European Institute of Knowledge & Innovation

Journal of Economics, Innovative Management, and Entrepreneurship (JEIME) ISSN: 3029-0791

Research Article

The Best Econometrics Model for Forecasting Equity Market Returns in Developing Countries

David Umoru[1]*, Beauty Igbinovia[1], and Lawrence Egbaju [2]

[1] Edo State University Uzairue, Nigeria
[2] Federal University of Technology Utuoke, Nigeria
* Correspondence: david.umoru@yahoo.com

https://doi.org/eiki/10.59652/jeime.v2i4.345

Abstract: The emerging market economies are fast improving in terms of the real sector and financial sector growth. This is due to the role played by equity market that facilitates re-allocation of funds. This paper aims to find the best GARCH model for forecasting stock returns of emerging markets, and besides to use maximum likelihood estimation method based on the Marquardt algorithm to estimate how returns respond to market news. It was observed the best model for predicting return in equity markets of Tunisia, Kenya, and Sudan is exponential GARCH with general error distribution (GED). For Egypt, Mauritius, South Africa, Namibia, and Nigeria, the gjrGARCH (1,1) with Student's-t distributions performs best. These market returns react differently to market news relating to them. Whereas, sGARCH with Gaussian normal distribution is mostly suitable for analysing symmetric responses of return to market news, implying returns in these markets does not react differently to market news. These findings have policy implications for investors in these respective economies. Amongst others, the study advises investors, particularly those in the equity market where volatility decays slowly and the market where volatility responds asymmetrically to be watchful as these could pose significant threat to their market portfolios. Investors in these markets, particularly those in the equity market where volatility decays slowly and the market where volatility responds asymmetrically, be watchful, as these could pose a significant threat to their market portfolio.

Keywords: eGARCH; sGARCH; gjrGARCH; GED distribution

Received: October 5, 2024
Accepted: October 21, 2024
Published: October 31, 2024

1. Introduction

The importance and significance of a stock market can be better understood in a free market economy, where businesses in need of cash can obtain funds by issuing company shares on the stock market, which investors can purchase at a set price. Share trading not only offers funds to a company but also gives the investor a stake in the company. This phenomenon lasts for a long time, and a reputable company does not receive a huge sum of money. A well-managed, organized, and well-known stock market helps a nation's monetary as well as commercial sectors. It facilitates saving and investment in an economy by allowing investors to participate in the purchase of assets. Increased productive activities result in profit for the company and dividends for shareholders as a result of such investment efforts. The equity market also facilitates the re-allocation of funds between firms and sectors (Agbonrha-Oghoye et al., 2022; Anwar & Raza, 2016). Every financial sector has been described as having two key pathways through which it might impact growth. These are achieved through the growth of the stock market and the banking sector. Stock markets, unlike short-term bank loans, provide long-term capital in the primary markets, allowing for more efficient capital allocation to lucrative ventures and giving stockholders a way to sell their stock on the secondary market. Investor confidence in the performance of the local economy has increased as a result of their growth and development. (Tachiwou, 2010).

The recent financial crisis, as well as the capital market's sensitivity to external shocks because of the worldwide financial meltdown, has had an impact on the economy's macroeconomic fundamentals. The emerging market economies are fast improving in terms of real sector and financial sector growth. Due to the potential of these economies, there has been an influx of investors in their stock markets. Unfortunately, despite the influx of investors in the stock markets of emerging and developing countries of Africa, empirical study on the subject in emerging African countries has yet to gain wide coverage, and hence the lack of adequate consensus regarding appropriate financial models for forecasting stock returns of emerging markets influences the influences the influence the stock market exerts on economic progress in emerging economies of Africa.

The research gap can be articulated as follows: Some studies have looked at the impact of stock markets and financial markets in general on economic growth in sub-Saharan Africa. These studies include Attah-Botchwey, Awadzie, and Agbenyezi (2022), Bello, Folorunsho, and Alabi (2019), Manuel, João, and Jelson (2022). On his part, Lakshmanasamy (2021) significant exchange rate volatility effect on volatility in stock market return. Algaeed (2020), Grbić (2020), Ibrahim & Mohammed (2020) evaluated the impact of capital market development and economic growth. Akintola & Cole (2020) assessed the impact of capital market and economic growth in Nigeria while Anderu (2020) found significant impact of capital market indices on economic growth.

While Twerefou, Abbey, Codjoe, and Ngotho (2019) discovered a considerable impact of stock market development on economic growth, Emmanuel and Elizabeth (2020), Acha and Akpan (2019), and Abina and Lemea (2019) reported a large positive effect of equity market outcome on economic growth in Nigeria. Asteriou and Spanos (2019), Angaye and Frank (2020) established a significant association between financial performance and GDP growth during the recent crisis using data from the EU. All of these researches came to the same conclusion of a growth effect of equity market performance, albeit in varied ways depending on the country because capital markets are not developed to the same extent everywhere.

Others have conducted empirical research on how stock returns react to asymmetric shifts in oil and exchange rates. Among the notable studies are Umoru, Effiong, Ugbaka, Iyaji, Okpara, et al. (2023), and Umoru, Effiong, Ugbaka, Iyaji, Oyegun, et al. (2023). Umoru, Effiong, Okpara, Iyayi, et al. (2023) have also researched the link between returns and oil-exchange rate volatilities. Nevertheless, these studies had no particular focus on the prediction of stock returns. Our research aim is to find the best GARCH model for forecasting stock returns of emerging markets in Africa and also to show how stock returns respond to market news in emerging market economies using asymmetric GARCH models.

The following research questions are before us in this study:

Which GARCH model performs best in forecasting stock returns in emerging market economies?

Do stock returns in African stock markets respond symmetrically or asymmetrically to market news?

The study is original as it is a contribution to the empirical debate regarding the validity of models for measuring volatility vis-à-vis the attitude of investors towards expected returns and risk (uncertainty) in ten African emerging market economies, which include Tunisia, Botswana, Egypt, Kenya, Nigeria, Namibia, Mauritius, Sudan, Morocco, and Malaysia, based on the Generalized Autoregressive Conditional Heteroskedasticity estimator and its variants. In particular, the study synthesizes the specifications of theoretical models with an empirically testable model. The contribution of the study upholds that there is not only one method that can be useful for predicting stock markets. In particular, the empirical findings contributed to the predictive performance of both symmetric and asymmetric models in finding the best model to forecast the returns of emerging markets. Besides, the research is of utmost significance as it empirically evaluates the GARCH model with the appropriate distribution that minimises errors in forecasting and simultaneously evaluates the explosive nature of the returns of stocks with enormous observations. In this regard, the superiority of the findings obtained in this study rests on the empirically made evidential preferred model's capacity to project the relationship be-tween returns and factors that determine returns.

Moreover, having utilized high-frequency data and based analysis on the recommendation of Andersen and Bollerslev (1998a) by utilizing cumulative squared returns from daily observations to measure integrated volatility shocks, the study offers more accurate prediction and evaluation models. Indeed, by empirically unveiling the suitable model for evaluating returns in each of the stock markets covered by the study, the study provides an addition to the methodology of correctly estimating returns with intra-day statistics and, by so doing, discerns models capable of providing higher-quality forecasting performance of returns. The study also validates the estimation of volatility with high-frequency data, with particular emphasis on daily series. This paper recommends the need for market participants, particularly brokers and jobbers, including stockholders, to use the aforementioned models in forecasting each corresponding emerging market return. The organisation of this study is in five sections, as follows: Section 2 is devoted to the literature review of both stock market hypotheses and empirical findings from previous studies. Section 3 discusses the techniques of estimation, while section 4 analyses the results. Section 5 contains concluding remarks.

2. Literature Review

2.1. Financial Intermediation Theory

The underlying theoretical foundation of the study is the financial intermediation theory. According to the hypothesis, financial intermediation leads to financial liberalization and growth. It also enhances the incentive to save and promotes investment due to an increase in credit supply, which has an impact on the economy's growth and development. The financial intermediary theories of Shaw (1973), Mckinnon (1973), and Goldsmith (1969) are very prominent. Financial markets, according to the named theorists, play a critical role in economic advancement, and integration by transferring capital from the surplus to the shortage sector. According to Goldsmith (1969), there is a direct link between financial development and a country's level of growth. Shaw (1973) proposed the financial intermediary theory, which claims that financial intermediation exists between savers of funds and investors. Similarly, Mckinnon (1973) advocated that physical capital and money have a complementary relationship that is represented in money demand. The demand for money is intimately linked to the accumulation of physical capital through financial intermediation.

2.2. Empirical Literature Review

Focusing attention on more recent studies in connection with stock market performance, we review as follows: Ajigal, Adeleye, and Tubokirifuruar (2024) found that leveraging the potential of ML in navigating the complexities of financial markets was the best form of prediction. Wang (2024) found that neural network models were the best for forecasting stock returns when solely firm-specific characteristic variables were in focus. Luo, Bu, Xu, and Huang (2023) uphold the new bagging model as the best prediction model for the performance of stock markets. Specifically, Luo, Bu, Xu, & Huang (2023) uphold that the machine learning models outperform traditional forecasting models and that the new bagging model constructed has the best forecasting ability. According to Yuling, Yunshuang, Xinyu, and Yucheng (2022), with a Student's *t* distribution, the ARMA (1,1)-TGARCH (1,1) model, ARIMA (4,4), and GARCH (1,1) model were the best models for forecasting the returns series of the Shenzhen composite index and Shanghai composite index, respectively. The empirical findings obtained by Ali, Suri, Kaur, and Bisht (2022) with the implementation of the GARCH (1,1) model demonstrated the persistence of volatility shocks in NSE returns, and the impact was felt by market participants more strongly for the bad news. The works of López-Cabarcos, Ribeiro-Soriano, and Piñeiro-Chousa (2020), Hongwiengjan and Thongtha (2021) found the TGARCH model to be the best method for the in-money pricing option. According to Zhifeng and Xiaoming (2021), what strengthens the forecast performance of stock market returns is the imposition of constraints on stock return forecasts. The MS-GARCH model was found to be better off by Živkov, Kuzman, and Andrejević-Panić (2021) in modelling and forecasting the two-way association between foreign exchange markets and national stocks in Africa. Using the GARCH-MIDAS model, Xu, Wang, and Liu (2021) reported that West Texas Intermediate crude oil market risk was driven by economic policy uncertainty. The asymmetric GARCH models were adopted by Kim, Kim, and Jung (2021) to calculate and forecast the volatility of company bond yield spreads. According to Zivkov, Kuzman, and Andrejević-Panić (2021), the MS-GARCH model was the best for forecasting returns. According to Hongwiengjan and Thongtha (2021), the TGARCH model does better than others. On their part, Xu, Wang, and Liu (2021) offered the quantile-based GARCH-MIDAS model as the best. Kim, Kim, and Jung (2021), Aliyev, Ajayi, and Gasim (2020), and Jiang, Ruan, Li, and Li (2018) also established sGARCH forecasting as empirically the best.

