Nigeria Stock Market Volatility in Comparison with some Countries: Application of Asymmetric GARCH Models

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This study estimated Asymmetric generalized autoregressive conditional heteroscadasticity models with endogenous break dummy on two innovation assumptions using daily all share index of Nigeria, Kenya, United States, Germany, South Africa and China spanning from February 14, 2000 to February 14, 2013. The best fitted models are compared in terms of conditional volatility reaction to market shocks and volatility persistence alongside the asymmetric properties. The results reveal that volatility of Nigeria and Kenya stock returns react to market shock faster than as other countries do. The results also suggest the absence of leverage effect in Nigeria and Kenya stock returns, but confirm its existence in others. In conclusion, the paper suggested that less developed stock markets should improve on market infrastructure, quality of instrument traded on the floor and regulatory practices as such efforts could moderate its fast response to market fluctuations.

Keywords: Stock Market, Volatility, EGARCH, TGARCH, Error Distributions

JEL Classification: C22, C52, C53

1.0 Introduction

Conceptually, equity market volatility measures the degree of variation of the current equity price from its average past values, which is synonymous with risk level of the market. The risk amplitude is represented by the extent of dispersion of returns around the mean. The greater the dispersion of returns around the mean, the larger the drops in the compound return. Generally, equity market volatility brings to picture the magnitude of rising and falling of equity prices. Thus, the relationship between volatility and equity market performance cannot be overemphasized. The performance of equity market, in terms of returns, gets better as volatility tends to decline; and plummets as volatility tends to rise.

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In most economies, effective equity market remains a critical segment of financial markets due to its role in mobilizing long term investible funds for productive investment. Literatures on the link between equity market and economic development abound (see Olofin and Afangideh, 2008; Ezeoha, Ogamba and Onyiuke, 2009 and Ogunmuyiwa, 2010). More so, empirical evidence suggests that movements in equity prices are fundamental in explaining aggregate investment behavior (see Barro, 1990). The effectiveness and efficiency of equity market could be measured by the volatility of equity market returns.

The Nigerian stock exchange (NGSE30) which tracks price movements of 30 most liquid equities listed on its mainboard averaged 30,677 points between 2005 and 2013. It peaked in March 2008 with 65,607 points and recorded the lowest in March 2009 with 19,886 points. This movement depicts some level of variability in equity prices. Just like other countries of the world, the volatility of equity prices in Nigeria could be attributed to endogenous and exogenous factors. In fully integrated economies, persistent volatility is usually as a result of exogenous factors, while segmented or relatively closed economies markets are mainly influenced by endogenous factor such as tax and interest rate policy, inflation, etc.

Since the deregulation of the Nigerian economy in 1986 and the subsequent liberalization of the capital market, the domestic markets have been greatly linked with the rest of the world markets. Overtime, more than 70 per cent of capital importations are into equity portfolio investment in Nigeria and record shows that between March 2012 and September 2013, capital importation from Kenya, South Africa, China, United States and Germany constitute an average of 72.02 per cent of the total. In fact, foreign portfolio investment from China alone shot up the value of equity securities from negative position of NGN162.8 billion in 2005 to NGN323.6 billion in 2010 (CBN, 2009), thereby creating a new dimension to volatility in the domestic market. Thus, the volatility of equity markets of these countries vis-à-vis that of Nigeria is worthy of examination as variations in these markets could have significant impact on the Nigeria stock market.

Persistent volatility could cause loss of investors' confidence thereby reducing market participation and liquidity; but this study will provide a firm understanding of the Nigerian stock market volatility vis-à-vis that of some selected countries. A firm understanding of equity market volatility of interlinked economies would enable foreign portfolio investors make informed risk management decisions across international markets and also put the regulators in a better position to formulate policies that will dampen the impact of volatility in the domestic equity market.

Literature on the volatility of Nigeria stock market in comparison with the rest of the world markets is sparse, which this paper considered a major gap considering the increasing linkage of economies of the world. This gap existed even when financial analysts attributed the extreme volatility of stock market in 2009 to the 2008/2009 global financial crisis, during which the value of equity securities in Nigeria recorded a significant drop due to capital reversal of NGN113.0 billion by foreign portfolio investors (CBN, 2010). Few studies on equity market volatility in Nigeria have attempted to model the volatility dynamics of stock returns using varieties of first-order volatility models like Autoregressive Conditional Heteroscadasticity (ARCH) and its extensions, such as Generalized ARCH, Threshold GARCH, Exponential GARCH and Power GARCH with Gaussian and most times do not give credence to error assumptions. However, theories have shown that financial time series like stock returns do not follow normality assumption of the error.

This study therefore uses the all share index of Nigeria, Kenya, South Africa, China, United States and Germany to estimate first order Asymmetric GARCH family models on Student's *t* and generalized error distribution (GED) to select the best stock market volatility models for these countries based on Akaike Information Criterion (AIC) (1974) with a view to comparing their market volatilities. In view of the fact that markets experience periods of significant shocks capable of influencing long term behavior of the series, the study accounts for the effect of structural break in the estimated model using Zivot and Andrews (1992) (Z-A) unit root test technique to endogeously identify the break date. The Z-A test reduces the bias in the regular Augmented Dickey and Fuller (1979) (ADF) unit root tests by endogenously determining the time of structural break in the series. The examination of these estimated volatility models in terms of speed of reaction of conditional volatility to market events (measured by ARCH coefficient) and volatility persistence (measured by GARCH coefficient) alongside the asymmetric properties form the basis for comparison. These countries are carefully selected based on their volume of trade with Nigeria, availability of stock market index series for the sample period (February 14, 2000 to February 15, 2013) and market similarity among some African countries.

