive terms. Furthermore, GARCH models can parsimoniously represent higher order ARCH processes.

The GARCH (p, q) is represented as follows:

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

where σ_t^2 is a function of lagged values of Y_t^2 and $\omega, \{\alpha_i\}, i = 1, \dots, p$ and $\{\beta_j\}, q$ are non-negative constants. GARCH models explain variance by two distributed lags, one on past squared residuals to capture high frequency effects and the second on lagged values of the variance itself. An appealing feature of the GARCH (p, q) model concerns the time series dependence in Y_t^2. If $q = 0$, the GARCH (p,q) model becomes an ARCH (p) model. In the interest of the coefficient estimates of the GARCH term to be identified, at least one of the parameters $\{\alpha_i\}, i = 1, \dots, p$ must be significant from zero. For the basic GARCH (p, q) model, Y_t^2 follows an autoregressive moving average (ARMA) process.

For covariance stationarity,

$$\sum_{i=1}^{p} \alpha_i + \sum_{j=1}^{q} \beta_j < 1. \quad (2)$$

The GARCH (1, 1) model is represented by:

$$\sigma_t^2 = \omega + \alpha_1 Y_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad (3)$$

According to Tsay (2005), building a volatility model for an asset return series consists of the following steps:

i. Specify a mean equation by testing for serial dependence in the data and, if necessary, building an econometric model (e.g., an ARMA model) for the return series to remove any linear dependence.

ii. Use the residuals of the mean equation to test for ARCH effects.

iii. Specify a volatility model if ARCH effects are statistically significant and perform a joint estimation of the mean and volatility equations.

iv. Check the fitted model carefully and refine it if necessary.

The random walk hypothesis (RWH) which states that stock market prices evolve according to a random walk, thus, stock market prices cannot be predicted. According to Belaire-Franch, McGreal, Opong, and Webb (2007), rejection of RWH behavior could be due to heteroscedasticity. In this work, the Wright's non-parametric variance ratios test using signs and ranks as detailed in Wright (2000) was used in testing the random walk hypothesis for all three equities. Tests based on signs and ranks are robust to many forms of conditional heteroscedasticity as communicated by Belaire-Franch, McGreal, Opong, & Webb (2007).

4. Results

Table 1 displays the descriptive statistics of the three equities; ETI, GCB and GOIL.

The statistics show that GCB had the highest mean log return (0.00263), followed by ETI with a log return of 0.001256. GOIL had the least mean log return (0.000795). Again, GCB had the highest maximum log return (1.77452) with ETI having the next highest maximum log return of 0.824833. GOIL recorded the least maximum log return (0.457137).

Table 1. Descriptive statistics of daily log returns of three (3) equities (2007-2014)

	LOG RETURNS		
SUMMARY MEASURES	**ETI**	**GCB**	**GOIL**
MINIMUM	-0.061875	-0.94161	-0.127833
MAXIMUM	0.824833	1.77452	0.457137
MEDIAN	0.000000	0.000000	0.000000
MEAN	0.001256	0.00263	0.000795
STANDARD DEVIATION	0.023386	0.05227	0.014196
RANGE	0.886709	1.77452	0.457137
SKEWNESS	27.08	0.81	10.88
KURTOSIS	894.66	122.24	260.62

Table 2. Wright's nonparametric ranks and signs variance ratio test

		Holding Period, K			
		K=2	K=4	K=8	K=16
ETI	R1	-1.293393	1.053974	3.191623*	4.214997*
	R2	0.646159	3.382096*	5.708189*	6.753253*
	S1	26.56961	42.89626*	63.14640*	90.74418*
	R1	13.04272*	20.95619*	26.79515*	30.79531 *
GCB	R2	12.52764*	19.94472*	25.17988*	28.44313*
	S1	22.88857*	36.26191*	50.11587*	66.17718*
	R1	2.975166*	6.638933*	11.213466*	16.255853*
GOIL	R2	3.699623*	7.676405*	12.330244*	17.409710*
	S1	26.00330*	41.72327*	61.07236*	86.51723*

* signifies significant at 0.05 level.

Figures in columns 3-6 of Table 2 represent the values of the test statistics R1, R2 and S1 for each index series. R1, R2 and S1 are based on the nonparametric test, following Wright (2000).

The results for the Wright's Ranks and Signs test in the table above show that there is strong support for the rejection of the Random Walk Hypothesis suggesting heteroscedasticity.

We now present the results obtained by modelling the three equities individually.