The asymmetric GARCH model with univariate analogy was the best model used by Aliyev, Ajayi, and Gasim (2020) to estimate and forecast the volatility of the Nasdaq-100. The authors also reported the asymmetric effect of shocks as well as persistent volatility tremors on returns. In another analysis, Salisu & Vob (2020) reported that the health-news-based model outclasses the historical forecasting model. The results obtained by Yuanwei, Zheng, Dongao, Ziyi, Junyi, and Xiaoling (2020) demonstrated that the GARCH model is more suitable in terms of forecasting stock returns than the ARMA model, whereas, in terms of forecasting sizable effects of volatility, the ARMA model did better off. Gulzar, Mujtaba

Kayani, Xiaofeng, Ayub, and Rafique (2019) also reported the fact that the GARCH-BEKK model overtook other models in forecasting volatility spillovers in emerging Asian stock markets. Milošević, Anđelić, Vidaković, and Đaković (2019) used the GARCH models to calculate and forecast the effect of holidays on returns from investment in financial markets. Going forward, Milošević, Anđelić, Vidaković, and Đaković (2019) recommended both ARCH and GARCH models for forecasting returns in financial markets. According to Zhong and Enke (2019), artificial neural networks and deep neural networks utilising principal component analysis (PCA) performed better than customary models. According to Gulzar, Mujtaba Kayani, Xiaofeng, Ayub, and Rafique (2019), the best model was the BEKK-GARCH model, and hence, the authors relied on the BEKK-GARCH modelling to estimate spillover effects from the NYSE on emerging economies.

As noted by Mallikarjuna and Rao (2019), a prediction of stock returns is a veritable instrument for diversifying a portfolio and managing the risk of investments. Studies such as Devpura, Narayan, and Sharma (2018), Salisu, Isah, and Akanni (2019), Salisu, Isah, and Raheem (2019), Salisu, Raheem, and Ndako (2019), Salisu, Swaray, and Oloko (2019) have all forecasted stock returns based on historical averages. According to Awajan, Ismail, and Wadi (2018), the empirical mode decomposition of Holt-Winters was the best forecasting model of stock market returns. The ANN models have been found to produce more accurate forecasts than traditional models (Mallikarjuna et al., 2018). Nayak & Misra (2018) reported that the genetic algorithm-based condensed polynomial neural network (GA-CPNN) was the most accurate model for predicting stock indices. The equity market also facilitates the re-allocation of funds between firms and sectors (Abidin et al., 2022; Anwar et al., 2022; Al-Rimawi & Kaddumi, 2021; Anwar & Raza, 2016).

The outcomes of Dritsaki (2017) upheld the enormous effect of negative shocks in the Stockholm stock market. Furthermore, the study endorsed that the ARIMA (0, 0, 1) model performed better in forecasting returns, while the EGARCH (1, 1) model with t-students is the best for forecasting the volatilities of the Stockholm Stock Exchange. Researchers like Chen (2017), Wu and Wen (2016), Yang and Cao (2016) upheld the ARMA-GARCH model as the best for forecasting stock prices. Wei and Meng (2014) also established the empirical suitability and fulfilment of the GARCH model in forecasting the RMB exchange rate against the US dollar. Dutta (2014) was not exempted from the list of researchers who based their analyses of estimation and forecasting on the GARCH models for Japan and the USA. The study also reported a sizable effect of good news on bad news. The study by Gao, Zhang, and Zhang (2012) reported that the GED-GARCH model performed healthier than the t-GARCH model, while the t-GARCH model did better than the N-GARCH model based on daily data from the China stock market. The sGARCH model was also found to be more suitable for forecasting the yield of the Shanghai and Shenzhen 300 index series. The results obtained by Tudor (2008) demonstrated that the GARCH-M model was better in terms of predicting expected returns and volatility in the stock markets of Romania and the US on both markets. Rather than the GARCH models, He (2008) found that the ARCH model is more suitable than the ARIMA model as regards the prediction of returns. For Lu (2006), the non-parametric GARCH model was better suited for predicting the unpredictability of the Chinese stock market. In the stock market-growth literature, the works of Donwa and Odia (2010) are reviewed succinctly.

3. Materials and Methods

3.1. Research Design

This study estimates three different GARCH-M models. These are the generalized autoregressive conditional heteroskedasticity-mean model, E-GARCH model, exponential-generalized autoregressive conditional heteroskedasticity model, and T-GARCH (GJR–GARCH) model, threshold-generalized autoregressive conditional heteroskedasticity model. The specification of the conditional variance equation based on GARCH (2, 2) is given in equation (1):

$$\sigma_t^2 = \phi_0 + \varsigma_1 e_{t-1}^2 + \varsigma_2 e_{t-2}^2 + \zeta_1 \sigma_{t-1}^2 + \zeta_2 \sigma_{t-2}^2 \tag{1}$$

where σ_t^2 is the current volatility, ϕ_0 is the intercept of the variance equation, (q_i where i=1 & 2) are the ARCH effects and (d_i   where i=1 & 2) are the GARCH effect both having coefficients greater than zero. The delaying rate of the volatility is calculated as1-(ς_1 + ζ_1), where 〖 ς〗 _1 + ζ_1≤1. This assumption satisfies the volatility persistence constraint. Equation (1) classifies all forms of shocks, both positive (good news) and negative (bad news) as having a symmetric effect on shocks as captured in terms of volatility but calculated as variance (Umoru, 2022). The exponential GARCH (eGARCH) model identified by Nelson (1991) comes conveniently as specified:

$$\log(\sigma_t^2) = \phi_0 + \zeta_1 \log(\sigma_{t-1}^2) + \psi \frac{e_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \mu \left| \frac{|e_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\rho}} \right| \quad (2)$$

where w is the leverage effect and signifies a fall in returns leads to higher volatility than its increase in returns of the same magnitude. Another variant of asymmetric GARCH is the gjrGARCH model proposed by Jagannathan and Runkle (1993).

$$\sigma_t^2 = \phi + \varsigma_1 e_{t-1}^2 + \varsigma_2 e_{t-2}^2 + \zeta_1 \sigma_{t-1}^2 + \zeta_2 \sigma_{t-2}^2 + \xi e_{t-2}^2 Q_{t-2} \quad (3)$$

where Q_(t-2)=1 if e_(t-1)<0 and 0 otherwise. The leverage parameter has to be positive and statistically significant. For persistency, the same assumption applied to standard GARCH holds for equations 2 to 3. To obtain the optimum p and q lags for the conditional mean and variance equation, simulation was run on several lag orders on different distributional assumptions ranging from Student's *t* distribution to normal distribution. The best model specification is obtained using BIC, SIC, AIC, and HQ. The GARCH model has different variants, and these include: GARCH-M model, Generalized Autoregressive Conditional Heteroskedasticity-Mean Model E-GARCH model, Exponential-Generalized Autoregressive Conditional Heteroskedasticity Model, and T-GARCH (GJR–GARCH) model, Threshold-Generalized Autoregressive Conditional Heteroskedasticity Model ARCH and GARCH models are mainly deployed to model non-stationary series, that is, the varying mean of a series, and heteroskedastic series, that is, varying variance with high frequency. In line with the recommendation of Stiglingh and Seitshiro (2022), we used the general error distribution (GED) in estimating EGARCH as it easily gains stationarity. The log-likelihood function for the GED is given by:

$$\ln L\left[(y_t),\phi\right] = \sum_{t=1}^{T}\left[\ln\left(\frac{e}{\lambda}\right) - \frac{1}{2}\left|\frac{z_t}{\lambda}\right|^{e} - (1+e^{-1})\ln(2) - \ln\Pi\left(\frac{1}{e}\right) - \frac{1}{2}\ln(\sigma_t^2)\right] \quad (4)$$

where $\lambda = \left[2^{-2/e}\dfrac{\Pi\left(\frac{1}{e}\right)}{\Pi\left(\frac{3}{e}\right)}\right]^{0.5}$

The GED integrates Laplace, normal, and unique distributions when, in sum, alternative GARCH model specifications include, GARCH, EGARCH, GJRGARCH, IGARCH, NGARCH, TGARCH, and AGARCH. The specification of these models is demonstrated as follows:

$$GARCH,\ \sigma_t^2 = \tau + \sum_{i=1}^{q} \varsigma_i e_{t-i}^2 + \sum_{j=1}^{p} \zeta_j \sigma_{t-j}^2 \quad (5)$$

$$GJRGARCH,\ \sigma_t^2 = \tau + \sum_{i=1}^{q}\left[\varsigma_i + \gamma_i I_{(e_{t-i}>0)}\right]e_{t-i}^2 + \sum_{j=1}^{p} \zeta_j \sigma_{t-j} \quad (6)$$

$$IGARCH,\ \sigma_t^2 = \tau + e_{t-1}^2 + \sum_{i=2}^{q}(e_{t-i}^2 - e_{t-1}^2) + \sum_{j=1}^{p} \zeta_j (\sigma_{t-j}^2 - e_{t-1}^2) \quad (7)$$

$$NGARCH\ \sigma_t^2 = \tau + \sum_{i=1}^{q} \varsigma_i (e_{t-i} + \gamma_i \sigma_{t-i})^2 + \sum_{j=1}^{p} \zeta_j \sigma_{t-j}^2 \quad (8)$$

$$TGARCH\ \sigma_t = \tau + \sum_{i=1}^{q} \varsigma_i \left[(1-\gamma_i)e_{t-i}^{+} - (1+\gamma_i)e_{t-i}^{-}\right] + \sum_{j=1}^{p} \zeta_j \sigma_{t-j} \quad (9)$$

$$AGARCH\ \sigma^{\delta} = \tau + \sum_{i=1}^{q} \varsigma_i \left[|e_{t-i}| - \gamma_i e_{t-i}\right]^{\delta} + \sum_{j=1}^{p} \zeta_j \sigma_{t-j}^{\delta} \quad (10)$$

$$EGARCH,\ \log(\sigma_t^2) = \tau + \sum_{i=1}^{q}\left[\varsigma_i e_{t-i} + \gamma_i(|e_{t-i}| - E|e_{t-i}|\right] + \sum_{j=1}^{p} \zeta_j \log(\sigma_{t-j}^2) \quad (11)$$

