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Original Article

Modelling the Stock Market Volatility of Dar es Salaam Stock Exchange (DSE) using Generalized Autoregressive Conditional Heteroscedasticity

Pendo T Kivyiro [1,*] and Doreen Laurent [1]

[1] Institute of Finance Management, 5 Shaaban Robert St, Dar es Salaam, Tanzania; doreen.rutagumirwa@ifm.ac.tz (D.L.)
* Correspondence: pendo.kivyiro@ifm.ac.tz (P.T.K.)

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Abstract: The existing empirical literature has extensively explored stock market return volatility in various emerging and developing markets; however, limited attention has been given to the Dar es Salaam Stock Exchange (DSE). This study seeks to address this gap by analyzing the volatility dynamics of stock returns in the DSE. The analysis is based on a dataset comprising 1,846 daily observations spanning the period from June 2014 to November 2021. Consistent with prior studies, the findings reveal a significant negative relationship between returns and risk, as modeled using the AR(1)-GARCH(1,1)-M framework. The application of the GARCH(1,1) model effectively captures volatility clustering, following the confirmation of heteroscedasticity in the return series. However, due to the GARCH model's limitations in capturing asymmetries in volatility (i.e., the leverage effect), the analysis was extended using the AR(1)-EGARCH model. The results support the presence of a leverage effect in the DSE, indicated by a negative and statistically significant leverage coefficient. This suggests that negative shocks have a greater impact on volatility than positive shocks of the same magnitude. Moreover, the study confirms a negative correlation between stock returns and volatility. These findings imply that higher levels of risk may lead to disproportionately larger losses for investors in the DSE. Therefore, market participants, policymakers, and portfolio managers must exercise caution and implement robust risk management strategies to safeguard investments against unexpected market fluctuations. The results also offer valuable insights for investors, scholars, and researchers interested in understanding the behavior of stock return volatility in frontier markets such as Tanzania.

Keywords: Stock Return Volatility; GARCH Models; Leverage Effect; Emerging Markets; Dar es Salaam Stock Exchange (DSE); Risk-Return Relationship.

1. Introduction

The Stock market plays an important role in the process of economic growth and development of a country by providing several opportunities for saving and investing to its investors. Similarly, the stock market is very essential for the development of financial systems since it is a place where stocks, equities, bonds and other securities are bought and sold. On the other hand, the stock market provides necessary indicators for information sharing among investors and regulators, for company valuation, pricing and forecasting of various macroeconomic indicators (Cherif & Gazdar 2010; Ugurlu et al., 2014; Panda & Nanda., 2018). Advances in technology have greatly impacted on financial systems worldwide by providing both opportunities and challenges to the stock markets operations. On the one hand, technology has facilitated an expansion of international financial transactions and the efficiency of global financial markets. On the other hand, financial markets are exposed to external risks and uncertainties as a result of global economic integration through technological advancements. One important issue of great concern to investors and practitioners is modelling stock market volatility, which have brought consensus of the need to examine the issue in depth (Bhowmik, 2013).

The stock market participants are more interested in modelling the volatility of stock returns because an increase in volatility could mean great gain or loss, thus leading to uncertainty. This unpredictability of stock returns makes the stock a risky investment venture that make it difficult for companies to raise capital in the capital markets which eventually affect the economy of a country. High levels of volatility tend to distort stability of capital markets, destabilize currency value and hinder international trade. In the present situation, the current interest in understanding the dynamics of volatility on the stock returns is highly crucial for researchers, financial analysts, investors and market regulators for making viable financial decisions (Hongyu & Zhichao, 2006; Frimpong & Oteng-Abayie, 2006; Bhowmik, 2013). Modelling volatility is an important area of research in financial markets and immense effort has been expended in improving volatility models. Better modelling forms a vital part of designing investment plans into better pricing of options, securities, risk management and it is also an important input for dynamic portfolio insurance plans. The primary function of various practitioners in the financial market is to understand the characteristics of the movements of stock returns and volatility that is vitality modelling (Poon & Granger, 2003; Srinivasan, 2011; Tamilselvan, 2016). Since volatility has great impact on the economy at large, modelling of the volatility in financial markets is important in creating healthy markets, establishing depth and funds transfer in market.

Volatility modelling has been carried out extensively in developed and emerging markets as compared to developing markets notably, in Dar Es Salaam stock market, Tanzania. Preliminary researches were conducted by Black (1976), Cox and Ross (1976), Christie (1982), Engle (1982), Bollerslev (1986) and more others. However, the results from early studies are mixed and hence impose a lot of arguments which provide room for further investigation about the phenomenon (Nelson, 1991; Lee et al., 2001; Chang et al., 2005; Ahmed & Suliman, 2011; Goudarzi & Ramanarayanan, 2010, 2011; Eryilmaz, 2015; Banumathy & Azhagaiah, 2015; Varughese & Mathew, 2017; Ogutu et al., 2018). It is against this backdrop that the study sought to determine the nature and behaviour of volatility of stock returns in the case of Dar Es Salaam Stock Exchange (DSE), Tanzania using different types of Generalized Autoregressive Conditional Heteroscedastic (GARCH) Models. The study contributes to the current literature in three-folds. First, to the best of our knowledge, while there are studies on modelling volatility in the literature, scholars have not yet modelled volatility using current daily data that capture two different political regimes in the case of Tanzania.

