Modeling Stock Market Volatility Using GARCH Models Case Study of Dar es Salaam Stock Exchange (DSE)

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ABSTRACT

This study was carried out to model volatility of stock returns at Dar es Salaam Stock Exchange (DSE) using daily closing stock price indices from 2nd January 2012 to 22nd November 2018. Modeling was done using both symmetrical and asymmetrical generalized auto regressive Heteroskedastic model (GARCH) models; these were GARCH (1,1), E-GARCH (1,1) and P-GARCH (1,1). The findings showed that all three (3) models were significant to forecast stock returns volatility at DSE. GARCH (1,1) and P-GARCH (1,1) both revealed that the magnitude of shocks in volatility is higher with good news as opposed to bad news. E-GARCH model (1,1) showed the evidence of leverage effect associated with the stock returns which can be detrimental to the trading companies' capital structures. P-GARCH (1,1) was found to be more accurate to in predicting stock returns based on both the Root Mean Squares Error (RMSE) and Theil Inequality Coefficient (TIC).

Keywords: Volatility, Dar es Salaam Stock Exchange (DSE), GARCH.

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1. INTRODUCTION

Volatility refers to the amount of risk or uncertainty pertaining to the variations in a security's value. Some securities are highly volatile which implies that their values fluctuate over a larger range of values while others are less volatile which means that their values can be spread out over s smaller range of values. Fama (1965) depict that this variation/deviation of securities' returns are not directly observable hence it's the duty of traders, institutional investors and other participants to have an understanding of the nature of the returns between return and volatility.

The Global growth of stock markets has aroused interest among researchers and practitioners about modeling volatility of stock returns. Modeling volatility forms a vital part of designing investment plans to reduce risk and improve stock returns and it is also very useful in securities and options pricing. However, its importance is not only confined to investors and other market participants, but also to the overall economy as well. High levels of volatility tend to distort stability of capital markets, destabilize currency value and hinder international trade (Bhowmik, 2013).

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Over the years numerous models have been devised by researchers seeking to model volatility in stock returns, these have been grouped into symmetrical and non-symmetrical models. Engle (1982) is considered to be the pioneer of volatility modeling designed Auto regressive Conditional Heteroskedastic (ARCH) model to forecast time series data volatility. After a few years (Bollerslev, 1986) developed a model known as Generalized-ARCH (GARCH) model. The other models include GARCH in Mean Model (GARCH-M) by (Engle et al, 1987); Exponential GARCH (EGARCH) model by (Nelson, 1991) and Threshold-GARCH (TGARCH) by (Zakoian, 1994).

Stock market volatility has been widely researched in developed countries; unfortunately the case is different for Sub Saharan Africa as only a few studies have been carried out over the years to investigate the matter. Studies such as those by (Wagala et al; 2012) on Nairobi Stock Exchange, (Ogege; 2016) on Nigerian Stock Exchange are among a few of these studies that forecast stock market volatility. So this paper aims to add knowledge about stock market volatility in Africa by modeling this phenomenon at Dar es Salaam Stock Exchange (DSE) using daily closing price indices in the period from 2nd January 2012 to 22nd November 2018.

1.1 Objectives of the Study

The main objective of this study is to model stock market volatility at Dar es Salaam Stock Exchange (DSE). The specific objectives are as follows;

a) To forecast stock returns volatility using both symmetrical and asymmetrical models.
b) To examine the accuracy of forecasting models in predicting volatility of stock returns.

1.2 Significance of the Study

This study is vital as it adds knowledge to the existing contrast between theories and empirical studies on the topic in Tanzania perspective. The financial analysts, investors and other key players in the Dar es Salaam Stock Exchange (DSE) will be able to get some insights on how stock returns behave so that they can be in a position to predict future behavior. This will help these market players to improve stock returns using scientific means rather than just predicting stock price behavior on individual intuition or gut feeling.