3.2. Data Aanalysis Methods

To actualize the study's objectives which is to evaluate the best GARCH Model for forecasting stock returns of emerging markets, secondary research data on eleven (11) emerging equity markets was sourced from the investing.com website, a database for different financial data. The chosen sample was informed in this study on the basis of available statistics. These data set with the start and end dates are reported in Table 1 below. Descriptive statistics including the mean value, standard deviation, minimum, maximum, sample size, and kurtosis were utilized to characterize the nature of our data and summarize the behavior of our variables in the study for appropriate empirical evaluation and ultimately to meet the research objective in line with the assessment of the research questions. In addition, Engle's ARCH LM test was further applied to ascertain the absence or presence of conditional heteroskedasticity. The rationale for the test was to identify time-varying fluctuations as it relates to the variables of the study. The diagnostic test enables us to evaluates the robustness of the model specification changes in terms of volatility measures and the associated error distribution. Finally, the GARCH regression models, specifically symmetric GARCH (sGARCH) model regressions were estimated for all Equity markets. The maximum likelihood estimation method was used in the estimation of the GARCH models based on the Levenberg–Marquardt algorithm (LMA) (Levenberg, 1944; Marquardt, 1963). Other methods, such as Gauss–Newton algorithm, Gradient descent, moving average convergence and divergence method, machine learning methods, Box-Jenkin ARIMA technique, frequency-domain estimation of fractional differencing parameter, and empirical mode decomposition method (EMD-HW), can be used to forecast stock returns. The LMA is a local minimization algorithm technique that uses iterative least squares to find a function's minimum and express it as the sum of squares of its nonlinear parameters. The techniques of the Gradient descent (GD) and the Gauss-Newton algorithm (GNA) are interpolated between by the LMA. Compared to the GNA and other estimating methods, the LMA is more reliable since it finds a speedy solution even when it starts very distant from the closing minimum. hence, it rapidly and accurately converges to accurate values from any point of beginning. Additionally, the LMA exhibits the stability of the technique with the highest gradient and could quickly converge even in the presence of a complex error distribution.

Table 1. Listed companies in Stock exchanges of emerging countries

Markets	Number of Observations	Start	End
Telnet Holding, Tunisia	4,557	1/03/2010	31/12/2022
Botswana Diamonds plc	4,557	1/03/2010	31/12/2022
Egyptian Iron & Steel	4,557	1/03/2010	31/12/2022
Total Kenya Ltd Ord 5.00	4,557	1/03/2010	31/12/2022
Petronas Chemicals Group Berhad, Malaysia	4,557	1/03/2010	31/12/2022
MTN South Africa Telecomunication	4,557	1/03/2010	31/12/2022
Nigeria_Breweries	4,557	1/03/2010	31/12/2022
Forsys Metals Corporation, Namibia	4,557	1/03/2010	31/12/2022
Mauritius Oil Refineries	4,557	1/03/2010	31/12/2022
White Nile Flour Mills Sudan	4,557	1/03/2010	31/12/2022
Disty Technologies, Morocco	4,557	1/03/2010	31/12/2022

Source: authors' computations using EViews 13.

4. Results

4.1. Descriptive Statistics of Data

The descriptive statistics of our variables encompass the mean value, Standard Deviation, Minimum, Maximum, Sample Size and Kurtosis are presented in Table 2 below. Table 2 presents the various descriptive statistics for ten emerging markets. Among the emerging markets, Total Kenya Ltd. has the highest mean value of 3597.24, followed by Forsys Metals Corporation and Disty Technologies, Morocco, with the values of 2040.72 and 713.23, respectively. On the other hand, the Namibian equity market has the highest standard deviation of 1578.46 compared to other equity markets. This implies that the Forsys Metals Corporation of Namibia equity market has high volatility compared to other equity markets among the emerging markets. The White Nile Flour Mills in Sudan has the lowest standard deviation, implying the relative stability of the bank in the equity market. The mean value is the third-lowest, with a value of 1.69, whereas Egypt tourism and Malaysia building society have the highest mean of 1.42 and 1.49, respectively. These equity markets in Egypt and Malaysia have relative stability among the emerging economies since their standard deviations are also 0.55 and 0.47, respectively.

Table 2. Descriptive statistics of equity markets

Equity Market	Mean	Standard Deviation	Minimum	Maximum	Sample Size	Kurtosis
Telnet Holding, Tunisia	4.74	1.23	2.64	8.91	2640	0.96
Botswana Diamonds plc	23.26	42.84	0	135	1052	0.39
Egyptian Iron & Steel	1.42	0.55	0	3.19	2471	-0.15
Total Kenya Ltd Ord 5.00	3597.24	1130.36	1004.7	6161.46	4744	-0.65
Petronas Chemicals Group Berhad, Malaysia	1.49	0.68	0.48	3.19	2377	-0.88
MTN South Africa Telecomunication	121.18	12.85	90	159.3	262	-0.32
Nigeria_Breweries	116.21	44.61	22	191.2	2288	-1.1
MTC Namibia	2040.72	1578.46	140	4900	1261	-1.19
Mauritius Oil Refineries	35.28	24.39	4	104	4505	-0.44
White Nile Flour Mills Sudan	1.69	0.47	0.91	3.7	1404	2.22
Disty Technologies, Morocco	713.23	191.55	345.5	1050	1537	-1.36

Source: Authors' computations using EViews 13.

The results of the symmetric GARCH model estimation for all the equity markets covered by the study are reported in Tables 3a to 3e. All the log-likelihood values are significant. For all the equity markets, the persistence coefficient of daily returns is robust for all markets, while the residual test of normality is significant for all markets. All the estimated coefficients are robust for each of the distributions. Also, even with the symmetric analysis, sGARCH (1,1) model with GED distribution had the leading logarithmic likelihood value, making it the best model for forecasting returns when asymmetry is not required for the analysis.

Table 3a. Results of symmetric GARCH (sGARCH) model for all Equity markets

Telnet Holding, Tunisia			
Parameters	**Student's-t**	**Gaussian Normal**	**GED**
τ	0.0460*** (0.0000)	0.0563*** (0.0000)	0.0470*** (0.0000)
ς_1	0.0820*** (0.0000)	0.0870*** (0.0000)	0.0860*** (0.0000)
ζ_1	0.7900*** (0.0000)	0.7930** (0.0039)	0.7910** (0.0060)
Persistence	0.87200	0.88000	0.87700
$Q^2(30)$	20.769 (0.980)	20.355 (0.980)	20.8931 (0.980)
Log-likelihood	−12450.3	−12780.3	−12425.3
Jarque-Bera	2357.1	2937.1	2899.1

	(0.000)	(0.000)	(0.000)
Botswana Diamonds plc			
Parameters	**Student's-t**	**Gaussian Normal**	**GED**
τ	0.0012***	0.0135***	0.0110***
	(0.0000)	(0.000)	(0.000)
ς_1	0.052***	0.042**	0.0150***
	(0.0000)	(0.0002)	(0.0000)
ζ_1	0.7210**	0.7230***	0.7200***
	(0.0045)	(0.0000)	(0.0000)
Persistence	0.77300	0.765000	0.735
$Q^2(30)$	23.058	22.567	20.046
	(0.5732)	(0.5560)	(0.5410)
Log-likelihood	−13550.0	−13580.0	−13510.5
Jarque-Bera	2387.1	23059.0	2245.0
	(0.000)	(0.000)	(0.000)

Source: authors' computation using EViews 13.

Table 3b. Results of symmetric GARCH (sGARCH) model for all Equity markets

Egyptian Iron & Steel			
Parameters	**Student's-t**	**Gaussian Normal**	**GED**
τ	0.0420**	0.0355***	0.0400***
	(0.011)	(0.0000)	(0.0000)
ς_1	0.0221***	0.0450**	0.0179***
	(0.0000)	(0.002)	(0.000)
ζ_1	0.8510***	0.8830***	0.8600**
	(0.0000)	(0.0000)	(0.0560)
Persistence	0.873100	0.928000	0.877900
$Q^2(30)$	15.024	15.0167	15.042
	(0.955)	(0.8980)	(0.9208)
Log-likelihood	−2358.30	−22591.0	−2230.6
Jarque-Bera	4666.1	4566.0	4560.0
	(0.000)	(0.000)	(0.000)
Total Kenya Ltd Ord 5.00			
Parameters	**Student's-t**	**Gaussian Normal**	**GED**
τ	0.0310**	0.0520***	0.0460**
	(0.0115)	(0.0000)	(0.0024)
ς_1	0.0520***	0.0580**	0.0520***
	(0.0000)	(0.0002)	(0.000)
ζ_1	0.9230***	0.9240***	0.92000***
	(0.0000)	(0.0000)	(0.0000)
Persistence	0.97500	0.982000	0.972000
$Q^2(30)$	10.004	10.0067	10.0032
	(0.4555)	(0.4580)	(0.4508)

Log-likelihood	−1220.30	−12251.0	−12050.0
Jarque-Bera	2456.0 (0.000)	2455.0 (0.000)	2590.0 (0.000)

Source: authors' computations using EViews 13.

Table 3c. Results of symmetric GARCH (sGARCH) model for all Equity markets

Petronas Chemicals Group Berhad, Malaysia			
Parameters	**Student's-t**	**Gaussian Normal**	**GED**
τ	0.0370** (0.0022)	0.0350** (0.0013)	0.0375*** (0.0000)
ς_1	0.0620*** (0.0000)	0.0300** (0.002)	0.0192*** (0.000)
ζ_1	0.6510*** (0.000)	0.6930*** (0.000)	0.6700*** (0.000)
Persistence	0.713000	0.723000	0.689200
$Q^2(30)$	26.0287 (0.540)	26.2380 (0.590)	26.2345 (0.572)
Log-likelihood	−1346.30	−1350.0	−1340.6
Jarque-Bera	1379.0 (0.000)	1375.0 (0.000)	1369.0 (0.000)
MTN South Africa Telecommunication			
Parameters	**Student's-t**	**Gaussian Normal**	**GED**
τ	0.0250*** (0.000)	0.0275*** (0.001)	0.0255*** (0.000)
ς_1	0.0740*** (0.000)	0.0760** (0.002)	0.0752*** (0.000)
ζ_1	0.8300*** (0.000)	0.8360*** (0.000)	0.8340*** (0.000)
Persistence	0.904000	0.912000	0.9092000
$Q^2(30)$	30.0571 (0.7009)	30.0567 (0.6540)	30.1948 (0.9702)
Log-likelihood	−5378.10	−5340.0	−5250.6
Jarque-Bera	1557.0 (0.000)	1559.0 (0.000)	1556.0 (0.000)

Source: authors' computation using EViews 13.