The rest of the study is organized as follows. Section 2 examines the theoretical framework, while the methodology is presented in section 3. Section 4 discusses the results and section 5 concludes the study.

2.0 Stock Exchange Market and Stylized facts of stock returns

2.1 Developments in the Selected Countries' Stock Exchange Market

Frankfurt stock Exchange is the biggest among the eight stock exchanges in Germany and also one of the most efficient in the world, accounting for more than 90% of the German market turnover. The Exchange has over 250 and 4,500 international trading institutions and traders, respectively and accounts for about 35% of the world's investment capital. The exchange stopped floor trading in 2011, a development that necessitated trading through the Xetra system. Trading indices in Frankfurt stock Exchange include CDAX, DAX or DAX 30 (Deutsche Aktien Xchange 30, formally referred as Deutscher Aktien-Index 30), DAXplus, DivDAX, EuroStoxx 50, LDAX, MDAX, SDAX, TecDAX and VDAX. The DAX averaged 2,778 Index points between 1970 and 2013. During this period, it climaxed in July 2007 with 8,106 Index points and recorded the lowest in November 1974 with 372 Index points. The DAX Index anchors the German equity market by tracking the development of 30 major German blue chip stocks traded on the Exchange and accounts for about 80 per cent of the market capitalization. The DAX Index, which has its base value of 1000 as of December 31, 1987, is free floating. According to a World Bank report published in 2012, the Market capitalization of listed companies as a percentage of GDP in Germany declined from 44.52% in January 2003 to 30.58% in January 2008 and remained at 33.17% in 2011.

The Chinese stock market evolved following the establishment of Shanghai Securities Exchange and the Shenzhen Securities Exchange in early 1990s. Thus, performance of the China stock is measured by the Shanghai and Shenzhen Composite indexes and shares are traded electronically on the exchanges. As at the end of 2006, China stock market valued at about $1.4 trillion was adjudged the 10th largest equity market in the world, compared to the US stock market valued at about $20 trillion. In 2005, 1,381 companies were listed on the Shanghai and Shenzhen stock market. About 95% of the firms listed on the Chinese stock exchanges are owned by the government and the market is not completely determined by market forces as the government places restrictions on the market and also interferes directly in trading.

However, prior to the listing of foreign firms in 2010, the 868 firms listed in Shanghai Exchange were predominantly domestic firms. The Shanghai SE (***SSE***) Composite is the major stock market index and tracks the development of all A-shares and B-shares listed on the Shanghai Stock Exchange. The SSE Composite averaged 1659 Index points from 1990 to 2013 and peaked at 6092 Index points in October 2007, but recorded the lowest in December 1990 at 100 Index points. The SSE Composite is a capitalization-weighted index with a base value of CNY100 as at December 19, 1990. The 2012 World Bank report revealed that the Market capitalization of listed companies as a percentage of GDP in China increased to 178.2% in January 2007 from 41.5% in January 2003 and remained at 46.4% in 2011.

The origin of the New York Stock Exchange (NYSE) is traced to Buttonwood Agreement in 1792. The exchange became a profit-public company following its merger with Archipelago (close rival to NYSE) in 2005 and later became the first transatlantic stock exchange (NYSE Euronext) in 2007. The NYSE averaged US$153 billion in 2008 was adjudged the world's largest in 2011 in terms of market capitalization. Between 1912 and 2013, the Dow Jones averaged 2281 Index points. It reached its highest level of 14,539 Index points in March, 2013 but recorded 41 Index points as the lowest in July 1932. The Dow Jones Industrial is a price-weighted index that tracks the movement of 30 well-developed U.S blue-chip companies listed in the New York Stock Exchange. The listed domestic companies in the U.S. exchanges are domestically incorporated and do not include investment companies, mutual funds, or other investment outfits. In 2011, the Market capitalization of listed companies as a percentage of GDP in the United States was 103.62% (World Bank, 2012), down from 128.64% in 2003.

Dealing in shares and stock began in Kenya while still under the colonial rule in 1920s without formal regulatory body. The first professional stock broking firm in Kenya was set up in 1951, which necessitated the setting up of Nairobi Stock Exchange (NSE) in 1953. Prior to the country's independence in 1963, dealings in shares stocks were restricted to the European community residents only. The NSE recorded the first crash at the wake of independence because of the uncertainty about what becomes of the market after the exit of British colony. The NSE All Share Index measures the overall market performance of 20 best performing companies listed on the Nairobi Securities Exchange. To reflect the objective of supporting trading, clearing and settlement of equities, debt, derivatives and other associated instruments, the Nairobi Stock

Exchange Limited was renamed as the Nairobi Securities Exchange Limited in 2011; giving way for the launch of the FTSE NSE Kenya 15 and FTSE NSE Kenya 25 Indices. The selection of these companies is based on a 12-month period weighted market performance in terms of market capitalization, turnover, number of deals and number of shares traded. Between 1990 and 2013, Kenya Stock Market (***NSE20***) averaged 2911 Index points. It reached its highest level of 6161 Index points in January, 2007 but recorded 800 Index points as the lowest in February, 1990.