1.3 Overview of Dar Salaam Stock Exchange (DSE)

The Dar es Salaam Stock Exchange (DSE) is a stock exchange located Dar es Salaam City, Tanzania. DSE was established by the capital markets and security authority (CMSA) under the Capital Markets and Securities (CMS) Act of 1994. It was incorporated in September 1996 but commenced trading in April 1998. DSE is a member of the African Stock Exchanges Association.

Trading is conducted five (5) days a week; from Monday through Friday from 10.00 am to 14.00 pm. DSE operations are monitored and supervised by the Capital Markets and Securities Authority (CMSA). Trading at DSE is carried out through an Automated Trading System (ATS). ATS is an automated electronic system that matches bids and offers by making use of electronic matching engine. The ATS is fully integrated with the

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CDS to assist automated validation of securities holdings and straight through processing of securities transactions.

Initially DSE was incorporated as a private company limited by guarantee and not having a share capital under the Companies Ordinate, however in June 2015; DSE re-registered and became a public limited company. DSE changed its name from Dar Es Salaam Stock Exchange Limited to Dar Es Salaam Stock Exchange Public Limited Company.

DSE offers several benefits to issuers of financial instruments including reduced corporate tax from 30% to 25% for three (3) successive years subsequent to listing of a company that have issued at least 25% of its shares to the public together with tax deductibility of all Initial Public Offering (IPO) costs for the purposes of income tax determination.

The investors at DSE enjoy zero capital gain tax as opposed to 10% for unlisted companies, zero stamp duty on transactions executed at the DSE compared to 6% for unlisted companies, 5% withholding tax on dividend income as opposed to 10% for unlisted companies and zero withholding tax on interest income from listed bonds whose maturities are three years and above. As of November 2018 a total of 28 companies were listed at DSE with a total market capitalization of TZS. 19.903071 Trillion.

2. LITERATURE REVIEW

A study by (Eryilmaz, 2015) modeled and examined stock market volatility of Istanbul Stock Exchange using BIST-100 index for the period 1997-2015.The research employed ARCH, GARCH, EGARCH and TARCH models and found out that the EGARCH best models volatility for BIST-100 and bad news that impact the market were observed to accelerate volatility at Istanbul Stock Exchange.

Srinivasan (2011) conducted a study forecasting stock market volatility of S&P 500 index returns of New York Stock Exchange (NYSE). The study made use of daily data from 1st January 1996 to 29th January 2010 and employed GARCH (1,1), E-GARCH (1,1) and T-GARCH (1,1) models. The results revealed that the symmetric GARCH model is more efficient in forecasting conditional variance as opposed to asymmetric GARCH models inspite of leverage effect.

Tamilselvan & Vali (2016) forecasted stock market volatility using four (4) indices from Muscat security market in the period 2001-2015. The study made use of GARCH, EGARCH and TGARCH models and results revealed a positive relationship between risk and return. The findings further showed that GARCH models generated significant evidence of asymmetrical relationship between return shocks and volatility adjustments in all four (4) indices.

Wagala et al (2012) examined stock volatility at Nairobi Stock Exchange (NSE) by employing the ARCH and GARCH models. The study used the Shwartz Bayesian Criteria (SBC), Akaike Information Criteria (AIC) and the Mean Squared Error (MSE) to evaluate the ARCH and GARCH models. The results revealed that the AR-Integrated GARCH (IGARCH) models are the most efficient models for forecasting volatility at this stock market.

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In another study, (Dima and Haim, 2008) modeled volatility of stock returns in using stock indices from Tel Aviv Stock Exchange (TASE) by employing GARCH and EGARCH models. The findings show that asymmetric GARCH model together with EGARCH model is more efficient in modeling stock indices volatility at TASE.

The other study by (Ogege, 2016) assessed the nature of stock returns at Nigerian Stock Exchange (NSE) employing monthly stock indices in the period January 2003-December 2014. The research used GARCH (1.1) model to analyze stock returns and the results provided strong evidence of volatility clustering in the NSE return series and volatility persistence for the Nigeria stock returns data.