Table 3d. Results of symmetric GARCH (sGARCH) model for all Equity markets

Nigeria_Breweries			
Parameters	**Student's-t**	**Gaussian Normal**	**GED**
τ	0.0140*** (0.0000)	0.0150*** (0.0000)	0.0173*** (0.0000)
ς_1	0.0510** (0.0004)	0.0460** (0.0020)	0.0582*** (0.0000)

ζ_1	0.8210*** (0.0000)	0.8240*** (0.0000)	0.8250*** (0.0000)
Persistence	0.8720000	0.87000	0.8832000
$Q^2(30)$	19.0472 (0.934)	19.0447 (0.993)	19.0578 (0.990)
Log-likelihood	−3334.50	−3339.0	−33310.6
Jarque-Bera	12405.0 (0.000)	12409.0 (0.000)	12407.0 (0.000)
Forsys Metals Corporation, Namibia			
Parameters	**Student's-t**	**Gaussian Normal**	**GED**
τ	0.0220*** (0.0000)	0.0224** (0.0020)	0.0230*** (0.0000)
ς_1	0.0720** (0.0004)	0.0750** (0.0020)	0.0710*** (0.0000)
ζ_1	0.8920*** (0.0000)	0.89530*** (0.0000)	0.8930*** (0.0000)
Persistence	0.964000	0.970300	0.964000
$Q^2(30)$	24.579 (0.5560)	24.567 (0.6900)	24.5809 (0.7220)
Log-likelihood	−3396.30	−33541.0	−3329.6
Jarque-Bera	2850.0 (0.0000)	2856.0 (0.0000)	2854.0 (0.0000)

Source: authors' computations using EViews 13.

Table 3e. Results of symmetric GARCH (sGARCH) model for all Equity markets

Mauritius Oil Refineries			
Parameters	**Student's-t**	**Gaussian Normal**	**GED**
τ	0.0760** (0.0500)	0.0784** (0.0020)	0.0770*** (0.0000)
ς_1	0.0450*** (0.0000)	0.0490** (0.002)	0.0460*** (0.000)
ζ_1	0.8910*** (0.0000)	0.8950*** (0.0000)	0.8940** (0.0500)
Persistence	0.936000	0.944000	0.94000
$Q^2(30)$	30.0465 (0.5890)	30.4968 (0.5992)	30.4975 (0.5920)
Log-likelihood	−2344.30	−2347.0	−2305.6
Jarque-Bera	3055.0 (0.000)	3059.0 (0.000)	3058.0 (0.000)
White Nile Flour Mills, Sudan			
Parameters	**Student's-t**	**Gaussian Normal**	**GED**
τ	0.0590*** (0.0000)	0.0599*** (0.0020)	0.0592** (0.0240)

ς_1	0.0330*** (0.0000)	0.03750** (0.0020)	0.03470*** (0.0000)
ζ_1	0.9000** (0.023)	0.9550*** (0.0000)	0.9240*** (0.0000)
Persistence	0.933000	0.992500	0.958700
$Q^2(30)$	29.0039 (0.7890)	20.0068 (0.7892)	20.0059 (0.7849)
Log-likelihood	−9257.50	−9255.0	−9250.6
Jarque-Bera	4912.0 (0.000)	2268.0 (0.000)	2259.0 (0.000)
Disty Technologies, Morocco			
Parameters	**Student's-t**	**Gaussian Normal**	**GED**
τ	0.0270*** (0.000)	0.0293** (0.002)	0.0290*** (0.000)
ς_1	0.0340 (0.000)	0.0370** (0.000)	0.0350*** (0.000)
ζ_1	0.8760** (0.026)	0.8950*** (0.000)	0.8850*** (0.000)
Persistence	0.91000	0.932000	0.92000
$Q^2(30)$	17.0566 (0.3314)	17.0589 (0.3343)	17.3058 (0.3359)
Log-likelihood	−5382.50	−5498.0	−5184.6
Jarque-Bera	2743.0 (0.000)	2487.0 (0.000)	2205.0 (0.000)

Source: authors' computations using EViews 13.

Regarding the ARCH LM test for heteroskedasticity, any series that does not pose heteroscedasticity cannot be adopted in GARCH modeling. So as a rule of thumb, the ARCH test for heteroscedasticity has to be adopted to check for ARCH effects. The null hypothesis (H0) for this test is that a series does not suffer from heteroscedasticity. Accepting this at a 95 percent confidence level implies such a series does not suffer from irregular movements in its residual. In other words, they do not pose any conditional volatility spikes. On the other hand, rejecting the null implies such a series can be modelled and forecasted using either the ARCH model or any of the standard GARCH models. The results of the ARCH test are presented in Table 4.

Table 4. ARCH LM test for Heteroscedasticity

Equity market	**lag1 [pvalue]**	**lag2 [pvalue]**	**lag3 [pvalue]**	**lag4 [pvalue]**	**lag5 [pvalue]**
Telnet Holding, Tunisia	405.47 [0.00]	434.12 [0.00]	448.88 [0.00]	454.16 [0.00]	463.07 [0.00]
Botswana Diamonds plc	0 [0.98]	0 [0.99]	0.00 [1.00]	0.00 [1.00]	0.01 [1.00]
Egyptian Iron & Steel	111.76 [0.00]	159.7 [0.00]	171.74 [0.00]	208.89 [0.00]	217.19 [0.00]
Total Kenya Ltd Ord 5.00	1058.87 [0.00]	1122.43 [0.00]	1164.4 [0]	1167.67 [0.00]	1169 [0.00]

Petronas Chemicals Group Berhad, Malaysia	1.14 [0.86]	6.28 [0.025]	8.3 [0.59]	16.27 [0.63]	17.82 [0.19]
MTN South Africa Telecommunication	23.66 [0.00]	44.48 [0.00]	49.06 [0.00]	48.87 [0.00]	48.85 [0.00]
Nigeria_Breweries	77.08 [0.00]	97.18 [0.00]	114.63 [0.00]	114.5 [0.00]	114.65 [0.00]
Forsys Metals Corporation, Namibia	337.17 [0.00]	369.06 [0.00]	384.58 [0.00]	384.88 [0.00]	388.3 [0.00]
Mauritius Oil Refineries	0 [0.978]	0.00 [1.00]	0.00 [1.00]	0.00 [1.00]	0.00 [1.00]
White Nile Flour Mills Sudan	99.31 [0.00]	99.82 [0.00]	102.56 [0.00]	103.43 [0.00]	103.44 [0.00]
Disty Technologies, Morocco	0.84 [0.36]	1.09 [0.58]	1.83 [0.60]	1.88 [0.79]	1.88 [0.43]

Source: authors' computations using EViews 13.

The calculated p-value at a 95 percent confidence level is presented in the square bracket at several lag values. The results indicated a piece of overwhelming evidence for accepting the H0 for the equity market index for Botswana Diamonds Plc and Disty Technologies of Morocco. This implies the markets cannot be modelled or the series forecasted using the GARCH modelling techniques. The partial evidence was presented for accepting the H0 in the sense that at lag 1, we ought to accept the series for Petronas Chemicals Group Berhad, Malaysia, which cannot be modelled. But this claim is not robust by increasing the lags. Accordingly, the following equity markets whose graphs are presented below, namely, Telnet Holding, Tunisia, Egyptian Iron & Steel, Total Kenya Ltd Ord 5.00, MTN South Africa Telecommunication, Nigeria_Breweries, Forsys Metals Corporation of Namibia, Mauritius Oil Refineries, and White Nile Flour Mills of Sudan, are the only markets that can be modelled by GARCH models (Figures 1-8).

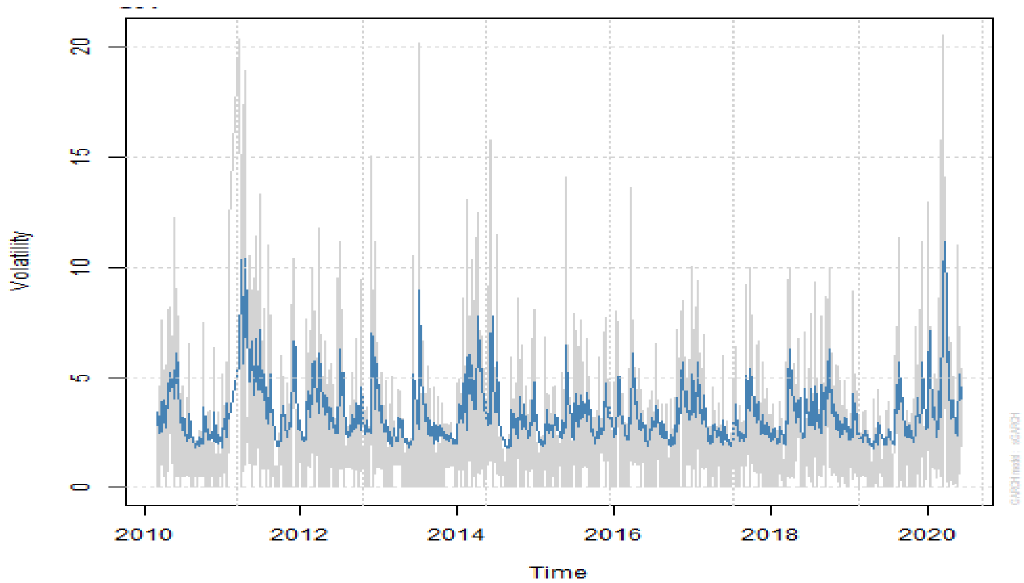

Figure 1. Pattern of returns of Telnet Holding, Tunisia.
Source: authors' plot, using EViews 13.