4.1 Modelling the EIT Data

4.1.1 Stationarity Test for ETI

We employed the KPSS Test for Level Stationarity with the hypotheses below:

H_o: Level stationary

H_a: Not stationary

With a p-value of 0.01, the null hypothesis for the KPSS test was rejected. This implies that the series is not stationary. After differencing once, the series for ETI became stationary.

4.1.2 Model Selection for ETI

The GARCH (1, 1) model had the smallest AICc as observed in Table 2. Thus, the GARCH (1, 1) model is selected. Apart from parameter β_1, all parameters of the GARCH (1, 1) are statistically significant at 5% level of confidence. The p-value of 0.9703 for the Box-Ljung test is greater than 0.05, thus, we cannot reject the hypothesis that the autocorrelation of residuals is different from zero. The GARCH (1, 1) model therefore represents the residuals adequately.

GARCH (1, 1) model for ETI:

$$\sigma_t^2 = 5.408e-4 \ + 3.464\mathrm{e}-02\ \mathrm{Y}_{t-1}^2 + 1.138\mathrm{e}-13\ \sigma_{t-1}^2 \tag{4}$$

Table 3. GARCH (p, q) model for ecobank transnational incoporated (ETI)

		ESTIMATE	STD ERROR	T VALUE	Pr(>|t|)	AICc
GARCH (1,1)	ω	5.408e-04	3.196e-05	16.924	<2e-16 ***	-10.67124
	α_1	3.464e-02	1.104e-02	3.137	0.0017 **	
	β_1	1.138e-13	5.905e-02	0.000	1.0000	
GARCH (1,2)						
	ω	5.134e-04	NA	NA	NA	-8.660539
	α_1	5.075e-02	NA	NA	NA	
	α_2	7.215e-14	NA	NA	NA	
	β_1	5.424e-02	NA	NA	NA	
GARCH (2,1)	ω	5.079e-04	NA	NA	NA	-10.67043
	α_1	1.486e-14	NA	NA	NA	-10.67043
	β_1	3.816e-02	NA	NA	NA	
	β_2	3.038e-02	NA	NA	NA	

GARCH (2,2)	ω	4.912e-04	NA	NA	NA	-8.660439
	α_1	3.526e-02	NA	NA	NA	-8.660439
	α_2	5.782e-15	NA	NA	NA	
	β_1	5.861e-02	NA	NA	NA	
	β_2	3.194e-02	NA	NA	NA	

4.2 Modelling the GCB Data

4.2.1 Stationarity Test for GCB

A similar KPSS Test for Level Stationarity was also conducted:

A p-value of 0.1 obtained implies that the null hypothesis of level stationarity cannot be rejected at 5% level of significance.

4.2.2 Model Selection for GCB

From Table 4, the GARCH (1, 1) model has the smallest AICc. Thus, the GARCH (1, 1) model was selected. All parameters have p-values less than 0.05 indicating statistical significance. A p-value of 0.8708 for the Box-Ljung test is greater than 0.05, thus, we cannot reject the hypothesis that the autocorrelation of residuals is different from zero. The GARCH (1, 1) model therefore represents the residuals adequately.

GARCH (1, 1) model for GCB:

$$\sigma_t^2 = 0.001177 + 0.204138\, \mathrm{Y}_{t-1}^2 + 0.444406\, \sigma_{t-1}^2 \quad (5)$$

Table 4. GARCH (p, q) models for ghana commercial bank (GCB)

GARCH (1,1)		**ESTIMATE**	**STD ERROR**	**T VALUE**	**Pr(>|t|)**	**AICc**
	ω	1.177e-03	7.956e-05	14.792	< 2e-16 ***	-9.885795
	α_1	2.041e-01	2.486e-02	8.211	2.22e-16 ***	
	β_1	4.444e-01	3.726e-02	11.928	< 2e-16 ***	
GARCH (1,2)	ω	1.709e-03	1.221e-05	139.92	< 2e-16 ***	-7.906969
	α_1	9.957e-02	1.671e-02	5.96	2.53e-09 ***	
	α_2	1.300e+00	2.174e-02	59.80	< 2e-16 ***	
	β_1	1.102e-02	5.895e-03	1.87	0.0615 .	
GARCH (2,1)	ω	1.040e-03	1.293e-04	8.042	8.88e-16 ***	-9.882602
	α_1	1.203e-01	2.294e-02	5.247	1.55e-07 ***	-9.882602
	β_1	5.221e-01	1.292e-01	4.039	5.36e-05 ***	
	β_2	8.283e-14	8.158e-02	0.000	1	
GARCH (2,2)	ω	1.709e-03	1.405e-05	121.646	< 2e-16 ***	-7.906969
	α_1	9.972e-02	1.715e-02	5.816	6.04e-09 ***	-7.906969
	α_2	1.300e+00	2.221e-02	58.535	< 2e-16 ***	
	β_1	1.095e-02	5.986e-03	1.830	0.0672 .	
	β_2	2.399e-08	5.155e-03	0.000	1.0000	