We believe that change in political power is vital in our analysis and may influence individual and institutional investor's decision-making process particularly in stock market participation. Secondly, unlike the relatively few previous studies conducted in Tanzania, this study employs more recent data to capture both symmetry and asymmetry effects of volatility clustering of DSE stock returns (See, e.g. Epaphra, 2016; Marobhe & Pastory, 2020). Third, the current study captures the period of onset of the Covid-19 pandemic (2019-2021), we believe this period is very important because the predicament impacted the stock markets forcefully globally, and Tanzania is not in isolation. In turn, the results from this study will be useful to practitioners in safeguarding portfolios from unforeseen market shocks so as to make better investment decisions in order to avoid large, unpredicted losses. The findings from this study therefore will be of great significance to practitioners, investors, policy makers, academicians and researchers.

1.1. Dar Es Salaam Stock Exchange (DSE) Profile

The Dar Es Salaam Stock Exchange (DSE) is located in Dar Es Salaam, the commercial capital and largest city in Tanzania. DSE was established in 1994 by the Capital Markets and Security Authority (CMSA) under the Capital Markets and Securities (CMS) Act of 1994 and was incorporated in September, 1996 as a company limited by guarantee without a share capital under the Companies Ordinance and commenced trading in April 1998.This marked an important milestone in the effort to develop a functioning capital market for the mobilization and allocation of long-term capital to the private sector. The DSE is the third stock Exchange in Africa to demutualize after the Johannesburg Stock Exchange (JSE) and the Nairobi Securities Exchange (NSE). It works under two segments namely the Main Investment Market segments (MIMS) and Enterprises Growth Market (EGM) (DSE, 2008; Norman, 2011; Mutaju & Pastory, 2019).

DSE was converted into public company limited by share on 29thJune, 2015. The enactment of DSE came as a result of government's policy of transforming its economy from public government dominated economy to private sector driven economy. As a result, DSE changed its name from Dar Es Salaam Stock Exchange Limited to Dar Es Salaam Stock Exchange Public Limited Company. DSE is a member of the African Stock Exchanges Association (DSE, 2020). The activities of the exchange are monitored and supervised by the Capital Markets and Securities Authority (CMSA). The DSE operates in close association with the Nairobi Securities Exchange in Kenya and the Uganda Securities Exchange in Uganda. Plans are underway to integrate the three to form a single East African bourse. There are two main financial products traded at the DSE namely, shares (i.e. equities) and bonds (i.e. debt instruments). According to the DSE official annual report (DSE, 2020), as on December 2020, there were 29 listed companies at DSE with a total market capitalization of TZS 15. 095billion. In this regard, the volatility analysis of stock markets is important for investors to measure and manage market risks more accurately. This in turn is useful in pricing capital assets, financial securities, and selecting portfolios.

This study aims to investigate the relationship between stock return and expected volatility of selected companies listed at Dar Es Salaam Stock Exchange (DSE) in Tanzania. Specifically, the study is seeking to examine whether the stock returns follow the hypothesis of random walk. That is, we need to see whether the series return is stationary or not. Furthermore, we examine whether stock return volatility changes over time and whether it is predictable. We use the GARCH family models with emphasis on GARCH-M model to capture the relationship between stock returns and volatility. The rest of this paper is organized as follows. Section 2 reports some previous related theoretical and empirical literatures while section 3 discusses the materials and methodologies employed. Section 4 presents and discusses the results while section 5 concludes the study with appropriate policy implications.

2. Literature Review

The The ability of Autoregressive Conditional Heteroscedastic (ARCH) and GARCH family models to investigate the relationship between stock returns and market volatility, both theoretically and empirically have been validated in many studies. For example, Lee at el. (2001) used the time series model to examine the relationship between returns and volatility on China's stock markets. They found out that GARCH and EGACH model provides strong evidence of time-varying volatility and concludes that volatility is highly persistent and predictable. Nevertheless, they found no evidence on the relationship between expected returns and risk when employing GARCH-M model. Miron and Tudor (2010) estimated different asymmetric GARCH family models (EGARCH, PGARCH and TGARCH) to capture volatility of returns of Romanian stock markets. The results of their analysis showed that EGARCH using GARCH-in-Mean Model are more accurate in the Romanian stock market. Wagala et al. (2012) examined stock volatility at Nairobi Stock Exchange (NSE) by employing the ARCH and GARCH type models. The results show that the AR-Integrated GARCH (IGARCH) models with Student's t-distribution are the best models for modelling volatility in the NSE.

In another study, Maqsood et al. (2017) modelled volatility of daily stock returns from Nairobi Stock Exchange (NSE) using GARCH models. They analysed data from March 2013 to February 2016.The findings showed a highly persistent volatility process and the presence of the leverage effect in the NSE return series. The study also revealed that the asymmetric GARCH models provide better fit for NSE than the symmetric models. Dima and Haim (2008) found that asymmetric GARCH model together with EGARCH model is more efficient in modelling stock indices volatility in the case of Tel Aviv Stock Exchange. Rusere and Kaseke (2021) modelled conditional volatility using GARCH, GARCH-M, TGARCH and EGARCH models. They analysed daily data of FTSE/JSE Top 40 index of the Johannesburg Stock Exchange from 2009 to 2019. The results showed that the EGARCH model is most suitable for predicting the behaviour of equity returns, even during the global oil crisis period. Singh & Tripathi (2016) investigated the volatility pattern of daily closing prices of S&P CNX Nifty Index from April 2006 to March 2016. The study employed both symmetric and asymmetric GARCH models and found out that GARCH-M and EGARCH models to be most appropriate model as per the Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC) and Log Likelihood ratios.