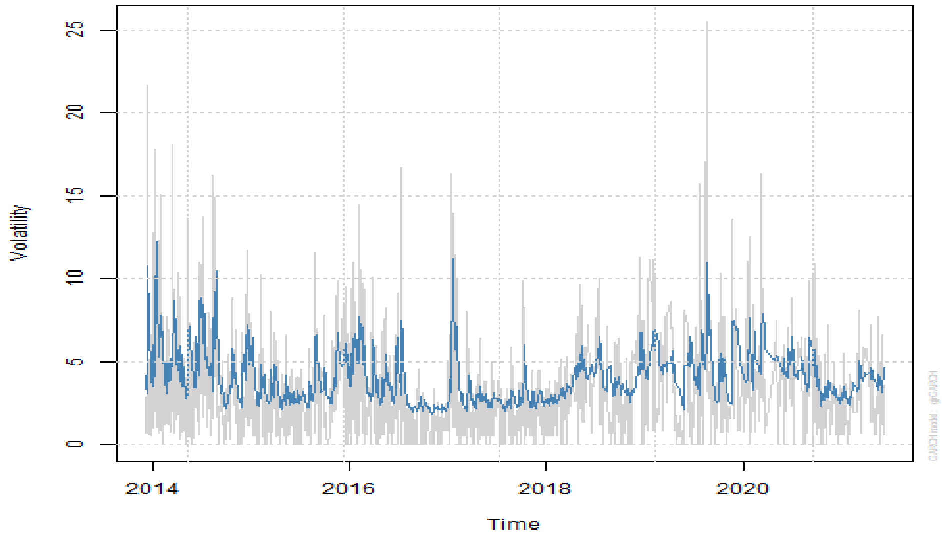

Figure 2. Pattern of returns in the Egyptian Iron & Steel.
Source: authors' plot, using EViews 13.

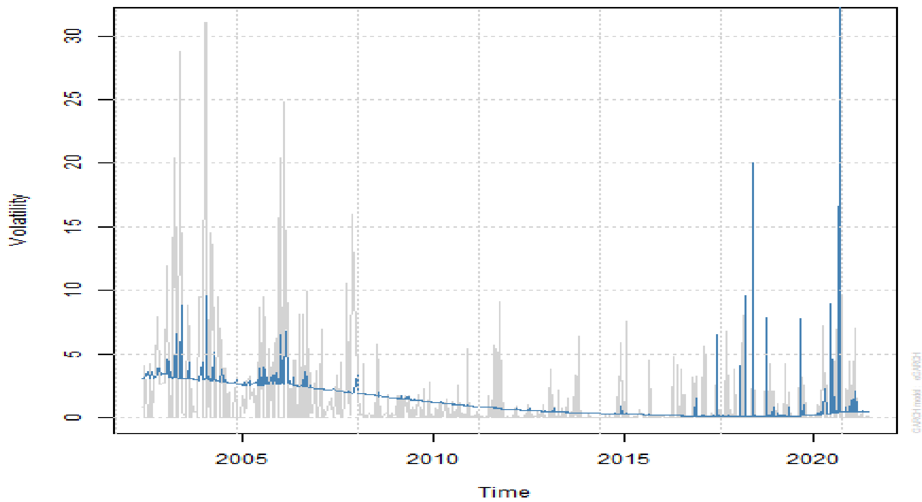

Figure 3. Pattern of returns of Total Kenya Ltd Ord 5.00
Source: authors' plot using Eviews 13, 2024.

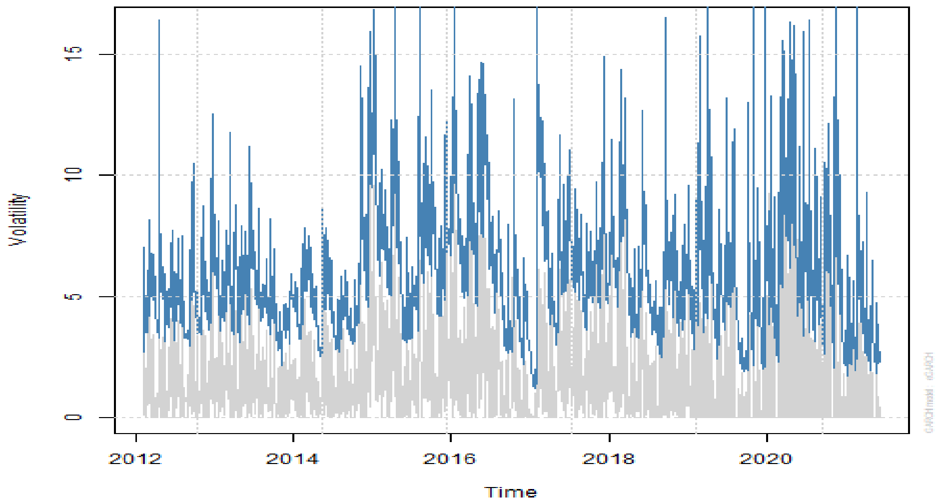

Figure 4. Pattern of returns of MTN South Africa Telecommunication.
Source: Authors' plot using EViews 13.

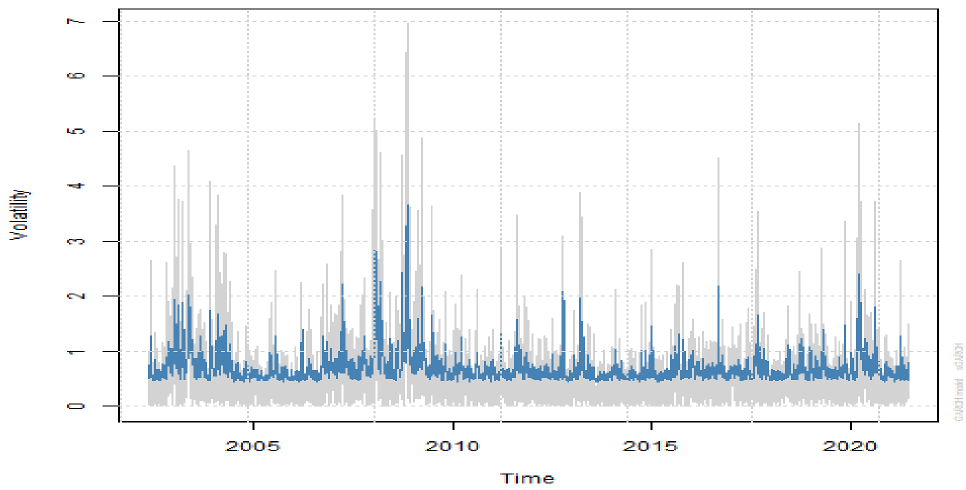

Figure 5. Pattern of returns of Nigeria_Breweries.
Source: authors' plot using EViews 13.

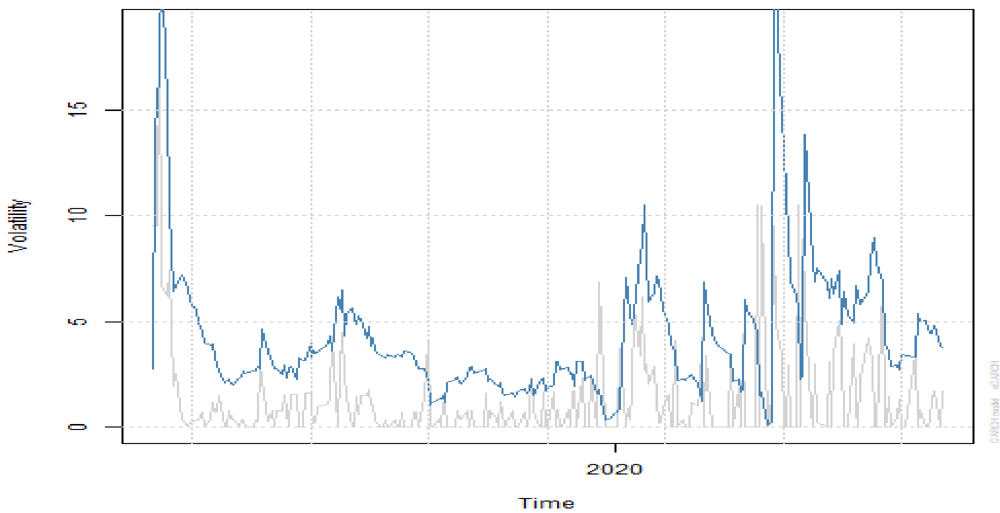

Figure 6. Pattern of returns of Forsys Metals Corporation, Namibia.
Source: authors' plot using EViews 13.

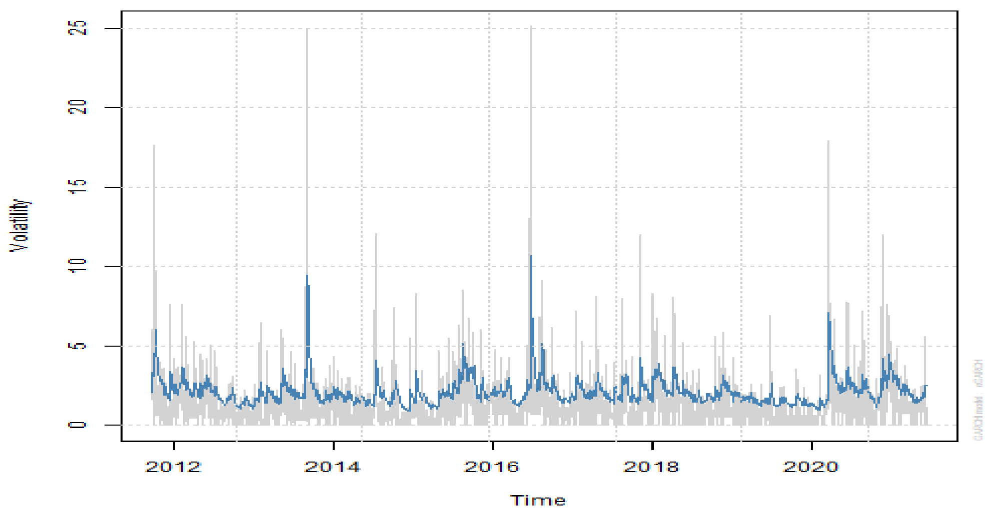

Figure 7. Pattern of returns of Mauritius Oil Refineries.
Source: authors' plot using EViews 13.