4.3 Modelling the GOIL Data

4.3.1 Stationarity Test for GOIL

Finally, KPSS Test for Level Stationarity was also conducted for the GOIL data.

A p-value of 0.1 obtained implied that the null hypothesis of level stationarity cannot be rejected at 5% level of significance.

4.3.2 Model Selection for GOIL

From Table 5, the GARCH (1, 1) model has the smallest AICc. Thus, the GARCH (1, 1) model is selected. All parameters have p-values less than 0.05 indicating statistical significance. The p-value of the Box-Ljung test is greater than 0.05 (0.9562), thus, we cannot reject the hypothesis that the autocorrelation of residuals is different from zero. The GARCH (1, 1) model therefore represents the residuals adequately.

GARCH (1, 1) model for GOIL:

$$\sigma_t^2 = 0.0001176 + 0.1232554\, Y_{t-1}^2 + 0.3213134\sigma_{t-1}^2 \quad (6)$$

Table 5. GARCH (p, q) models for Ghana oil company limited (GOIL)

GARCH (1,1)		ESTIMATE	STD ERROR	T VALUE	Pr(>|t|)	AICc
	ω	1.176e-04	1.084e-05	10.845	< 2e-16 ***	-11.08503
	α_1	1.233e-01	2.545e-02	4.844	1.28e-06 ***	
	β_1	3.213e-01	6.252e-02	5.140	2.75e-07 ***	
GARCH (1,2)	ω	1.691e-04	1.090e-05			-9.08019
	α_1	3.921e-02	6.293e-03			
	α_2	1.268e-01	9.546e-03			
	β_1	1.867e-14	6.467e-02			
GARCH (2,1)	ω	1.350e-04	NA	NA	NA	-11.08293
	α_1	1.024e-01	NA	NA	NA	-11.08293
	β_1	2.315e-01	NA	NA	NA	
	β_2	7.310e-17	NA	NA	NA	
GARCH (2,2)	ω	1.632e-04	1.212e-05	13.461	< 2e-16 ***	-9.080438
	α_1	5.533e-02	1.020e-02	5.425	5.79e-08 ***	-9.080438
	α_2	1.286e-01	1.052e-02	12.225	< 2e-16 ***	
	β_1	3.018e-02	7.690e-02	0.393	0.695	
	β_2	1.506e-13	4.812e-02	0.000	1.0	

5. Conclusion

Taking each company into account, starting with ETI, it was observed that the series for ETI was not stationary. The series was differenced once to achieve stationarity. The residuals of the series exhibited ARCH effects. This indicated that the error term (residuals) did not have constant variance (that is to say they were heteroscedastic). A GARCH (1, 1) model was fitted to the residuals of the series. An in-sample forecast of the volatilities showed that the model accurately predicted the volatilities over the period under discussion. It was observed that the periods of high volatility were in the year 2008 which was an election year. This could be attributed to the fact that investors become skeptical about investing during an election year. The GARCH (1, 1) model was therefore used to perform an out-of-sample volatility forecast for ETI.

For GCB, the series was stationary. The residuals of the series exhibited ARCH effects. A GARCH (1, 1) model was fitted to the series. All parameters obtained were statistically significant at 5% level of confidence. High volatilities were observed in the year 2008 and 2014. The year 2008 being an election year in Ghana and the year 2014 having several economic challenges may have reduced trading activities on the stock market for GCB. The fitted GARCH (1, 1) model clearly depicted the in-sample volatility for GCB. The model was used to perform an out-of-sample volatility for GCB.

Finally, the series for GOIL was found to be stationary. The residuals of the series for GOIL exhibited ARCH effects. A GARCH (1, 1) model was fitted to the series and all parameters obtained were found to be statistically significant. High volatilities were observed in the year 2008. The GARCH (1, 1) model was used to perform an out-of-sample forecast of volatility of GOIL. The study recommends the use and comparison of other variants of the GARCH model in estimation of volatility.

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