Additionally, the study confirms the existence of a positive and insignificant risk premium as per GARCH-M model. The asymmetric effect (leverage) captured by the parameter of EGARCH and TGARCH models show that negative shocks have significant effect on conditional variance (volatility). Similar findings were also observed by Banumathy & Azhagaiah (2015). However, the study by Mathur et al. (2016) revealed high volatility for the period 2007-2009 using the daily returns from the portfolio of 20 companies on Bombay Stock Exchange. Concluded that the Indian economy was highly impacted by global financial crisis. Ahmed and Suliman (2011) examined volatility of daily stock returns of Khartoum Stock Exchange by employing both symmetric and asymmetric GARCH models and found that asymmetric models are far better in estimating volatility as compared to symmetric models. Eryilmaz (2015) modelled and analysed stock market volatility of Istanbul by employing ARCH, GARCH, EGARCH and TARCH models. The results indicated that the EGARCH is the most suitable model for modelling volatility returns and bad news that impact the market were observed to accelerate volatility. Furthermore, volatility continuity was observed.

Dennis et al. (2006) used the data for 50 individual stocks traded on Chicago Board Option Exchange (CBOE) to study the relationship between stock returns, implied volatility innovations and the Asymmetric volatility phenomenon. They found out that, the relationship between stock returns and innovativeness in systematic volatility is substantially negative. However, the study did not undertake model-fitting tests to confirm the models. The results from early studies are attributed and affected by the methodology used in the analysis. More recent studies have typically employed most popular techniques such as the Auto regressive Conditional Heteroscedasticity process (ARCH) which was proposed by Engle (1982), and General Auto regressive Conditional Heteroscedasticity (GARCH) which was initially proposed by Bollerslev (1986). Panait and Slavescu (2012) used the GARCH-in-mean model to compare the volatility for seven Romanian companies traded on Bucharest Stock Exchange (BSE) and three market indices, during the period from 1997 to 2012. The results of their study showed that persistency is more evident in the daily returns as compared with the monthly and weekly series. Conversely, the GARCH-in-mean model failed to confirm that an increase in volatility leads to a rise in future returns. Though the paper provides substantial empirical evidence of the characteristics of BSE, it did not undertake rigorous discussion of the reviewed literatures. Joldes (2019) analysed the volatility of daily returns in the Romanian stock market over the period January 2005 to December 2017 using four stock market indices (BET, BETC, BETPlus and ROTX). The GARCH models, the results show clear evidence of volatility shifting over the period. Further, the study found a great influence of international stock markets on the capital market operations in Romania.

Abdalla and Winker (2012) analyzed stock market volatility using daily closing prices on the general indices in the two markets over the period of 2006 to 2010in two African exchanges; Khartoum Stock Exchange (KSE)from Sudan and Cairo and Alexandria Stock Exchange (CASE)from Egypt. They employed different univariate specifications of the GARCH model, including both symmetric and asymmetric models and the results found that while the conditional variance (volatility) is an explosive process for the KSE index returns series, it is quite persistent for the CASE index returns series. The results also support the hypothesis that there is a positive relationship between volatility and the expected stock returns. Furthermore, the results confirm the presence of leverage effect in the returns series. In a study by Gökbulut & Pekkaya (2014), EGARCH and TGARCH appeared to be superior for modelling the volatility of financial instruments in Turkey during the years 2002–2014. It was further observed that there is non-normality, volatility clusters, negative skewness, large kurtosis, and autocorrelation in the financial time series data. Thus, from the reviewed literature it may be explicated that results are inconclusive, since no unanimous conclusions have been reached so far about the robust volatility model to use. However, differences in the methodologies employed, the length of the data used, other variables in the assessment of volatility and the samples employed have been pointed out to be one of the causes of such diverse results. It is these methodological variations and observed literature gaps that motivated researchers to undertake this study in Tanzania.

3. Materials and Methods

In modelling the relationship between the stock return and volatility of Dar Es Salaam Stock exchange, we have used daily closing prices of the DSE index. The data used in the analysis have been extracted from the website of the same stock market (https://www.dse.co.tz), and the period covered is from June 25, 2014, to November 11, 2021 which constitute 1846 observations. As we have pointed out from the introductory part, we expect to test almost three hypotheses. The first hypothesis is to examine whether stock returns follow random walk as claimed by other prominent researchers. Most specifically, we test the existence of the unit root and stationarity concepts. The next hypothesis to be examined is whether stock return of DSE index exhibit volatility clustering over time and whether they are predictable. This is the most prominent feature of the time series of DSE, and to achieve this effect, we used up to date time series models proposed initially by Engle (1982) and then extended by Bollerslev (1986). These models are the family of Autoregressive Conditional Heteroscedastic (ARCH). These models are one of the particular non-linear models mostly used in financial econometrics used to capture the time-varying pattern of stock market volatility. The volatility of stock return has been modelled as a conditional mean in GARCH framework and was generalized by Bollerslev (1986). In this study we employ all ARCH type models whereby according to Engle, ARCH process is any series μ_t of the following form:

$$\begin{aligned} y_t &= \beta_1 + \beta_2 x_{2t} + \beta_3 x_{3t} + \ldots + \beta_k x_{kt} + \mu_t \\ \mu_t &= z_t \sigma_t \quad z_t \approx N(0,1) \\ \sigma_t^2 &= \alpha_0 + \sum_{i=1}^{q} \alpha_i \mu_{t-i}^2 \\ &= \alpha_0 + \alpha_1 \mu_{t-1}^2 + \alpha_2 \mu_{t-2}^2 + \cdots + \alpha_2 \mu_{t-p}^2 , \end{aligned} \tag{1}$$