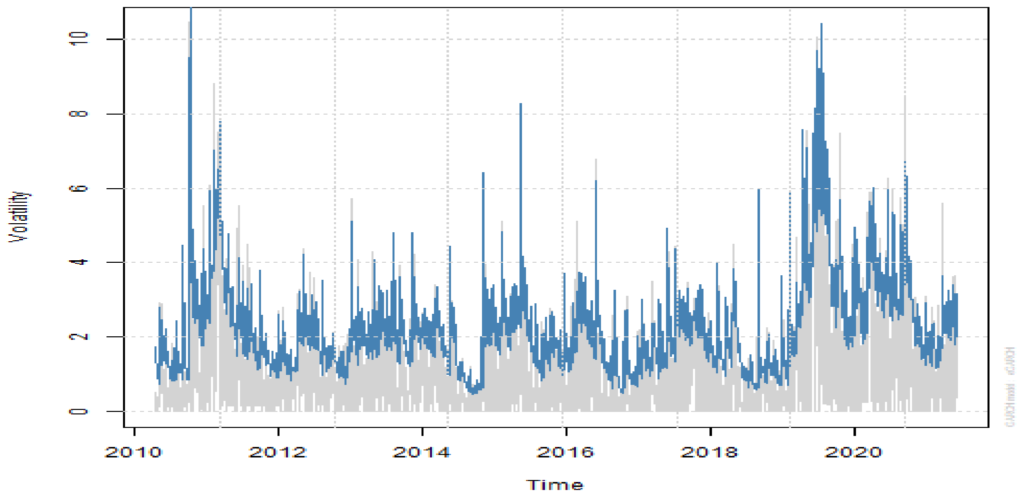

Figure 8. Pattern of returns of White Nile Flour Mills of Sudan.
Source: Authors' plot using EViews 13.

Table 5. Best GARCH model

Equity Market	Best ARMA model	Best GARCH Model	Distribution
Telnet Holding, Tunisia	ARMA(1,1)	eGARCH(1,1)	GED
Egyptian Iron & Steel	ARMA(1,1)	gjrGARCH(1,1)	Student's-t
Total Kenya Ltd Ord 5.00	ARMA(1,1)	eGARCH(1,1)	GED
MTN South Africa Telecomunication	ARMA(1,1)	gjrGARCH(1,1)	Student's-t
Nigeria_Breweries	ARMA(1,0)	gjrGARCH(1,1)	Student's-t
Forsys Metals Corporation, Namibia	ARMA(0,1)	gjrGARCH(1,1)	Student's-t
Mauritius Oil Refineries	ARMA(0,1)	gjrGARCH(1,1)	Student's-t
White Nile Flour Mills Sudan	ARMA(1,1)	eGARCH(1,1)	GED

Source: authors' computations using EViews 13.

Table 6. GARCH model results for each equity market

Parameters	Tunisia	Egypt	Kenya	South Africa	Nigeria
mu	-0.06*** [-0.01]	-0.08 [-0.04]	0.01 [-0.01]	-0.10*** [-0.02]	-0.02 [-0.02]
gama	0.09* [-0.04]	-0.10*** [-0.02]	0.64*** [-0.03]	-	-
alpha	-0.34*** [-0.04]	-	-0.36*** [-0.04]	-0.09*** [-0.02]	-
beta	0.02** [-0.01]	0.50*** [-0.11]	0.06*** [-0.01]	0.07*[-0.03]	0.29* [-0.13]
alpha1	0.01[-0.05]	0.16*** [-0.02]	0.21*** [-0.02]	-0.02[-0.02]	0.90* [-0.37]
alpha2	-0.02[-0.05]				
beta1	0.99*** [0.00]	0.81*** [-0.02]	0.68*** [-0.04]	0.95*** [-0.02]	0.87*** [-0.03]
gamma1	0.80***	-	-	0.29***	0.02

	[-0.07]			[-0.05]	[-0.05]
gamma2	-0.51*** [-0.05]	-	-	-	-
alpha	0.57*** [-0.07]	0.47*** [-0.41]	1.84*** [-0.47]	2.90*** [-0.19]	2.10*** [-0.09]
Variance	egarch	gjrGARCH	gjrGARCH	egarch	egarch
Distribution	GED	Student's-t	Student's-t	GED	GED
Persistence	0.99	0.98	0.89	0.95	0.87
Convergence	0	0	0	0	0
N	2639	2466	4743	2376	261
Log-likelihood	-4529.92	-6149.18	-4578.27	-4493.17	-483.43
AIC	2.44	2.99	1.93	2.79	1.75
BIC	2.06	2.01	1.95	2.81	1.83
SIC	2.45	2.00	1.54	2.79	1.75
HQ	2.46	2.01	1.44	2.11	1.30

Parameters	**Namibia**	**Mauritius**	**Sudan**
mu	0.0 [-0.02]	0.01*** [0.00]	-0.18*** [-0.05]
ma1	-0.10*** [-0.02]	-	-0.37*** [-0.03]
omega	0.12*** [0]	-0.01*** [0.00]	0.76** [-0.27]
alpha1	0.15 [-0.09]	-0.12*** [0.00]	0.16*** [-0.04]
alpha2	-0.14 [-0.09]	0.11*** [0.00]	-
beta1	0.97*** [0.00]	1.00*** [0.00]	0.75*** [-0.04]
gamma1	1.25*** [-0.12]	0.13*** [0.00]	0.17** [-0.06]
gamma2	-0.57*** [-0.12]	-0.12*** [0.00]	-
alpha1	2.10*** [-0.01]	2.10*** [-0.01]	5.45*** [-0.72]
Variance	eGARCH	eGARCH	gjrGARCH
Distribution	GED	GED	Student's-t
Persistence	0.97	1	1
Convergence	0	0	0
N	2287	1260	1403
Log-likelihood	-4950.4	-1091.76	-3796.73
AIC	2.05	1.75	1.32
BIC	2.17	1.88	1.45

SIC	2.04	1.02	1.13
HQ	2.06	1.09	1.25

Note: *Mu* is the constant, *ma* is the moving average, *ar* is an autoregressive term, *alpha* is the arch effect, *beta* is the GARCH effect, *gamma* is the leverage effect, and *omega* is ARCH effect, N is the total observations. *AIC, BIC, SIC, and HQ* are the information criterion. * $p<0.05$ ** $p<0.01$ *** $p<0.001$.

Source: authors' computations using EViews 13.

5. Discussion

We have established the stationarity properties of the series, and from the results presented in Table 2, we find evidence for adopting GARCH models to examine the series at this level. There are two stages in GARCH modelling. The first stage involves estimating the mean equation (presented as the ARMA model), and the second stage involves the estimation of the conditional mean equation (GARCH model). The appropriate p and q order for the ARMA model is essential to estimating the best ARMA model. The same goes for the GARCH model. In addition to the GARCH model, the best distribution has to be obtained for the model. The failure to obtain the most appropriate p and q order and type of distribution could lead to poor performance of the GARCH model, particularly in forecasting. This seminar paper adopts a simulation technique to get the best p and q order for the ARMA and GARCH models. The best model was selected using information criteria. In addition, the simulation also leads to obtaining the best distribution (among others, like the normal distribution and the Student's *t* distribution) for the series. The results, as presented in Table 5, indicated the best models for estimating conditional volatility and forecasting. For Petronas Chemicals Group Berhad of Malaysia, MTN South Africa Telecomunication, and Nigeria Breweries, the best mean equation is ARMA (0,1), ARMA (0,0), and ARMA (0,1), respectively. These countries' best GARCH model for estimating and forecasting returns is eGARCH with GED distribution. The same eGARCH model with the GED also goes for Telnet Holding of Tunisia and Forsys Metals Corporation of Namibia. While for White Nile Flour Mills Sudan, the gjrGARCH model with Student's-t distribution happens to be the GARCH model. For Egyptian Iron & Steel, the gjrGARCH model with the Student's *t* distribution is the most appropriate, whereas for Total Kenya Ltd. Ord 5.00, the corresponding best GARCH model is gjrGARCH (1,1) with the Student's-t distribution.

Using the obtained ARMA and GARCH models presented in 5, this paper proceeds to estimate the conditional volatilities. The results are presented in Table 6. The values in the square brackets are the parameters' standard errors. Starting with Telnet Holding of Tunisia, all the parameters in the ARMA and GARCH models (except the arch effect) are all significant at the 5 percent level. For the GARCH equation, this implies that the GARCH effect (beta) is statistically significant, as is the ARCH effect. The leverage effect (gamma) is significant for all the equity markets, namely, Telnet Holding of Tunisia, Egyptian Iron & Steel, Total Kenya Ltd. Ord 5.00, MTN South Africa Telecommunication, Nigerian Breweries, Forsys Metals Corporation of Namibia, Mauritius Oil Refineries, and White Nile Flour Mills of Sudan. This implies that market news has an asymmetric effect on the return of these markets. That is, positive news on the market has a different impact on market return compared to negative news. In addition, the model persistence is very close to but not equal to 1, which implies the volatility of all listed companies on the various stock exchanges of the selected emerging countries in Africa is very long and thus decays slowly.

Likewise, MTN South Africa Telecommunication can best be modelled and best fore-casted using the exponential GARCH model. All the parameters in the estimated ARMA and GARCH models are significant at 5 percent, except the parameters of the ARMA model. From the GARCH model, the GARCH effect (beta) and the ARCH effect (alpha) are present and statistically significant. The leverage effect (gamma) is not statistically significant. Thus, this seminar paper finds no significant evidence to support the claim that the claim that market news has an asymmetric effect on the shares of the telecommunications network (MTN) in South Africa. Market participants do not react to the news differently. In addition, the persistence coefficient is less than 1, which implies the volatility of MTN is persistence and decay slowly at 13 percent. For Egypt Tourism Resort, the best model is the standard GARCH model, which performs best in forecasting the series. Also, all the parameters in the ARMA and GARCH models are significant at the 5 percent level except the mean equation constant (mu). In other words, the GARCH effect (beta) and the ARCH effect (alpha) are present and statistically significant. In addition, the model persistence is greater than 1, which implies the volatility of Tunisia's bank is very long and thus decays slowly. Also, all the parameters in the ARMA and GARCH models are significant at 5 percent except the mean equation constant (mu). In other words, the GARCH effect (beta) and the ARCH effect (alpha) are present and statistically significant. In addition, the model persistence is less than 1, which implies the volatility of Tunisia Bank is very long and thus decays slowly.