Banumathy and Azhagaiah (2012) also modeled stock market volatility on Indian stock market using daily closing prices of S&P CNX Nifty Index for the period 2003 - 2012. Both symmetric and asymmetric models of GARCH were used to analyze volatility and the results found GARCH (1,1) and TGARCH (1,1) models to be the most appropriate models to forecast symmetric and asymmetric stock volatility respectively.

Ahmed and Suliman (2011) analyzed volatility of daily stock returns at Khartoum Stock Exchange (KSE) in the period (January 2006 - November 2010). The study employed both symmetric and asymmetric GARCH models and found out that asymmetric models far better estimations of volatility as compared to symmetric models the fact which shows the evidence of leverage effect. The findings indicate high levels of volatility in stock returns at KSE.

3. METHODOLOGY

3.1 Research Design

This study employs a quantitative research design; modeling stock market volatility involves statistical analysis using quantitative stock market index data.

3.2 Types of Data

The study uses time series data from DSE daily closing price index, these statistics were obtained from DSE website which is the commonly used source for providing stock market information of listed companies together with the market indices in real time.

3.3 Study Period

The study covers a period of from 2nd January 2012 to 22nd November 2018 which is deemed to be sufficient period of time to generate appropriate conclusions due to substantial number of data sets/observations.

3.4 Data Analysis and Model Specifications

Data analysis tools were applied with respect to the specific objectives of the study and this was done using STATA 14 software.

3.4.1 Normality Diagnostics

Before commencing stock return volatility modeling it is vital to examine whether the daily time series data are normally distributed as a prerequisite. The basic descriptive

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statistics were carried out namely; Mean, Standard deviation, Variance, Skewness and Kurtosis.

Lastly, the study conducted the Shapiro normality test as proposed by (Shapiro and Francia, 1972) to statistically test whether the daily stock return data used for modeling are normally distributed. The following hypothesis was developed and tested for this test;

H_o = The time series data are not normally distributed
H_1 = The time series data are normally distributed

3.4.2 Unit Root Test

Modeling stock market returns requires time series data to be stationary i.e. must not have a unit root. To test for unit root or stationarity of daily stock returns the Augmented Dick Fuller Test (ADF) developed by (Dickey and Fuller, 1979). The ADF is presented as shown in the equation below;

$$\Delta y_t = \alpha y_{t-1} + \sum_{s=1}^{m} a_s \Delta y_{t-s} + v_t$$

Whereby Yt = Variable Y at current time "t"
Yt-1 = Variable Y at previous time "t-1"

The following hypothesis was developed and tested;
H_o = Time series data does not contain a unit root
H_1 = Time series does contain a unit root

3.4.3 Heteroskedasticity Diagnosis

Heteroskedasticity is a condition whereby the variability/standard deviation of a variable is not constant over a period of time. Stock returns can sometimes exhibit this behavior and so before applying the forecasting models it was vital to test for presence of autoregressive conditional heteroskedasticity effects This was done by employing Langrage Multiplier for autoregressive conditional heteroskedasticity. The following hypothesis was developed;
H_0: There are autoregressive conditional Heteroskedastic effects in the time series data.
H_1: There are no autoregressive conditional Heteroskedastic effects in the time series data.

3.4.4 The autoregressive model

To model volatility of stock returns using ARCH and GARCH models it is vital to first develop an autoregressive equation which is as follows

$$\mathbf{SR_t = \beta_1 SR_{t-1} + \beta_o + e}$$

Whereby;
SR_t = Stock return at the current time "t" **SR_{t-1} =** Stock return at the previous time "t-1"
β_1 = Coefficient of stock market return at time (t-1) **β_o =** The intercept
e = A stochastic error term
The important variable in this model is the stock market return which refers to the gains/losses an investor realizes from the changes in stock's price.

$$\textbf{Stock return (SR)} = \log (SR_t/SR_{t-1})$$

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The autoregressive model presented above is an indication of the fact that the stock return of the current period is dependent upon two (2) factors; firstly, the stock returns from previous period and stochastic error term. This model must first be developed and tested before going into detail to model stock returns volatility.