Whereby z_t in an independently and identically distributed process whose properties are such that; $E(z_t) = 0$, $Var(z_t) = 1$ as indicated in Equation 2 and σ_t^2 is the time varying volatility. Equation 2 above is the general model that consists of mean and variance equation. To be more specific a conditional variance for ARCH (q) is given by:

$$\sigma_t^2 = Var(\mu_t | \Omega_{t-1}) = E[(\mu_t - E(\mu_t))^2 | \Omega_{t-1}], \tag{2}$$

That is conditional variance of error μ_t given its past values and Ω is known as the information set. However, it is assumed that $E(\mu_t) = 0$, hence Equation (2) can be written as indicated in Equation (3) (Brook, 2014)

$$\sigma_t^2 = Var(\mu_t | \Omega_{t-1}) = E[\mu_t{}^2 | \Omega_{t-1}], \tag{3}$$

But ARCH(q) model has some weakness in the sense that it requires long lag length and large number of parameters, hence we also employed GARCH(1,1) model as proposed by Bollerslev in order to offset the above weakness. The general form of the model is as indicated in Equation (4):

$$\sigma_t^2 = \alpha_0 + \alpha_1 \mu_{t-1}^2 + \beta \sigma_{t-1}^2, \tag{4}$$

Whereby generally GARCH (p, q) in expressed in the following form:

$$\sigma_t{}^2 = \alpha_o + \sum_{i=1}^{q} \alpha_i \mu_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 , \tag{5}$$

Whereby μ_{t-i}^2 (the ARCH term) indicates information about volatility from the previous period, measured as the lag of the squared residual from the conditional mean equation. σ_{t-j}^2 is the last period's forecast variance (the GARCH term) and α_0 is the constant term. The problems associated with GARCH model is that, the non-negativity constraints may be violated and the model cannot account for the leverage effects. The leverage effect (asymmetric volatility) is a phenomenon which describes the negative relationship between asses vale and volatility. The effect explicates that negative shocks/news increases the volatility more than positive shocks/news of equal size (Black, 1976; Christie, 1982, Kim 2018; Moffat, 2017). Due to the weakness of GARCH model, Nelson (1991) suggested another crucial model known as Exponential Generalized Autoregressive Conditional Heteroskedastic (EGARCH). The model was the first of its kind introduced to estimate the asymmetric volatility and is as indicated in Equation (6):

$$\log(\sigma_t^2) = \varpi + \beta \log\left(\sigma_{t-1}^2\right) + \gamma \frac{\mu_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\frac{|\mu_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right], \quad (6)$$

Whereby ${\sigma_t}^2$ is the conditional variance to be examined, α is parameter which stands for symmetric effects of the model, "the ARCH effect", β is the coefficient for the logged GARCH term which measures the persistence in conditional volatility irrespective of any information happening in the market, γ captures the scale of asymmetric or leverage effect. Whereby when $\gamma = 0$, the model is symmetry i.e., no asymmetric volatility. When $\gamma < 0$, then negative shocks (e.g. bad news) will decrease the volatility more than positive shocks. Otherwise, when $\gamma > 0$, it indicates that positive shocks e.g., innovations decrease the volatility more than negative shocks that is to say bad news increases volatility (Kim 2018; Moffat, 2017; Su, 2010). ϖ is the intercept for the variance. Generally, equation 6 states that, conditional volatility depend on lagged volatility, lagged absolute returns which is expressed as the function of previous error terms, and lagged returns. The third hypothesis that we expect to employ in our study will be testing the relationship between expected return and volatility clustering. Most financial models claim that investors should be rewarded for taking additional risk by obtaining higher returns. For example, according to Capital Asset Pricing Model (CAPM), investors need to compensate in two ways, the time value of the money captured by risk free interest rate and risk which is represented by beta. Engle et al. (1987) suggested GARCH-M model to explain this phenomenon where conditional variance of asset return enters conditional mean equation as specified in the Equation (8):

$$y_t = \mu + \delta\sigma_{t-1} + \mu_t, \quad \mu_t \approx N(0, \sigma_t^2), \quad (7)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \mu_{t-1}^2 + \beta\sigma_{t-1}^2, \quad (8)$$

Whereby equations 8 and 9 are the mean and conditional variance equations respectively.

4. Results

4.1. Descriptive Statistics Analysis

Figure 1 depicts price process of the index used in calculating the overall prices of Dar Es Salaam stock exchange, Tanzania. It can be revealed from the figure that, the series exhibit non-stationary, cyclic and downward continuous trend, with the lowest peak in year 2019. This might be attributed to COVID 19 pandemic which plagued the stock market worldwide most specifically during this specific period. The daily returns on the indices were calculated in order to test for stationary process by using Equation (9).

$$R_t = \log\left(\frac{P_t}{P_{t-1}}\right) \times 100, \quad (9)$$

Whereby P_t is the current closing price, P_{t-1} is the previous day closing price and R_t is the current return.

Figure 1. The series of price of DSE index

Figure 1 shows the movement of the stock return from year 2014 to 2021. It can be revealed that the higher returns are associated with higher volatility.