The Nigerian breweries, an equity market, can also be modelled and forecasted using the eGARCH model. All the parameters in the estimated ARMA and GARCH models are significant at 5 percent, except the parameters of the ARMA model. From the GARCH model, the ARCH effect (alpha) is statistically insignificant. This implies that previous shocks do not have a significant effect on current market volatility. The GARCH effect has a significant impact. The model persistence is close to 1 and strongly indicates that market volatility does not die out. Similarly, the best estimating model found for White Nile Flour Mills in Sudan is the gjrGARCH model, which performs best in forecasting the series. Also, all the parameters in the ARMA and GARCH models are significant at 5 percent. In other words, the GARCH effect (beta) and the ARCH effect (alpha) are present and significant. In addition, the model persistence is 1, which implies the volatility of the Telnet Holding of Tunisia is very long and does not decay as time passes. The Namibia Breweries can best be modelled using the eGARCH model. All the parameters in the estimated ARMA and GARCH models are significant at 5 percent. The GARCH effect (beta) and the ARCH effect (alpha) at lag 1 are present and statistically significant. The leverage effect (gamma) at lag 1 is significant. This implies that market news has an asymmetric effect on Namibian breweries. That is, positive news on the market has a different impact on market volatility compared to negative news. In addition, the model is highly persistent. By and large, our findings uphold that in emerging market economies, eGARCH performs best, with the implication that the returns in these markets respond asymmetrically to bad and good news. In effect, our findings corroborated the results obtained by studies reviewed in the literature that based forecasting on asymmetric GARCH models. These include studies by Kim, Kim, and Jung (2021), López-Cabarcos, Ribeiro-Soriano, and Piñeiro-Chousa (2020), and Milošević, Anđelić, Vidaković, and Đaković (2019).

5. Conclusions

In this study, an attempt was made to find the best GARCH model for forecasting the stock returns of emerging economies in Africa. We utilized the daily data series of ten stock markets in Africa. Overall, the issues raised by the reviews of empirical literature are greatly consistent with the findings of our present investigation. In sum, Botswana, Malaysia, and Morocco stock returns do not possess the ARCH effect, whereas other emerging markets pose the ARCH effect. For Egyptian Iron & Steel, Total Kenya Ltd. Ord. 5.00, and White Nile Flour Mills of Sudan, the best GARCH model for estimating and forecasting returns is gjrGARCH (1,1). This implies that market returns respond symmetrically to bad and good news concerning stock returns. For Telnet Holding of Tunisia, Nigeria Breweries, MTN South Africa Telecommunication, and Forsys Metals Corporation of Namibia, the best GARCH models are eGARCH and gjrGARCH for Sudan.

For the Sudan stock market, the best GARCH model for estimating and forecasting returns is gjrGARCH. These stock returns also respond differently to both good and bad news relating to stock returns. The contribution of the study to the literature derives from the empirical fact that the study established exponential GARCH (eGARCH) as the best model for forecasting returns in Telnet Holding of Tunisia, Nigerian breweries, the MTN South Africa Telecommunication Stock Market, gjrGARCH (1,1) as the best model for forecasting returns at Total Kenya Ltd Ord 5.00, and White Nile Flour Mills of Sudan. The study also established that in emerging markets where eGARCH and gjrGARCH are applicable, the stock market returns react differently to the market news relating to them, while in markets where sGARCH is applicable, as in the case of Botswana Diamonds Plc., Petronas Chemicals Group Berhad, Malaysia, and Disty Technologies, Morocco, the returns in these markets do not react differently to market news. Overall, the most suitable GRACH models are supported by the student-t and general error distributions.

This paper recommends the need for market participants, particularly brokers and jobbers, including stockholders, to use the aforementioned models in forecasting each corresponding emerging market return. Also, we do recommend that investors in these markets, particularly those in the equity market where volatility decays slowly and the market where volatility responds asymmetrically, be watchful, as these could pose a significant threat to their market portfolio. The small sample of stock market coverage to represent the population of markets is a limitation of the present research. This calls for the need for future researchers to engage in expanded coverage of the stock markets of both emerging and industrialized countries. In this regard, a comparative analysis based on the modelling and forecasting of stock market returns between advanced and unindustrialized financial markets could be undertaken to evaluate the best GARCH model for forecasting stock returns and volatility through the maximum likelihood estimation of the GARCH models based on the Marquardt algorithm or the panel Bayesian VAR modelling technique.

Conflicts of Interest: The authors declare no conflict of interest.

References

Abidin, S. H. S. J., Hasnan, S., Marzuki, M. M., & Mohamed Hussain, A. R. (2022). A contemporary review of stock market liquidity studies in emerging countries. *Corporate & Business Strategy Review, 3*(1), 8–18. https://doi.org/10.22495/cbsrv3i1art1

Abina, A. P., & Lemea, G. M. (2019). Capital market and performance of Nigerian economy. International Journal of Innovative Finance and Economics Research, 7(2), 51-66.

Acha, I. A., & Akpan, S. O. (2019). Capital market performance and economic growth in Nigeria. *Noble International Journal of Economics and Financial Research, 4*(2),10-18.

Adam, A. M., & Gyamfi, E. N. (2015). Time-varying world integration of the African stock markets: A Kalman filter approach. *Investment Management and Financial Innovation 12*, 175–181.

Adoms, F. U., Yua, H., Okaro, C. S., & Ogbonna, K. S. (2020). Capital market and economic development: a comparative study of three sub-Saharan African emerging economies. *American Journal of Industrial and Business Management, 10*, 963-987. https://doi.org/10.4236/ajibm.2020.105065.

Agbonrha-Oghoye, I. I., Ohiokha, G., Umoru, D., Akhor, S. O., & Igele G. A. (2022). Target capital structure for managerial decision making: Dynamics and determinants. *Investment Management and Financial Innovations, 19*(3), 322-334.

Ajigal, D. I., Adeleye, R. A., & Tubokirifuruar, T. S. (2024). Machine learning for stock market forecasting: a review of models and accuracy. *Finance & Accounting Research Journal, 6*(2), 10-18.

Akintola, A. F., & Cole, A. A. (2020). Capital market and economic growth in Nigeria (1984-2015). *IOSR Journal of Humanities and Social Science, 25*(46), 38-46. https://doi.org/10.9790/0837-2504063846

Alabede, J. O. (2015). An Evaluation of the performances of the Nigerian stock exchange. *The Gubi Journal, 1*(73), ASUP, Bauchi.

Algaeed, A. H. (2020). Capital market development and economic growth: an ARDL approach for Saudi Arabia, 1985-2018. *Journal of Business Economics and Management,* 1-22. https://doi.org/10.3846/jbem.2020.13569.

Ali, F., Suri, P., Kaur, T., & Bisht, D. (2022). Modelling time-varying volatility using GARCH models: evidence from the Indian stock market. *F1000Research, 11*, 1098. https://doi.org/10.12688/f1000research.124998.2

Aliyev, F., Ajayi, R., & Gasim, N. (2020). Modeling asymmetric market volatility with univariate GARCH models: Evidence from Nasdaq-100. *The Journal of Economic Asymmetries, 22*, e00167. https://doi.org/10.1016/j.jeca.2020.e00167

Al-Rimawi, M. A., & Kaddumi, T. A. (2021). Factors affecting stock market index volatility: Empirical study. *Journal of Governance & Regulation, 10*(3), 169–176. https://doi.org/10.22495/jgrv10i3art15

Andersen, T. G. & Bollerslev, T. (1998a). Answering the skeptics: Yes, standard volatility models do provide accurate Forecasts. *International Economic Review, 39*(4), 885-905.

Anderu, K. S. (2020). Capital market and economic growth in Nigeria. *Jurnal Perspektif Pembiayaan dan Pembangunan Daerah, 8*(3), 295-310. https://doi.org/10.22437/ppd.v8i3.9652

Angaye, P. E., & Frank, B. P. (2020). Capital market development and economic growth in Nigeria. *American Journal of Business Management, 3*(7), 58-63.

Anwar, A., Mohd-Rashid, R., & Che-Yahya, N. (2022). A review of the flipping activity of IPO: Evidence from developed and emerging markets. *Corporate Governance and Organizational Behavior Review, 6*(1),56–63. https://doi.org/10.22495/cgobrv6i1p4

Anwar, T., & Raza, Y. M. (2016). Economic Integration of Stock Markets: An Evidence from Pakistan, China, and Malaysia stock exchanges. *Management and Organizational Studies, 3*(3), 52-59. http://dx.doi.org/10.5430/mos.v3n3p52

Asteriou, D. & Spanos, K. (2019). The relationship between financial development and economic growth during the recent crisis: Evidence from the EU. *Finance Research Letters, 28*, 238-245.

Attah-Botchwey, E., Awadzie, D.M., & Agbenyezi, W., (2022). Financial deepening and stock market performance in selected Sub-Sahara African countries. *Journal of Economics, Finance, and Accounting, 9*(1), 30-38. http://doi.org/10.17261/Pressacademia.2022.1543

Awajan, A. M., Ismail, M. T., & Wadi, S. A. (2018). Improving forecasting accuracy for stock market data using EMD-HW bagging. *PLoS One, 13*(7), 1–20.

Bello, A. H., Folorunsho, A. I., & Alabi, O. O. (2019). A study on Johansen co-integration approach in analyzing the relationship between the capital market on the economic growth in Nigeria. *FUW Trends in Science & Technology Journal, 4*(2), 560–568.

Chen, X. L. (2017). Stock price prediction based on the ARIMA model and neural network model. *Economic Mathematics, 34*(4), 30-34.

Devpura, N., Narayan, P. K., & Sharma, S. S. (2018). Is stock return predictability time-varying? *Journal International Financial Market, Institution & Money, 52*, 152–172.

Donwa, P. & Odia, J. (2010). An empirical analysis of the impact of the Nigerian capital market on her socio-economic development. *Journal of Social Science, 24*(2), 135-142. https://doi.org/10.1080/09718923.2010.11892845

Dritsaki, C. (2017). An empirical evaluation in GARCH volatility modeling: evidence from the Stockholm Stock Exchange. *Journal of Mathematical Finance, 7*, 366-390. https://doi.org/10.4236/jmf.2017.72020.