3.4.5 Symmetrical Volatility Models

This study aims to forecast volatility using both symmetrical and non symmetrical forecasting models. The first part of modeling employed symmetrical models, the models and their descriptions are as follows;

Generalized Auto Regressive Conditional Heteroskedastic (GARCH) Model

GARCH model was introduced by (Bollerslev, 1986) is an improvement to the previous ARCH model which includes a moving average aspect in modeling time series data volatility in addition to autoregressive aspect. But the problem with this model is that it does not capture asymmetrical volatility of returns. This is presented as follows;

Mean equation; $rt = \mu + \varepsilon\, t$ ……………………………………………………….(i)

Variance equation; $\sigma_t^2 = \alpha_0 + \sum^{q}_{i=1} \alpha_i\, \varepsilon^2_{t-1} + \sum^{p}_{j=1} \beta_j\, \alpha^2_{t-j}$………………………(ii)

Where; σ_t^2 = Conditional variance; μ = Average return; εt= residual returns

Assume $\alpha_0 > 0$; $\alpha_i \geq 0$, i = 1, q; $\beta_j \geq 0$, j = 1, p; $\sum^{q}_{i-1} \alpha_i + \sum^{p}_{j-1} \beta_j < 1$ for ensuring $\{\sigma^2_t\}$ as weak stationary.

3.4.6 Asymmetrical Volatility Models

a) Exponential Generalized Auto Regressive Conditional Heteroskedastic (E-GARCH) Model

E-GARCH was put forward by (Nelson, 1991) to model volatility of time series data based on the asymmetrical effect of positive and negative error terms on volatility. The model forecasts volatility of a time series variable by using conditional variance as a multiplicative function rather than addictive functions of lagged innovations. It incorporates both the symmetrical and asymmetrical volatility of returns. This is presented as follows;

$$\mathrm{Log}(\sigma_t^2) = c + \sum^{q}_{i=1} \alpha_i \left((|\mathcal{E}_{t-1}/\alpha_{t-1}| - E(|\mathcal{E}_{t-1}/\alpha_{t-1}|)\right) + \sum^{p}_{j=1} \beta_j \log\alpha^2_{t-j} + \sum^{p}_{i=1} \gamma_i\, (\mathcal{E}_{t-1}/\alpha_{t-1})$$

Whereby; α = The symmetric effect;

β = measures the lagged conditional variance and γ reflects the asymmetric performance.

b) Power Generalized Auto Regressive Conditional Heteroskedastic (P-GARCH) Model

PGARCH was developed by (Ding et al, 1993) and the model took a different approach compared to the preceding models by using conditional standard deviation rather than conditional variance as a measure of volatility. It does not impose power parameter as in

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the E-GARCH but it generated its own power based on the nature of volatility. This is presented as follows;

$$\sigma_t^{\sigma} = \text{ш} + \beta_1 \alpha^{\sigma}_{t-1} + (|\varepsilon_{t-1}| - \gamma_1 \varepsilon_{t-1})^{\sigma}$$

Whereby; $\alpha 1$ and $\beta 1$ = standard ARCH and GARCH parameters; $\gamma 1$= The leverage parameter

σ = The parameter for the power term.

3.4.7 Forecasting accuracy

The forecasting accuracy of each forecasting model tested was measured by the following tools;

3.4.7.1 Root Mean Squares Error (RMSE)

This test estimates the differences between the observed values and the forecasted dependent variables by summing them up together and dividing the total by degrees of freedom to obtain the mean error sum of squares. Then the square root of the mean error sum of squares is the RMSE. The forecasting model accuracy is measured by the magnitude of RMSE and usually a smaller value means less errors.

3.4.7.2 Theil Inequality Coefficient (TIC)

TIC as proposed by (Theil, 1958) is an index that measures forecasting accuracy using the ratio of the Mean Square Error (MSE) of the predicted values and Mean Square Error (MSE) of the observed actual values. The coefficient ranges from 0 to 1 with the values near to zero (0) indicating less errors and more accurate forecast.