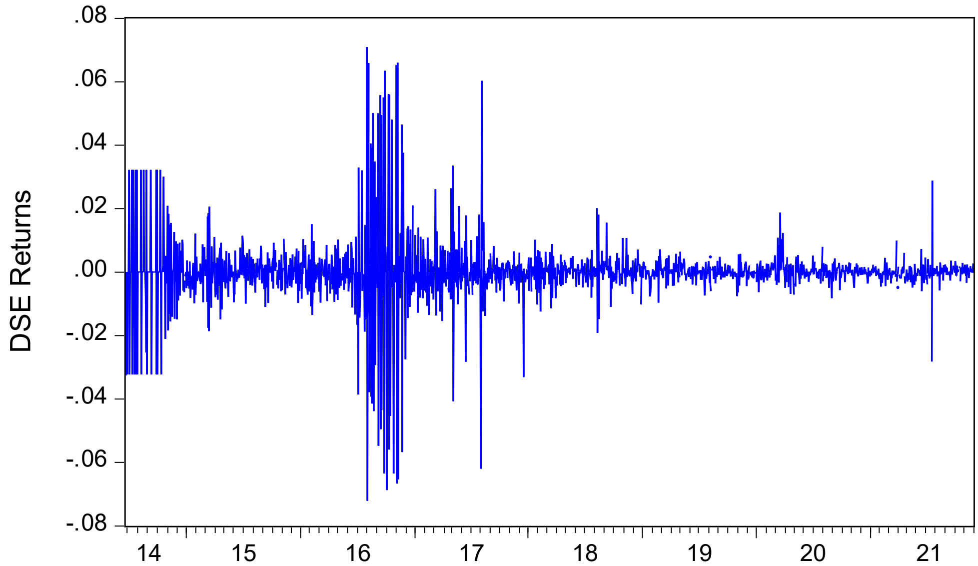

Figure 2. The log return series of DSE index

Figure 2 portrays the general overview of the data used in the analysis and gives the preliminary descriptive statistics. It can be pointed out that the returns are not normally distributed because the value of kurtosis is greater than zero. At the same time the Jarque and Bera test rejects the null hypothesis of normality. The mean of daily returns is also significantly higher with higher standard deviation.

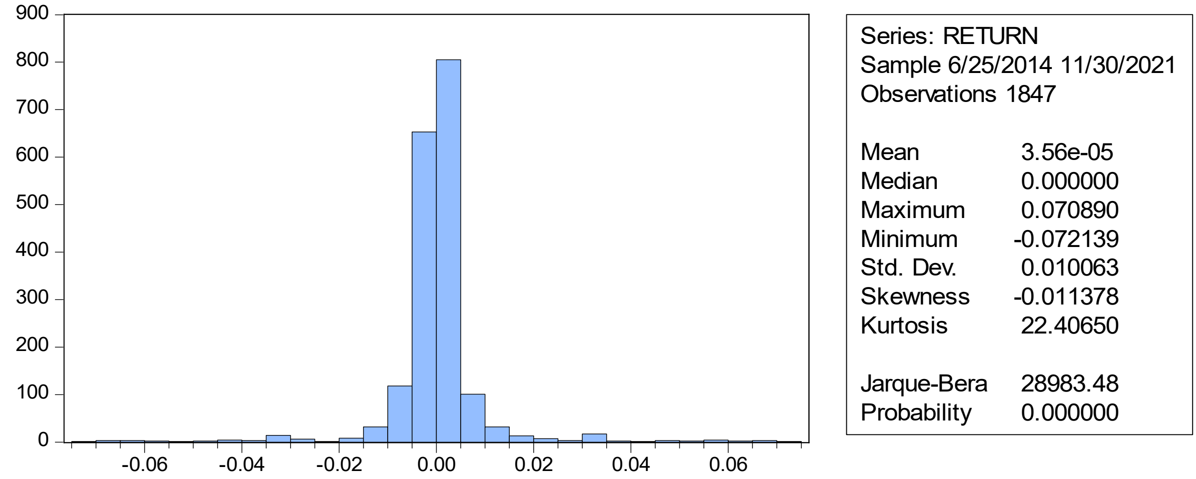

Figure 3. Descriptive statistics of DSE index

4.2. Test of Stationery (Unit Root Test)

Given a set of observations, we must start looking at possible stationarity. This is a stage where the data are analyzed to investigate if they are stationary. A stationary process has the property that the mean, variance and autocorrelation structure do not change over time. The presence of stationarity can be tested using statistical tests that test the unit root. These statistical tests are Dickey–Fuller test, Augmented Dickey–Fuller (ADF) test, Phillips-Perron (PP) test, KPSS (Kwiatkowski, Phillips, Schmidt and Shin) test. Once observations are assessed and found not stationary, they need to be made to avoid spurious results. The unit root tests were applied whereby in our case we employed the ADF and PP and the results are shown in Tables 1aand b respectively.

Table 1. Result of unit root test using Augmented Dickey-Fuller and Phillips-Perron

	ADF			**PP**		
	I(0)	**I(1)**	**I(2)**	**I(0)**	**I(1)**	**I(2)**
Test Statistics	-10.1812	-15.0075	-20.0367	-80.743	-676.3	-766.84
Critical Value	-3.9631	-3.9631	-3.963	-3.963	-3.9631	-3.963

The results from Table 1 indicate that the null hypothesis of a unit root in both cases should be rejected at 1% level. Hence, we concluded that, the returns have no unit root. In addition to unit root test, we have also employed KPSS test equation to verify whether the return series are stationary or not. The results are revealed in the Table 2.