Following the opening of mining and financial companies in the late 19th century, there was a dire need for a stock exchange in South Africa and the Johannesburg Securities Exchange was eventually established in 1887. There was no formal documented regulatory procedure of the operation of the exchange until enactment of the Stock Exchanges Control Act. To further bring sanity into stock trading in South Africa, the South African Institute of Stockbrokers was subsequently constituted to represent, train, set standards and ensure that stockbrokers follow the rules governing stock trading. Johannesburg Securities Exchange was renamed ***JSE*** Securities Exchange, which provided a market for securities trading with a regulated procedure. The JSE's market capitalization stood at USD614 billion as at end May 2009 and the market turnover was USD300 billion in 2008 calendar year (SARB, 2009)[2]. Between 1995 and first quarter 2013, JSE averaged 15,656 Index points reaching an all-time high of 40,984 Index points in March of 2013 and a record low of 4,308 Index points in September of 1998. The FTSE/JSE All Share Index has a base value of 10815.083 as of June 21, 2002.

The Nigeria Stock Exchange is the physical market of the Nigerian capital market, established in 1960 to provide listing and trading services, as well as electronic Clearing, Settlement and Delivery (CSD) services through Central Securities Clearing System (CSCS) Plc Act. The instruments listed in the exchange are Federal Government Development Loan Stocks, State Government bonds, Commercial and Industrial loan stock, equity stocks, preference shares etc. At the exchange, about 200 equities and 258 securities are listed. The value of equity stock of the market constitutes over 80 per cent of the securities in the market. The equity market is made up of Main Board and Alternative Security Exchange Markets. The former is further segmented

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[2] South Africa Reserve Bank Quarterly Bulletin, September 2009.
[3] http://www.tradingeconomics.com

into primary and the secondary markets. The primary market deals with new issues of securities, while the secondary market is a market for trading in existing securities. The latter is introduced to encourage small and medium scale indigenous companies to seek quotation on the stock market. The ***NGSE30*** averaged 30677 Index points between 2005 and 2013. During this period, it climaxed in March 2008 with 65607 Index points and recorded the lowest in March 2009 with 19886 Index points. The NGSE30 Index anchors the Nigeria equity market by tracking the development of 30 most liquid stocks listed on the Exchange. In January 1, 2007, the NGSE30 Index has its base value as 1000.

The movement of NGSE30, NSE20, Dow Jones, DAX, FTSE/JSE, and SSE Composite Indices from February 14, 2000 to March 14, 2013 is represented in Figure 1a to Figure 1f, with the arrows indicating worst period of 2008/2009 global financial crisis.

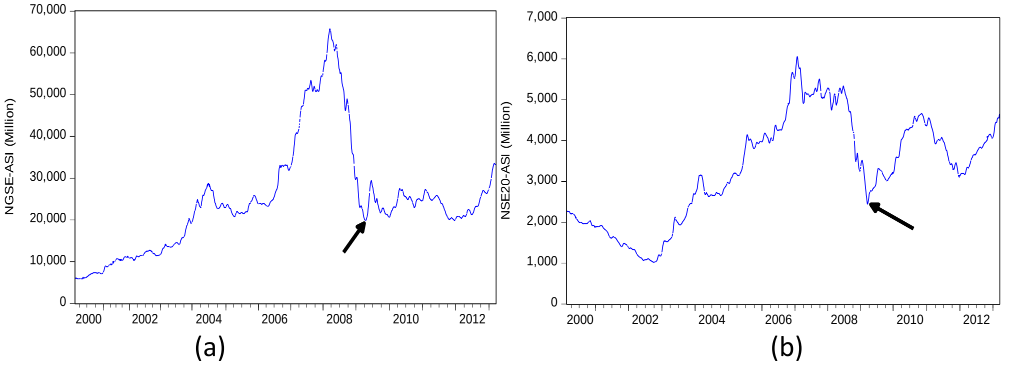

Fig. 1: Movement of the (a) NGSE-ASI and (b) NSE-ASI from February 14 2000 to March 14 2013

In summary, visual inspection of the plots of stock indices of these countries reveals that the markets were affected by the 2008/2009 global financial crisis and volatility was very high, even though the time for worst incidence varies. This is a clear indication that there is a tie in the global markets and comparing their volatility is unarguably significant for portfolio management and regulations. For instance, New York, Johannesburg, Nairobi and Frankfurt stock markets were badly affected in March 2009; while Nigeria and Shanghai stock market were greatly impacted in April 2009 and November 2008, respectively. Just before the global financial crisis commenced till the end of this study sample period, the movements in the Nigeria and Shanghai stock markets were relatively similar with events occurring in the Nigerian market after about four to five months such event had occurred in the China market. At the beginning of the sample period, the Shanghai market was relatively calm up to first half of 2001. Similar trend