4. RESEARCH FINDINGS AND RESULTS

4.1 Descriptive Statistics

The descriptive statistics for weekly DSE returns for the study period are presented in table 1 below;

Table 1: Results from descriptive statistics for daily DSE returns

50%	.00235		Mean	.0114493
		Largest	Std. Dev.	.8177528
75%	.1695	4.8252		
90%	.47235	6.7253	Variance	.6687197
95%	.7152	7.1094	Skewness	.2965913
99%	1.4425	14.2504	Kurtosis	121.6332

Source: Field data (2018)

The results presented in table 1 show the mean stock returns of 0.011%, which indicates positive average returns to the stock investors at DSE. The stock returns are skewed to the positive side with the skewness value of 0.2965 which indicates that the time series data of stock returns is asymmetrical i.e. skewed to the right. Kurtosis value is high which is an indication that normal distribution curve has fatter and longer tails which makes it leptokurtic.

4.2 Shapiro-Francia Normality Test Results for DSE daily Returns

The results for Shapiro-Francia normality test for DSE daily stock returns are presented in table 2 below:

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Table 2: Results from Shapiro-Francia normality test

Variable	Obs	W	V	z	Prob>z
stockreturnt	1,690	0.50727	501.313	16.117	0.00000

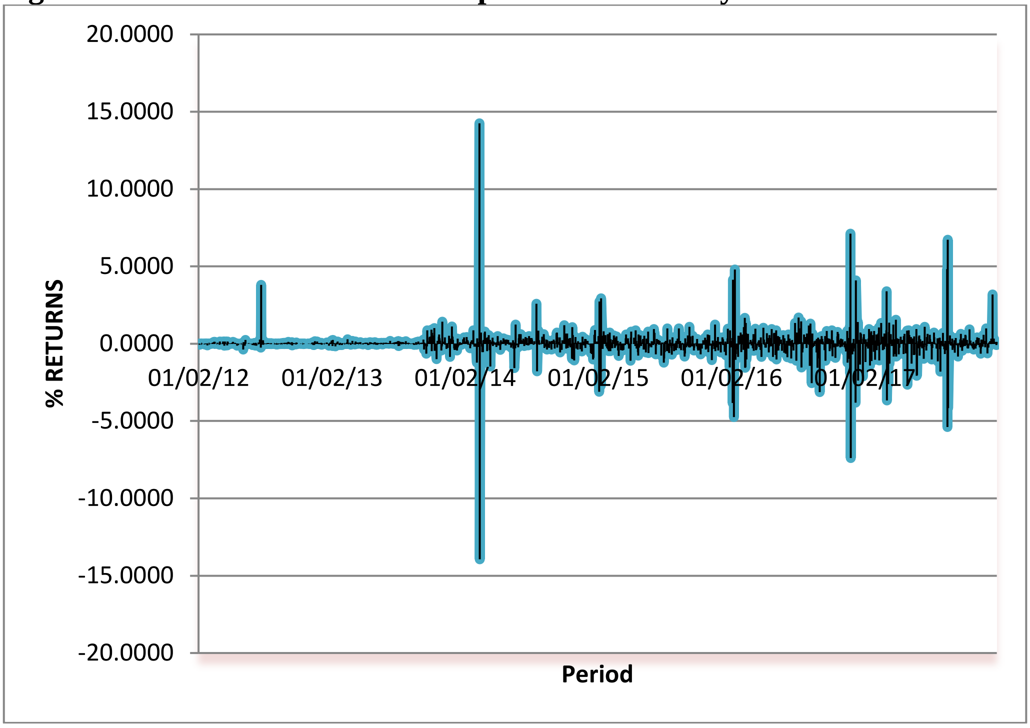
Source: Field data (2018)

The results from table 2 indicate that the p value is very small i.e. far less than 0.05 level of confidence hence the null hypothesis is rejected. This shows that DSE returns used in this study are not normally distributed which is a common phenomenon in financial time series data.