Dutta, A. (2014). Modeling Volatility: Symmetric or asymmetric GARCH models? *Journal of Statistics: Advances in Theory and Applications, 12*, 99-108.
Emmanuel, A. O., & Elizabeth, O. E. (2020). Capital market performance as a panacea for economic growth in Nigeria. *International Business Research, 13*(2), 1-1. https://doi.org/10.5539/ibr.v13n2p1
Gao, Y., Zhang, C., & Zhang, L. (2012). Comparison of GARCH models based on different distributions. *Journal of Computers, 7*. https://doi.org/10.4304/jcp.7.8.1967-1973.
Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *Journal of Finance, 48*(5), 1779–1801.
Goldsmith, R. W. (1969). *Financial structure and development.* New Haven, Coon: Yale University Press.
Grbić, M. (2020). Stock market development and economic growth: The case of the Republic of Serbia. *Post-Communist Economies*, 1-16. https://doi.org/10.1080/14631377.2020.1745566
Gulzar, S., Mujtaba Kayani, G. M., Xiaofeng, H., Ayub, U., & Rafique, A. (2019). Financial co-integration and spillover effect of the global financial crisis: A study of emerging Asian financial markets. *Economic Research-Ekonomska Istraživanja, 32*(1), 187–218. https://doi.org/10.1080/1331677X.2018.1550001.
He, B. L. (2008). The optimal selection model for stock price prediction. *Statistics and Decision, 6*, 135-137.
Hongwiengjan, W., & Thongtha, D. (2021). An analytical approximation of option prices via TGARCH model. *Economic Research-Ekonomska Istraživanja, 34*(1), 948–969. https://doi. org/10.1080/1331677X.2020.1805636
Ibrahim, U. A., & Mohammed, Z. (2020). Assessing the impact of capital market development on economic growth: Evidence from Nigeria. *IOSR Journal of Economics and Finance, 11*(2), 01-15. https://doi.org/10.9790/5933-1102070115
Jiang, W., Ruan, Q., Li, J., & Li, Y. (2018). Modeling returns volatility: Realized GARCH incorporating realized risk measure. *Physica A: Statistical Mechanics and Its Applications, 500*, 249–258. https://doi.org/10.1016/j.physa.2018.02.018.
Kim, J.-M., Kim, D. H., & Jung, H. (2021). Estimating yield spreads volatility using GARCH-type models. *The North American Journal of Economics and Finance, 57*, 101396. https://doi.org/10.1016/j.najef.2021.101396.
Lakshmanasamy, T. (2021). The causal relationship between capital market performance and economic growth: A vector error correction model estimation. *Indian Journal of Applied Business and Economics Research, 2*(1), 99-119.
Levenberg, K. (1944). A method for the solution of certain non-linear problems in least squares. Quarterly of Applied Mathematics, 2(2), 164–168. https://doi.org/10.1090/qam/10666
López-Cabarcos, M. Á., Ribeiro-Soriano, D., & Piñeiro-Chousa, J. (2020). All that glitters is not gold. The rise of gaming in the COVID-19 pandemic. *Journal of Innovation & Knowledge, 5*(4), 289-296. https://doi.org/10.1016/j.jik.2020.10.004
Lu, W.B. (2006). Chinese stock market volatility prediction based on a non-parametric GARCH model. *Mathematical Statistics and Management, 25*(4), 455-461.
Luo, Q., Bu, J., Xu W., & Huang, D. (2023). Stock market volatility prediction: Evidence from a new bagging model. *International Review of Economics & Finance, 87*(C), 445-456. https://doi.org/10.1016/j.iref.2023.05.008
Mallikarjuna M., Arti G., & Rao R. P. (2018). Forecasting stock returns of selected sectors of Indian capital market. *SS International Journal of Economics and Management, 8*(6), 111–126.
Mallikarjuna, M., & Rao, R. P. (2019). Evaluation of forecasting methods from selected stock market returns. *Finance Innovation, 5*, 40. https://doi.org/10.1186/s40854-019-0157-x
Manuel, E. F., João, D., & Jelson, S. (2022). Stock market and economic growth: Evidence from Africa. Working Papers REM 2022/0228, ISEG - Lisbon School of Economics and Management, REM, Universidade de Lisboa.
Marquardt, D. (1963). an algorithm for least-squares estimation of nonlinear parameters. *SIAM Journal on Applied Mathematics, 11*(2), 431–441. https://doi.org/10.1137/0111030
McKinnon, R. I. (1973). *Money and Capital in Economic Development.* Washington DC: Brookings Institutions Press.
Milošević, M., Anđelić, G., Vidaković, S., & Đaković, V. (2019). The influence of holiday effect on the rate of return of emerging markets: A case study of Slovenia, Croatia, and Hungary. *Economic Research-Ekonomska Istraživanja, 32*(1), 2354-2376. https://doi.org/10.1080/1331677X.2019.1638281.
Nayak, S. C., & Misra, B. B. (2018). Estimating stock closing indices using a GA-weighted condensed polynomial neural network. *Financial Innovation, 4*(21), 1–22.
Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica, 59*(2), 347–370.
Salisu, A. A. & Vob, X. V. (2020). Predicting stock returns in the presence of covid-19 pandemic: The role of health news. *International Review of Financial Analysis, 71*, 101546. https://doi.org/10.1016/j.irfa.2020.101546
Salisu, A. A., Isah, K. O., & Akanni L. O. (2019). Improving the predictability of stock returns with Bitcoin prices. *North American Journal of Economics and Finance, 48*, 857–867. https://doi.org/10.1016/j.najef.2018.08.010
Salisu, A. A., Raheem, I. D., & Ndako U. D. (2019). A sectoral analysis of asymmetric nexus between oil price and stock returns. *International Review of Economics and Finance, 61*, 241-259. https://doi.org/10.1016/j.iref.2019.02.005
Salisu, A. A., Swaray, R., & Oloko, T. F. (2019). Improving the predictability of the oil-US stock nexus: The role of macroeconomic variables. *Economic Modelling, 76*, 153–171. https://doi.org/10.1016/j.econmod.2018.07.029
Salisu, A.A., Isah, K. O., & Raheem I. D. (2019). Testing the predictability of commodity prices in stock returns of G7 countries: Evidence from a new approach. *Resources Policy, 64*. https://doi.org/10.1016/j.resourpol.2019.101520
Shaw, E. S. (1973). *Financial Deepening in Economic Development.* Oxford University Press, New York.
Stiglingh, Z. & Seitshiro, M. (2022). Quantification of GARCH (1, 1) model misspecification with three known assumed error term distributions. *Journal of Financial Risk Management, 11*, 549-578. https://doi.org/10.4236/jfrm.2022.113026.
Sun, W. (2003). Relationship between Trading Volume and Security Price and Return. MIT Laboratory for Information and Decision Systems. http://ssg.mit.edu/group/waltsun/docs/Area.ExamTR2638.pdf.
Tachiwou, A. M. (2010). Stock Market Development and Economic Growth: The case of West African Monetary Union. *International Journal of Economics and Finance, 2*(3), 97–111.
Tudor, C. (2008). Modeling time series volatilities using symmetrical GARCH models. *The Romanian Economic Journal, 30*, 183-208.

Twerefou, D., Abbey, E., Codjoe, E., & Ngotho, P. (2019). Impact of stock market development on economic growth: evidence from selected sub-Saharan African countries. *Acta Universitatis Agriculturae et Silviculturae Mendelianae Brunensis, 67*, 1071-1083. 10.11118/actaun201967041071.

Umoru, D. (2022). Devaluation of naira, shocks, and realities: Evidence disciplining strength. 4th Inaugural Lecture Series of Edo State University Uzairue, Nigeria.

Umoru, D., Effiong, S. E., Okpara, E., Iyayi, D., Oyegun, G., Iyaji, D., …Ekeoba, A. A. (2023f). Fiscal effects of exchange rate devaluation and capital flows to emerging countries. *Journal of Governance & Regulation, 12*(1), 387–400. https://doi.org/10.22495/jgrv12i1siart17.

Umoru, D., Effiong, S. E., Ugbaka, M. A., Iyaji, D., Okpara, E., Ihuoma, C. C., …Omomoh, O. H. (2023e). Evaluating structural relations between money demands and its determinants. *Corporate Governance and Organizational Behavior Review, 7*(2), 71–95. https://doi.org/10.22495/cgobrv7i2p7

Wang, C. (2024). Stock return prediction with multiple measures using neural network models. *Finance Innovation, 10*(72). https://doi.org/10.1186/s40854-023-00608-w

Wei, H. Y., & Meng, C. J. (2014). Short-term exchange rate prediction based on the GARCH model. *Economic Mathematics, 31*(1), 81-84.

Wu, Y. X., & Wen X. (2016). Short-term stock price prediction based on the ARIMA model. *Statistics and Decision, 23*, 83-86.

Xu, Y., Wang, X., & Liu, H. (2021). Quantile-based GARCH-MIDAS: Estimating value-at-risk using mixed-frequency information. *Finance Research Letters*, 101965. https://doi.org/10.1016/j.frl.2021.101965

Yang, Q., & Cao, X. B. (2016). Analysis and prediction of stock price based on the ARMA-GARCH model. *Mathematical Practice and Cognition, 46*(6), 80-86.

Yuanwei, H., Zheng, T., Dongao, X., Ziyi, P., Junyi, Z., & Xiaoling, C. (2020). Research on stock returns forecast of the four major banks based on ARMA and GARCH Model. *Journal of Physics: Conference Series, 1616*, 012075. https://doi.org/10.1088/1742-6596/1616/1/01207

Yuling, W., Yunshuang, X., Xinyu, L., & Yucheng, Z. (2022). Volatility analysis based on GARCH-type models: Evidence from the Chinese stock market. *Economic Research-Ekonomska Istraživanja, 35*(1), 2530-2554. https://doi.org/10.1080/1331677X.2021.1967771

Zhifeng, D., & Xiaoming, C. (2021). Predicting stock return with an economic constraint: can interquartile range truncate the outliers? *Mathematical Problems in Engineering*. https://doi.org/10.1155/2021/9911986

Zhong, X., & Enke, D. (2019). Predicting the daily return direction of the stock market using hybrid machine learning algorithms. *Financial Innovation, 5*(4), 1–20.

Živkov, D., Kuzman, B., & Andrejević-Panić, A. (2021). Nonlinear bidirectional multiscale volatility transmission effect between stocks and exchange rate markets in the selected African countries. *Economic Research-Ekonomska Istraživanja, 34*(1), 1623-1650.