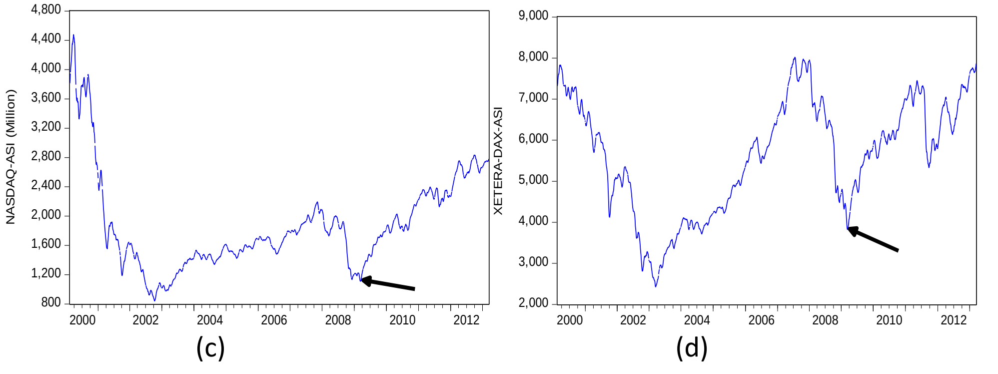

Fig. 1: Movement of (c) NASDAQ-ASI and (d) XETERA-DAX-ASI from February 14 2000 to March 14 2013

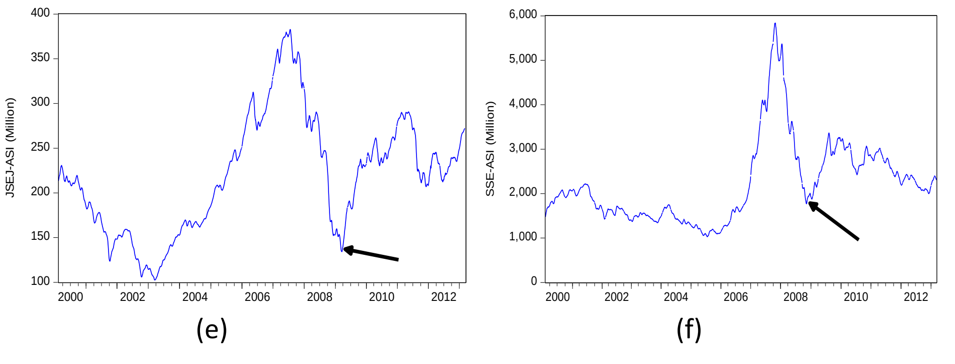

Fig. 1: Movement of (e) JSEJ-ASI and (f) SSE-ASI from February 14 2000 to March 14 2013

was observed in the Nigeria market up till the first half of 2004. On the other hand, this development was different in the other four markets. Just before the recent crisis period, all the markets were trending high, with the exception of the US stocks. Just as the Nigeria market seems to depict the China market, the Nairobi stock market also seems to depict that of Frankfurt. US stock market seems to be the most relatively calm. This observed trend may not be unconnected to the linkages among these markets.

2.2 Stylized Facts of Stock Returns

Theoretical and empirical works have established that financial time series such as stock market data are found to exhibit some common characteristics, often referred to as stylized facts. These stylized facts include fat tails, volatility clustering, leverage effects, long memory and co-movement in volatility.

Fat tails, also called heavy tails, implies leptokurtic distributions which captures the density of the distribution towards the tail areas. High frequency financial time series tends to have a fourth moment (kurtosis), which is higher than the normal value of 3 and makes normality assumption inappropriate for such series. Volatility clustering is an indication of persistence in past shock. It implies that prolonged period of low volatility is followed by prolonged period of high volatility. According to Black (1976), leverage effect implies that price movements are negatively correlated with volatility. Long memory is also an indication of persistent volatility and evidence of near unit root behavior of the conditional variance process. Basically, a unit root and long memory process are two distinctive approaches to modeling this fact. ARCH family models are applied for the second approach. Lastly, co-movement in volatility arises when looking at two or more different markets. It suggests that big movements in one financial time series are matched by other big movements from a different market.

2.3 Literature Review

Several empirical works have been done since the seminar paper of Engel (1982) on volatility modelling, especially in the area of finance, even though a number of theoretical issue are still unresolved (see Frances and McAleer (2002). However, Anders (2006) believes that previous research on the effects of error distribution assumptions on the variance forecasting performance of Asymmetric GARCH family models is scarce. For instance, work on volatility modelling estimate a particular GARCH model with normal and/or student's *t* distribution, while some applied a particular error distribution to few ARCH family models to either establish the best forecasting model for conditional variance, the best fitted volatility model or confirm the ability of the models to capture stylized fact inherent in high frequency financial time series.

Yeh and Lee (2000) examined the volatility in the China stock market using TGARCH model with data from May 22, 1992 to August 27, 1996 and found that volatility responds more to positive shocks than negative shock in the China market, which led investors in China's stock market to be more interested in good news than bad news. Also Jingli and Sheng (2011) examines the stock market volatility of Shanghai Composite Index and Shenzhen Stock Index from 30th July, 2003 to 30th July, 2010 using ARIMA-EARCH-M (1, 1) and ARIMA-TARCH-M (1, 1) models. The result shows that the indices in both markets have the character of clustering, asymmetry, fat tail and leverage effect returns. Hou (2013) estimated the volatility of daily closing prices of two Chinese primary indices; Shanghai stock exchange composite index (SHCI) and Shenzhen stock exchange component index (SZCI) from 2nd Jan. 1997 to 31st Aug. 2007 using the generalized additive non-parametric smoothing technique. The researcher ascertained that an asymmetric effect of negative news exist in the Chinese stock market which have impact on return volatility. Also, the effect is higher in Shanghai composite index than the Shenzhen composite index.