4.3 DSE Daily Stock Returns Trend

This study models volatility of DSE daily stock returns from 2^{nd} January 2012 to 22^{nd} November 2018. The trend of these returns is presented in figure 1 below;

Figure 1: DSE stock returns in the period 2^{nd} January 2012 to 22^{nd} November 2018)



Source: Field data (2018)

The graphical presentation of stock returns shows how they behavior over time. It can be observed that variations in returns have increased over time from 2014. Volatility clustering has increased from this year to date as compared to the period before 2014 which indicates the increase in the magnitude of volatility at DSE. Understanding how returns behave is vital for forecasting how volatile they and the trend shows that volatility has increased over time which can cause investors to be skeptical in making stock investment.

4.4 Augmented Dickey-Fuller (ADF) Unit Root Test Results

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The ADF results for unit root of DSE stock returns are presented in table 3 below;

Table 3: Results from Augmented Dickey Fuller test for unit root

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-3.725	-3.960	-3.410	-3.120

MacKinnon approximate p-value for Z(t) = 0.0208

Source: Field data (2018)

The ADF test results presented in table 3 above show that the test statistic value of -3.725 is less than the 1% critical value of -3.960, so the null hypothesis cannot be rejected at 1% confidence interval. This indicates that the DSE stock returns are stationary i.e. do not contain a unit root which makes them appropriate for volatility modeling.

4.5 Langrage Multiplier (LM) Heteroskedasticity Test Results

The results for this crucial test required before applying GARCH models to forecast stock returns are presented in table 4 below;

Table 4: Results from Langrage Multiplier test for auto regressive conditional Heteroskedastic effects

lags(*p*)	chi2	df	Prob > chi2
1	183.133	1	0.0000

Source: Field data (2018)

The LM test results presented in table 4 shows that the p-value to be less than the 0.05 confidence interval so the null hypothesis is rejected which means that DSE daily returns have ARCH effects. This is a common feature of stock returns because the variance of returns over time changes which is a condition known as heteroskedasticity.

4.6 Symmetrical Volatility Modeling Results

4.6.1 Generalized Auto Regressive Conditional Heteroskedastic (GARCH) Modeling Results

The study modeled DSE stock returns by first employing GARCH model which is the most appropriate tool in the family of symmetrical models. The results for this model are presented in table 5 below;

The results presented in table 5 indicate that GARCH model is significant to explain volatility of DSE daily stock returns. This can be explained by the fact that the p-value is very small and far less than the 0.05 confidence interval. The GARCH coefficient of 0.6539662 is greater than zero (0) i.e. positive, so the argument can be made that positive or good news have a greater impact on stock returns volatility as opposed to negative or bad news.

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Table 5: Results from generalized auto regressive conditional Heteroskedastic (ARCH) modeling

dse	Coef.	OPG Std. Err.	z	P>|z|	[95% Conf.	Interval]
dse						
_cons	.007442	.002148	3.46	0.001	.0032319	.011652
ARCH						
arch L1.	1.427424	.0282911	50.45	0.000	1.371975	1.482874
garch L1.	.6539662	.0039723	164.63	0.000	.6461806	.6617518
_cons	.0004225	.0000608	6.95	0.000	.0003034	.0005417

Source: Field data (2018)

4.7 Asymmetrical Volatility Models

4.7.1Exponential Generalized Auto regressive Conditional Heteroskedastic (E-GARCH) Modeling

E-GARCH model results for stock returns volatility are presented in table 6;

Table 6: Results from exponential generalized auto regressive conditional Heteroskedastic (ARCH) modeling

dse	Coef.	OPG Std. Err.	z	P>|z|	[95% Conf.	Interval]
dse						
_cons	.0092916	.0152567	0.61	0.543	-.0206111	.0391943
ARCH						
egarch L1.	-.4317501	.0275647	-15.66	0.000	-.485776	-.3777242
arch L1.	.1355331	.0055158	24.57	0.000	.1247223	.146344
_cons	-1.26079	.0275875	-45.70	0.000	-1.314861	-1.20672

Source: Field data (2018)

The EGARCH modeling results presented in table 6 indicate that the model is significant to explain daily stock returns volatility at DSE as shown by the p-value which is far less than 0.05 confidence interval. The model has a coefficient of -0.4317501 which is less than zero (0) i.e. negative which indicates the fact that shocks in stock returns caused by bad or negative news are exceed those shocks caused by positive news. This is an indication of leverage effect on companies' capital structure which can increase risks caused by increasing proportion of debts.