Table 2. Result of unit root test using Kwiatkowski-Phillips-Schmidt-Shin

Asymptotic critical values*:	**LM-Stat.**
Kwiatkowski-Phillips-Schmidt-Shin	0.059621
1% level	0.216000
5% level	0.146000
10% level	0.119000

The results in Table 2 indicate that the null hypothesis should not be rejected. The coefficient is not significant at 1%, 5% and 10%. Hence series return is stationary.

4.3. Tests for Linearity

In this subsection, we discuss some nonlinearity tests available in the literature that have well defined power against the nonlinear models. The tests statistics used to capture non-linearity of time series can be categorized into parametric and non-parametric. The Ljung–Box statistics of squared residuals, the bispectral test, and the Brock, Dechert, and Scheinkman (BDS) test are nonparametric methods. The RESET test (Ramsey, 1969), the F tests of Tsay (1986, 1989), and other Lagrange multiplier and likelihood ratio tests depend on specific parametric functions. In this analysis we have employed the BDS test to test linearity of the time series data. The results are indicated in Table 3 below.

Table 3. Result of Linearity Testing

Dimension	BDS Statistic	Std. Error	z-Statistic	Prob.
2	0.045066	0.003091	14.58093	0.0000
3	0.084356	0.004931	17.10832	0.0000
4	0.109087	0.005899	18.49391	0.0000
5	0.124482	0.006179	20.14688	0.0000
6	0.132582	0.005990	22.13371	0.0000

The null hypothesis to be tested states that, the series is linearly dependent to its previous lag values, but the results suggest that the null hypothesis in all dimensions should be rejected since the reported probabilities are very small. Hence the series are non-linear.

4.4. Conditional Mean

We examined critically the conditional mean process by employing univariate time series models. We used Auto Regressive process (AR(1)), Moving Average process(MA(1)) and ARMA (1, 1). The results for AR (1) are Tabulated in Table 4 and 5 below.

Table 4. Summary of statistics for AR(1) model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	3.72E-05	0.000158	0.235122	0.8141
AR(1)	-0.374076	0.021595	-17.322	0.0000
R-squared	0.139946	Mean dependent var		3.83E-05
Adjusted R-squared	0.13948	S.D. dependent var		0.010065
S.E. of regression	0.009337	Akaike info criterion		-6.50861
Sum squared resid	0.160754	Schwarz criterion		-6.50263
Log likelihood	6009.448	Hannan-Quinn criter.		-6.50641
F-statistic	300.0521	Durbin-Watson stat		2.158641
Prob(F-statistic)	0.000000			

Table 5. Correlogram of AR (1) residuals

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
*| |	*| |	1	-0.083	-0.083	12.751	
**| |	**| |	2	-0.207	-0.215	92.080	0.000
| |	| |	3	0.022	-0.018	92.953	0.000
| |	*| |	4	-0.030	-0.079	94.636	0.000
| |	| |	5	-0.022	-0.034	95.531	0.000
| |	*| |	6	-0.045	-0.078	99.273	0.000
| |	| |	7	0.042	0.019	102.60	0.000
| |	| |	8	0.034	0.012	104.76	0.000
| |	| |	9	-0.026	-0.011	105.99	0.000
|* |	|* |	10	0.087	0.093	120.03	0.000

We can observe that the results exhibit high correlation in the residuals, and this was achieved by testing correlogram of residuals by using Q-statistics. All the Autocorrelations (AC) and Partial Autocorrelations (PAC) are significant which means we should reject the null hypothesis of no autocorrelation. The same results have been shown when employing MA (1) (See Table 6 and 7).

Table 6. Summary of statistics for Moving Average MA (1)

Variable(s)	Coefficient	Std. Error	t-Statistic	Prob.
C	4.47E-05	0.000102	0.439183	0.6606
MA(1)	-0.517188	0.019771	-26.15929	0.0000
R-squared	0.191652	Mean dependent var		3.56E-05
Adjusted R-squared	0.191214	S.D. dependent var		0.010063
S.E. of regression	0.009050	Akaike info criterion		-6.571019
Sum squared resid	0.151110	Schwarz criterion		-6.565041
Log likelihood	6070.336	Hannan-Quinn criter.		-6.568815
F-statistic	437.4342	Durbin-Watson stat		1.940922
Prob(F-statistic)	0.000000			

Table 7. Correlogram of residuals of MA (1) residual

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
| |	| |	1	0.029	0.029	1.6087	
| |	| |	2	-0.030	-0.031	3.2501	0.071
| |	| |	3	0.014	0.015	3.5877	0.166
| |	| |	4	-0.046	-0.048	7.4818	0.058
| |	| |	5	-0.023	-0.019	8.4800	0.075
| |	| |	6	-0.044	-0.046	12.138	0.033
| |	| |	7	0.035	0.038	14.457	0.025
| |	| |	8	0.043	0.036	17.873	0.013
| |	| |	9	-0.019	-0.019	18.510	0.018
|* |	|* |	10	0.081	0.079	30.635	0.000

The results are also consistent with ARMA (1, 1) as indicated in Table 8 and 9, we can observe that the residuals exhibit some degree of autocorrelation. Hence, we reject the null hypothesis which states that "residuals exhibit no autocorrelation" in all cases.