In the American market, Pan and Hsueh (1998) analysed the movements in return and volatility between future prices of US S&P 500 and Japan Nikkei 225 stock indices, using 2-step GARCH model. The result revealed that there is a unidirectional spillover and a major lagged volatility from US to Japan. Furthermore, the US market is four times influential on Japans' returns. Schwert (1998) compares the US stock market volatility returns with stock market returns in UK, Germany, Japan, Australia and Canada after the 1987 stock market crash using the monthly, daily and intra-day intervals of the indices. This analysis shows that stock volatility has been low and stable in these markets, but Japan had high return volatility and decrease in stock value in 1990. Using the GARCH and TGARCH models, Onyeaso and Roger (2004) determined the stock volatility movements and predictions in the small cap (SC) 600 index from 3rd January, 1995 to 19th August, 2002. The results show that the volatility of the index was predictable and the index does not have the same behaviour observed in other stocks.

In some of the studies carried out in Europe, Guidi (2008) used GARCH family models to determine the volatility, long term relationship and variance in German, Swiss and UK stock market indices. The result of the GARCH family shows evidence of asymmetric effects on the returns volatility. Kiymaz and Berument (2003) ascertained the daily effect of stock market volatility and volume of Germany, Canada, Japan, U.K and U.S.A, using the conditional variance method with data from 1st January, 1988 to 28th June, 2002. The result shows that there is an effect of the day of week on both returns and volatility. Dania and Spillan (2013) examined the dynamics of volatility transmission in stock markets from developed markets (France, US, UK and Germany) to less developed markets i.e Middle East and North Africa (MENA) (morocco, Kuwait, Bahrain, Jordan, Oman, Qatar & UAE) using GARCH AND T-GARCH MODELS with monthly data from September 2005 to February 2011. The findings reveals that there is different level of volatility and leverage effect between the stock returns of both countries, and more so the less developed i.e the MENA countries stock markets are not united with the developed markets.

Chinzara and Aziakpono (2009) investigate the return and volatility linkages between South Africa and some world equity markets (Australia, US and China) as well as analysing the risk premium hypotheses and long term trend of volatility in the markets using VAR and uni-variate GARCH models. The study reveals that there exist relationship in returns and volatility between South Africa and the other countries. Mandimika and Chinzara (2010) investigates the long term behaviour of volatility, risk-return relationship and if long term trend of volatility had structural breaks during major world shocks and financial crises from 1995 to 2009 using Asian and sub-prime financial crises and US September 11 attack as dummy and 3-GARCH models for analysis (one-symmetric and two-asymmetric). Cumulatively, there exists asymmetric and leverage effects on volatility in South Africa's industry and sectoral levels of the stock market. Also, Kambadza and Chinzara (2012) used data for eight African stock market (Egypt, Mauritius, Ghana, Morocco, Namibia, Kenya, Nigeria and South Africa) between 31st January, 2000 to 28th July, 2010 and examines if there is a relationship between returns and volatility among the major selected African stock markets, using three GARCH type models for measuring the volatilities of the markets. It showed that there were partial returns and volatility interactions among the markets except among close trading partners and large economies.

Ndako (2013) examined the day of the week effect on mean and variance equations for Nigeria and South Africa's equity markets using the E-GARCH model from the pre-liberalisation and post liberalisation periods, but focus was on post-liberalisation for Nigeria only. The result reveals that there exists an effect of day of the week in the mean equation for Fridays while the variance equation effects were on Tuesdays and Thursdays for the Nigerian Equity market. For the South African market, there is an effect on Mondays and Fridays for the pre-liberalisation era while for the post-liberalisation period there was effect on Thursdays and Fridays for mean and variance equations, respectively.

Olweny and Omondi (2011) used EGARCH and TGARCH models to examine the effect of macroeconomic factors on volatility of Kenya stock market return with the impact of foreign exchange rate, interest rate and inflation variability's using monthly data from January 2001 to December 2010. It was observed that the returns are symmetric as well as the exchange rate, interest rate and inflation rate affects the volatility in the Kenya's stock market. Also, Tah (2013) evaluates the stochastic behaviour of monthly stock market return and volatility relationship between two emerging markets. Using GARCH-M model, a negative relationship between the conditional mean and variance in Zambia's stock exchange was found, while there was no relationship between expected returns and conditional variance for Kenya stock market.

Jayasuriya (2002) examines the effect of stock market liberalization on stock return volatility using Nigeria and fourteen other emerging market data, from December 1984 to March 2000 to estimate asymmetric GARCH model. The study inferred that positive (negative) changes in prices have been followed by negative (positive) changes. The Nigerian session of the result reveals that returns series exhibited business cycle behaviour than volatility clustering behaviour. Ogunm, Beer and Nouyrigat (2005) apply the Nigeria and Kenya stock data on EGARCH model to capture the emerging market volatility. The result of the study differed from Jayasuriya (2002). Though volatility persistence is evidenced in both market; volatility responds more to negative shocks in the Nigeria market and the reverse is the case for Kenya market. The study failed to examine the contribution of innovation assumptions. Ade and Dallah (2010) examine the volatility of daily stock returns of Nigerian insurance stocks using twenty six insurance companies' daily data from December 15, 2000 to June 9 of 2008 as training data set and from June 10 2008 to September 9 2008 as out-of-sample dataset. The result of ARCH (1), GARCH (1, 1) TARCH (1, 1) and EGARCH (1, 1) shows that EGARCH is more suitable in modelling stock price returns as it outperforms the other models in terms of model estimation evaluation and out-of-sample volatility forecasting. Okpara and Nwezeaku (2009) randomly selected forty one companies from the Nigerian Stock Exchange to examine the effect of the idiosyncratic risk and beta risk on returns using data from 1996 to 2005. By applying EGARCH (1, 3) model, the result shows less volatility persistence and establishes the existence of leverage effect in the Nigeria stock market, implying that bad news drives volatility more than good news.