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4.7.2 Power Generalized Auto Regressive Conditional Heteroskedastic (GARCH) Modeling Results

The results for PGARCH modeling of DSE daily stock returns are presented in table 7 below:

Table 7: Results from power generalized auto regressive conditional Heteroskedastic (PGARCH) modeling

dse	Coef.	OPG Std. Err.	z	P>|z|	[95% Conf.	Interval]
dse						
_cons	.0096765	.0008598	11.25	0.000	.0079913	.0113616
ARCH						
pgarch						
L1.	.6739781	.0043132	156.26	0.000	.6655244	.6824318
arch						
L1.	.7586091	.0196685	38.57	0.000	.7200596	.7971586
_cons	-.0000672	.0000122	-5.52	0.000	-.000091	-.0000433

Source: Field data (2018)

The results from PGARCH model for DSE daily stock returns show a very small p-value that is far less than 0.05 confidence interval which implies that this particular model is significant to forecast DSE daily stock returns. The model has a coefficient of 0.6739781 which is greater than zero (0), so the case can be made that based on PGARCH, positive or good news have a tremendous impact on stock returns volatility as opposed to negative or bad news.

4.8 Forecasting Accuracy

It has been observed that GARCH, EGARCH and PGARCH models are all significant in forecasting DSE daily stock returns. So after this, the study forecasted stock returns based on each of these significant models for the period 2nd January 2012 to 22nd November 2018. The forecasted figures were compared with the actual observed to test for forecasting accuracy. Two (2) tools namely; Root Mean Squared Error (RMSE) and Theil Inequality Coefficient (TIC) were used to assess forecasting accuracy and the results are presented in table 8;

Table 8: Root Mean Squared Error and Theil Inequality Coefficient Results for forecasting accuracy

No.	Model	Root Mean Squared Error (RMSE)	Theil Inequality Coefficient (TIC)
1.	GARCH (1,1)	17.969	0.5876
2.	E-GARCH (1,1)	29.875	0.6101
3.	P-GARCH (1,1)	2.6814	0.4724

Source: Field data (2018)

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The results from table 8 indicate that P-GARCH (1,1) forecasting model has the lowest RMSE compared to the other forecasting model which makes it more accurate in forecasting DSE stock returns volatility. On the other hand, P-GARCH (1,1) has also the lowest TIC compared to the other two (2) forecasting models. TIC ranges from 0 to 1 and the smaller it is, the smaller is the difference between observed values and forecasted values hence more accuracy. So in this case the argument can be made that P-GARCH (1,1) is more accurate in forecasting stock returns volatility at DSE.

4.9 Conclusions

Stock markets play an important role by enabling companies to raise extra capital from the public which enables them to expand their operations, increasing national income by paying taxes from profits and employ more people. Benefits from stock markets are not only confined to listed companies but also investors, brokers and the economy as well. So a well-functioning stock market is crucial for economic development especially of developing countries such as Tanzania.

One of the key issues that concerns market participants is that of volatility of stock returns. Highly volatile markets lower investors' confidence hence affecting the total market capitalization due to fear of losses due to the unpredictability of the markets. Stock markets that are less volatile are considered to be stable and create investors' confidence which increases their propensity to invest their funds. So the crucial aspect among experts is to understand the behavior or volatility of stock returns by forecasting or modeling them so that proper decisions can be made based on strong grounds. For instance options can be correctly priced if volatility is well forecasted which can help dealers and investors improve their profits.

This study has modeled volatility of stock returns at DSE using both symmetrical and asymmetrical models so as to ensure that the most efficient forecasting model is identified and put into use in this case the P-GARCH (1,1) was found to be more accurate as opposed to GARCH (1,1) and P-GARCH (1,1). So DSE participants are urged to apply this model in their efforts to forecast stock returns volatility and reduce uncertainties associated with these returns.

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