4.5. Modeling Volatility of Return

The signal for presence of volatility clustering in the return was initially examined by the results in ARMA (1, 1) as reported in Table 9.

Table 8. Summary statistics for ARMA (1, 1) model

Variable(s)	Coefficient	Std. Error	t-Statistic	Prob.
C	6.41E-05	8.37E-05	0.765746	0.4439
AR(1)	0.189820	0.038378	4.946069	0.0000
MA(1)	-0.676014	0.028269	-23.91366	0.0000
R-squared	0.204968	Mean dependent var		3.83E-05
Adjusted R-squared	0.204105	S.D. dependent var		0.010065
S.E. of regression	0.008979	Akaike info criterion		-6.586140
Sum squared resid	0.148601	Schwarz criterion		-6.577168
Log likelihood	6082.007	Hannan-Quinn criter.		-6.582832
F-statistic	237.5731	Durbin-Watson stat		2.026989
Prob(F-statistic)	0.000000			

Table 9. Correlogram of ARMA (1, 1) residuals

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
| |	| |	1	-0.014	-0.014	0.3558	
| |	| |	2	0.028	0.028	1.7753	
| |	| |	3	0.058	0.058	7.8980	0.005

| |	| |	4	-0.018	-0.017	8.5151	0.014
| |	| |	5	0.005	0.001	8.5579	0.036
| |	| |	6	-0.031	-0.034	10.358	0.035
| |	| |	7	0.044	0.045	13.870	0.016
| |	| |	8	0.042	0.044	17.090	0.009
| |	| |	9	-0.027	-0.025	18.462	0.010
|* |	|* |	10	0.088	0.080	32.979	0.000

Table 9 shows the results that residuals show autocorrelation patterns which could be attributed by the presence of volatility clustering (i.e. large changes tend to be followed by large changes of either sign and small changes tend to be followed by small changes). To be more precise we tested the “ARCH effect”. The results are revealed in Table 10.

Table 10. ARCH effect testing at 5 lags

Heteroskedasticity Test: ARCH LM Test				
F-statistic	95.49556	Prob. F(5,1836)		0.0000
Obs*R-squared	380.1697	Prob. Chi-Square(5)		0.0000
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	3.54E-05	1.02E-05	3.468972	0.0005
RESID^2(-1)	0.280181	0.023299	12.02553	0.0000
RESID^2(-2)	0.042599	0.023811	1.789083	0.0738
RESID^2(-3)	0.087291	0.023727	3.678919	0.0002
RESID^2(-4)	0.183123	0.023760	7.707141	0.0000
RESID^2(-5)	0.045213	0.023240	1.945510	0.0519

The procedures for testing the ARCH effects were achieved by first generating residuals from ARM (1, 1) model. This was done by regressing returns series against the constant, AR (1) and MA (1) models. Then the second step was to regress the squared residual on lagged squared residual and the constant term. The results in Table 7 indicate the presence of ARCH effect in the return series since all the two coefficients are positive and significant. We are now in a position for modelling volatility of the returns.

4.6. Modelling Volatility of Return using GARCH (1, 1)

We have examined from the previous subsection that; the returns series exhibit ARCH effect. Hence, the study uses GARCH (1, 1) model to model the volatility of the returns. By examining the regression coefficients of estimated GARCH (1,1) in Table 11 we can observe that they are highly significant.

Table 11. Summary statistics of GARCH (1, 1) model

Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
C	9.91E-05	7.45E-05	1.329643	0.1836
AR(1)	-0.148398	0.025598	-5.797325	0.0000
	Variance Equation			
C	3.96E-07	4.51E-08	8.786769	0.0000
RESID(-1)^2	0.131613	0.009219	14.27631	0.0000
GARCH(-1)	0.874224	0.008021	108.9899	0.0000
R-squared	0.088962	Mean dependent var		3.83E-05
Adjusted R-squared	0.088468	S.D. dependent var		0.010065
S.E. of regression	0.009610	Akaike info criterion		-7.685045
Sum squared resid	0.170284	Schwarz criterion		-7.670092
Log likelihood	7098.297	Hannan-Quinn criter.		-7.679533
Durbin-Watson stat	2.524658			

The parameters α and β sum up to almost 1.005837 which indicates presence of strong and persistent volatility in the series and this suggest that asymmetric GARCH models are more appropriate in modelling volatility in the case of DSE as compared to symmetric GARCH models. The study also tested ARCH effects to see whether there are no more ARCH effects in the residuals after running GARCH (1, 1) model. ARCH LM test was carried out for 5 lags and the results are reported in Table 12. The results show that the standardized residuals do not exhibit ARCH effect.

Table 12. No ARCH effect left testing at lag 5

Heteroskedasticity Test: ARCH TEST				
F-statistic	0.468966	Prob. F(5,1836)		0.7996
Obs*R-squared	2.349493	Prob. Chi-Square(5)		0.7990
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.975420	0.109700	8.891715	0.0000
WGT_RESID^2(-1)	0.029410	0.023337	1.260249	0.2077
WGT_RESID^2(-2)	0.001437	0.023345	0.061555	0.9509
WGT_RESID^2(-3)	-0.013719	0.023342	-0.587743	0.5568
WGT_RESID^2(-4)	0.013954	0.023344	0.597756	0.5501
WGT_RESID^2(-5)	-0.007678	0.023336	-0.329015	0.7422

4.7. Modeling the Asymmetries

We tested for leverage effect using EGARCH model. The results are indicated in Table 13. α is 0.210285 and this parameter captures the persistence in conditional volatility irrespective anything happening in the market.