From the search of literature, authors have consistently ignored the contribution of error assumptions on volatility modeling. Such neglect could undermine the robustness of model results.

3.0 Methodology

3.1 Data Source, Transformation and Test Procedures

This study uses the daily all share index (ASI) of Nigeria, Kenya, South Africa, China, United State of America and Germany represented as NGSE30, NSE20, JESJ, SSE, NASDAQ and XETERA-DAX, respectively. The ASI spans from February 14, 2000 to February 14, 2013. The data is obtained from *www.reuters.com*. The daily ASI of from the six exchanges are transformed to daily stock returns, y_t, expressed as

$$y_t = 100\, ln(Z_t / Z_{t-1}) \tag{1}$$

where Z_t is the current period ASI, $Z_{t-1}$is the preceding period ASI, and y_t is the current period stock returns (ASI-RT). The existence of volatility clustering in y_t is established by plotting the residuals of the equation:

$$y_t = \Gamma + \boldsymbol{\xi_t} \tag{2}$$

Γ is a constant and $\boldsymbol{\xi_t}$ is the residual series. The null hypothesis that there is no ARCH in the residuals is tested using the Lagrange Multiplier (LM) test up to order 20 at 5% significance level. The presence of ARCH effect is a precondition for GARCH modeling and GARCH models account for ARCH effect in a financial series.

Unit root test of the stock returns is essential because any meaningful econometrics time series modeling requires stationarity of the series. If the series are not stationary, the important test statistics used in the evaluation of the econometric results become unreliable. Zivot Adrew unit root technique is applied to test the null hypothesis that the series has a unit root with a structural break in the intercept. It is important to note that returns are not trended series; hence we focused on the intercept in formulating the hypothesis. Having determined the asymptotic distributions of the test statistic, the null hypothesis is rejected if the estimated value of Z-A test statistic is less than the critical values. The endogenously determined break date for each series is incorporated in the mean and variance equations of the asymmetric models with the use dummy. The dummy assumes zero value before the occurrence of the break and one at the time of the break and thereafter.

3.2 Innovation Process

The TGARCH and EGARCH models are estimated, allowing the error to follow student's t distribution (t) and generalized error distribution (GED) since normality assumption has demonstrated some levels of weaknesses in volatility modeling. The assumption that TGARCH and EGARCH models follow GED tends to account for the kurtosis in returns, which are not adequately captured with normality assumption. The contribution of GED to the asymmetric GARCH models is expressed by its log likelihood below:

$$L(\theta_t) = -\frac{1}{2} log\left(\frac{\Gamma 1/v^3}{\Gamma(3/v)(v/2)^2}\right) - \frac{1}{2} log\sigma_t^2 - \left(\frac{\Gamma(3/v)\left(y_t - X_t'\theta\right)^2}{\sigma_t^2 \Gamma(1/v)}\right)^{v/2} \qquad (3)$$

$v > 0$ and it accounts for the skewness of the returns. The higher the value of v, the greater the weight of tail. GED reverts to normal distribution if $v = 0$

For Student's t distribution, the log likelihood contributions to the two models are expressed as:

$$L(\theta)_t = -\frac{1}{2} log\left(\frac{\pi(r)\Gamma r/2^2}{\Gamma((r+1)/2)^2}\right) - \frac{1}{2} log\sigma_t^2 - \frac{(r+1)}{2} log\left(1 + \frac{\left(y_t - X_t'\theta\right)^2}{\sigma_t^2 (r-2)}\right) \qquad (4)$$

Here, r is the degree of freedom and controls the tail behaviour and $r > 2$.

3.3 Model Selection

From the estimated mean and conditional variance equations with the specified distributions, the best model for each stock return is selected based on the AIC values. Comparison of the stock returns volatility of the selected countries is based on the estimated coefficients of the best conditional variance models. The diagnostic tests for remaining ARCH effect and serial correlation using ARCH-LM test and Q-Statistics (correlogram of square residuals) are conducted to ascertain the robustness of the estimated models.

4.0 Analysis of Results

4.1 Pre-Test Result

From the descriptive statistics presented in table 1 below, the difference in the number of observations (N) among the countries stock returns is mainly attributed to observed national holidays in those countries. Only NASDAQ recorded negative mean returns, meaning that, on the average, investors recorded losses more than gains during the sample period.; again, retruns on investment was higher in less-developed markets like NGSE30 and NSE as their mean return were 0.00055 and 0.00022. The value of skewness which measures the level of symmetry of the returns series indicates that none of the series is symmetric.

Table 1: Descriptive Statistics of daily returns

Series	NGSE30	NSE	JSEJ	SSE	NASDAQ	XETERA-DAX
N	3128	3250	3393	3170	3290	3331
Mean	0.00055	0.00022	0.00007	0.00014	-0.00010	0.00002
S.D.	0.00420	0.00369	0.00345	0.00455	0.00466	0.00401
Skewness	-0.19542	0.14968	-1.08738	-0.13248	-0.78220	-1.09860
Kurtosis	5.86706	6.56128	6.02291	3.66897	5.68922	6.33842
Jarque-Bera	1091.3	1729.6	1960.5	68.4	1326.9	2216.9
Probability	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000

N: Number of observations
S.D.: Standard Deviation

The skewness of a symmetric series is 0. Except NSE, all other stock returns are negatively skewed. The kurtosis of the six stock returns are more than that of a normal distribution. The Jarque-Bera values and their corresponding small p-values provide further evidence that the series are not normally distributed. The high kurtosis also indicates traces of ARCH effect in the series, which can only be accounted for by modelling the series with volatility models.

The graphical representation of the six selected stock markets is shown in Fig. 2.Visual inspection of the plots indicates that the return series oscillates around the mean, meaning that the series is mean reverting. Mean reversion is a stylized fact of high frequency financial time series. In each series, volatility was high over a sustained period and this period is also followed by another period of low volatility. The series also exhibit claustering behavior, which is another stylized fact that can be accounted for by applying a conditional volatility model. Thus, the level of peakedness, non-normality, ARCH Effect and volatility claustering of the daily stock returns provide justification for the application of asymmetric conditional volatility models like TGARCH and EGARCH to account for these characteristics.

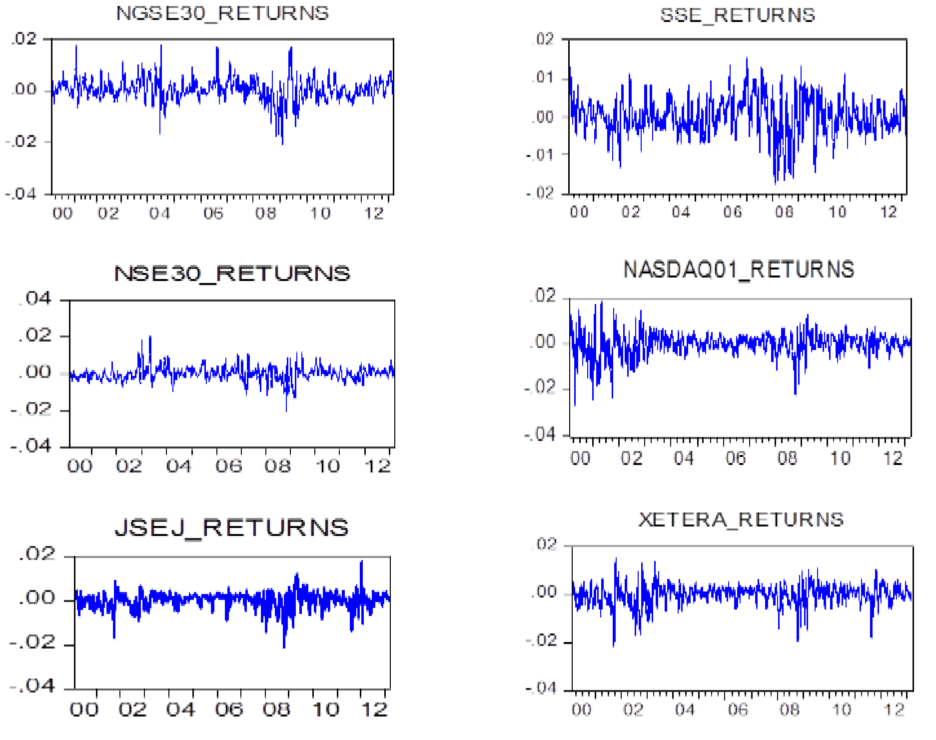

Figure 2: Volatility Claustering of the Daily Return Series

Table 2: Zivot-Andrews Unit Root Test Result of Stock Returns

Stock Returns	Break point	Zivot-Andrews test statistic	Prob. Value
NGSE30	3/6/2008	-11.80269	0.002148
NSE20	9/20/2002	-12.4799	0.023274
NASDAQ	10/9/2002	-12.21557	0.002428
XETERA-DAX	3/13/2003	-12.86322	0.000868
JSEJ	7/18/2007	-11.36501	0.009578
SSE	10/17/2007	-11.33351	0.000445

Critical values (CV): 1% = -5.34; 5% = -4.93 & 10% = -4.58.

The Zevot Andrew's unit root test result with endogenously determined break date is presented in table 2.

The probability values are calculated from a standard t-distribution and do not take into account the break selection process. Hence, decisions on the level of stationarity of the returns are based on the calculated Z-A test statistics and the value of the BF at different critical values. Since the calculated Z-A test statistics for the returns series are lower than the critical values at the three conventional significance levels (1%, 5% and 10%), there is justification to reject the null hypothesis and infer that the returns are stationary with one point break at the intercept as shown in table 2 above.