Table 13. Summary Statistics of EGARCH (1, 1) model

Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
C	0.000199	5.80E-05	3.433691	0.0006
AR(1)	-0.175397	0.022433	-7.818661	0.0000
	Variance Equation			
ϖ	-0.223204	0.016603	-13.44376	0.0000
β	0.210285	0.010459	20.10558	0.0000
γ	-0.016442	0.006934	-2.370991	0.0177
α	0.992213	0.001307	759.3695	0.0000
R-squared	0.100114	Mean dependent var		3.83E-05
Adjusted R-squared	0.099626	S.D. dependent var		0.010065
S.E. of regression	0.009551	Akaike info criterion		-7.680346
Sum squared resid	0.168199	Schwarz criterion		-7.662402
Log likelihood	7094.959	Hannan-Quinn criter.		-7.673730
Durbin-Watson stat	2.480600			

The figure is relatively large, and then volatility takes a long time to die out following any crisis in the market. The value of β which captures "GARCH effect" is 0.992213, and the parameter is also highly significant at 1% level. This indicates higher degree of persistence in volatility. The leverage effect parameter γ is negative (-0.016442) and statistically significant at 5% level and this indicates that the leverage effect exists, and negative shocks (bad news) decrease volatility more than positive shocks of the same magnitude in the case of DSE. But also, the coefficient indicates that returns and volatility are negatively correlated which is somehow contrary to our expectations. Similar results have been achieved by previous studies (Birau et al., 2021; Chimrani et al., 2018; Gökbulut & Pekkaya, 2014).

4.8. GARCH-M Modeling Results

To be more precise on the nature of relationships between stock return and volatility of DSEI, we employed the GARCH-M model which centers on the concept that, higher returns are associated with higher risk. This means investors are willing to accept higher risk, with the expectation of acquiring higher returns. We used AR (1)-GARCH (1, 1) in our study and the results are indicated in Table 14.

Table 14. Summary statistics of AR (1)-GARCH-M Model

Variable	Coefficient	Std. Error	z-Statistic	Prob.
@SQRT(GARCH)	0.019044	0.040543	0.469718	0.6386
C	2.21E-05	0.000185	0.119924	0.9045
AR(1)	-0.148219	0.025827	-5.738917	0.0000
	Variance Equation			
C	3.97E-07	4.51E-08	8.801800	0.0000
RESID(-1)^2	0.131321	0.009206	14.26408	0.0000
GARCH(-1)	0.874318	0.008019	109.0266	0.0000
R-squared	0.088269	Mean dependent var		3.83E-05
Adjusted R-squared	0.087279	S.D. dependent var		0.010065
S.E. of regression	0.009616	Akaike info criterion		-7.684059
Sum squared resid	0.170413	Schwarz criterion		-7.666115
Log likelihood	7098.386	Hannan-Quinn criter.		-7.677444
Durbin-Watson stat	2.523850			

The coefficient is positive (0.019044) although not significant. Similar results have been reported by previous studies (Birau et al., 2021; Prasad et al., 2019; Chimrani et al., 2018). The results, therefore, vindicate the validity of all the three hypotheses tested and therefore volatility clustering and leverage effect are noticeable in the case of DSE. The leverage coefficient was negative, and this shows that negative shocks decrease volatility than positive shocks of equal size and stock market returns and volatility are negatively correlated. This contravenes some of the findings from previous studies in the extant literature (see. e.g. Adu et al., 2015; Ivanovski et al., 2015; Kim 2018; Moffat, 2017). The results from these empirical studies indicate that negative news increases the volatility than positive news of the same magnitude. However, the span of frequency of the data used in various studies has been pointed out to be one to sources of such contradicting conclusions (Ait-Sahalia et al., 2013; Aït-Sahalia et al., 2017; Kalnina & Xiu, 2017).

5. Conclusions

By employing prominent time series models designed to capture volatility clustering—specifically ARCH, GARCH, EGARCH, and GARCH-M—this study utilized the GARCH(1,1) model to examine volatility clustering and the EGARCH(1,1) model to capture the leverage effect. These two models demonstrated superior effectiveness and efficiency compared to the traditional ARCH model, as widely discussed in the existing literature. The study concludes that the Dhaka Stock Exchange (DSE) exhibits a high degree of volatility persistence along with a significant leverage effect. The negative coefficient associated with the leverage effect indicates that negative shocks or news reduce volatility more than positive shocks of equivalent magnitude. Furthermore, the results reveal an inverse relationship between returns and volatility, thereby contradicting the conventional risk-return tradeoff theory in finance. According to this theory, investors are expected to demand higher returns as compensation for taking on greater risk. In contrast, the findings of this study suggest that, during the examined period—likely influenced by the global economic turmoil caused by the COVID-19 pandemic—higher returns were associated with lower volatility. This anomaly may reflect the market's atypical behavior in response to the unprecedented crisis.The implications of these findings are critical for investors, as they highlight the potential for greater risks to result in diminished returns within the DSE. Therefore, understanding such dynamics is essential for portfolio management and for formulating strategies to mitigate the adverse effects of unexpected market shocks. The insights derived from this study hold practical value for investors, financial practitioners, policymakers, academics, and researchers. However, this study is limited to a single stock market. Future research should consider a comparative analysis involving multiple stock markets across Sub-Saharan African countries to enhance the generalizability of the findings.

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