Table 3: Heteroskedasticity Test: ARCH Effect Test

	Lag 1		Lag 5		Lag 10		
Return Series	F-statistic*	Obs R-squared*	F-statistic*	Obs R-squared*	F-statistic*	Obs R-squared*	P-Value
NGSE30	1001.597	758.9184	373.3484	1169.631	194.5532	1200.472	0.0000
NSE20	1107.632	826.3417	227.3666	842.9775	117.2337	862.9337	0.0000
JSEJ	898.243	710.4666	256.5118	931.4833	128.3583	932.6457	0.0000
SSE	74.7153	73.03884	42.14959	197.939	40.97137	363.797	0.0000
NASDAQ	376.2571	337.8063	148.5909	606.7869	95.86357	743.7041	0.0000
XETERA-DAX	55.06301	54.1991	119.3018	506.5478	76.08792	620.6864	0.0000

The pre-ARCH test result reported in Table 3 reveals the presence of ARCH effect in the stock returns at 1% significant level, when the high values of the F and Chi-Squared statistics are matched with their corresponding small p-values up to lag 10, thus providing further justification for the application of conditional volatility models in the stock returns to account for it. This result is obtained when the residuals from equation (9) is estimated in equation (10) above.

4.1 Model Selection

The models reported in table 4a are the estimated TGARCH and EGARCH models of stock returns under two innovation assumptions with no structural break. Based on the values of the AIC, TGARCH model under Student-t was adjudged the best for modeling NGSE30, NSE20 and NASDAQ returns series. TGARCH under generalized error distribution was confirmed the best model for XETRA-DAX returns. The table also shows that EGARCH under Student-t innovation was most suitable for JESJ and SSE returns.

Table 4a: AIC Values of Estimated Asymmetric Models with No Structural Break (NSB)

Stock Returns	EGARCH		TGARCH		Min. AIC
	GED	Student-***t***	GED	Student-***t***	
NGSE30	-11.13816	-11.16707	-11.13823	**-11.17548**	-11.17548
NSE20	-11.6476	-11.65361	-11.6503	**-11.65446**	-11.65446
NASDAQ	-10.15377	-10.15479	-10.15931	**-10.1595**	-10.1595
XETERA-DAX	-10.45711	-10.45528	**-10.45887**	-10.4573	-10.45887
JSEJ	-11.28463	**-11.30177**	-11.28606	-11.29958	-11.30177
SSE	-10.30024	**-10.30125**	-10.29873	-10.2997	-10.30125

Similarly, table 4b presents the criteria for choosing the best from the estimated EGARCH and TGARCH models under GED and Student-***t*** innovations with structural break. The AIC values in the table confirm the model choice in table 4a.

Comparing tables 4a and 4b, the minimum AIC values suggest that models with structural breaks are more suitable for modeling the volatility of NGSE30, NSE20, NASDAQ, XETERA-DAX and JESJ returns. However, model with no structural break is chosen for modeling SSE returns volatility. Further discussion is centered on the most robust model.

Table 4b: AIC Values of Estimated Asymmetric Models with Structural Break (SB)

Stock Returns	**EGARCH**		**TGARCH**		Min. AIC
	GED	Student-***t***	GED	Student-***t***	
NGSE30	-11.13479	-11.1742	-11.14194	***-11.18264***	-11.18264
NSE20	-11.64938	-11.65598	-11.6526	***-11.65685***	-11.65685
NASDAQ	-10.15592	-10.15679	-10.16106	***-10.16151***	-10.16151
XETERA-DAX	-10.45947	-10.45781	***-10.46129***	-10.45985	-10.46129
JSEJ	-11.2886	***-11.30499***	-11.289	-11.30212	-11.30499
SSE	-10.29965	***-10.30084***	-10.29799	-10.29902	-10.30084

4.1.1 ARCH-LM Test Result of the Best Fitted Asymmetric Models

Testing for remaining ARCH effect is essential because its presence in the estimated volatility model could lead to serious model misspecification and inappropriate parameter standard error. Stiglitz and Weiss (1992) support this assertion that the presence of ARCH will lead to the identification of ARMA models that are overparametized.

Table 5: ARCH-LM Test Results of the Best Fitted Asymmetric Models

Lag	SB Models					NSB Model
	NGSE30	NSE20	NASDAQ	XETERA-DAX	JSEJ	SSE
	TGARCH-t	TGARCH-t	TGARCH-t	TGARCH-GED	EGARCH-t	EGARCH-t
1	{0.030705} [0.8609]	{0.973168} [0.3239]	{6.393402} [0.0115]	{7.233551} [0.0072]	{85.10682} [0.00000]	{0.210632} [0.6464]
5	{0.31685} [0.9973]	{5.897448} [0.3163]	{8.442163} [0.1335]	{13.90854} [0.0162]	{89.70371} [0.00000]	{4.940209} [0.4236]
10	{1.557832} [0.9987]	{14.40974} [0.1551]	{15.01804} [0.1314]	{18.61303} [0.0455]	{91.98681} [0.00000]	{15.12628} [0.1275]

Numbers in { } and [ ] are chi-squared values and p-Values, respectively

The diagnostic test results of the best conditional variance models, using the ARCH LM test resented in table 5 suggest that ARCH effect has been accounted for. The null hypothesis that there is no remaining ARCH effect in the models is accepted based on the Chi-squared values and the high probability values in the ARCH-LM test result in Table 5.

4.2 Parameter Estimates of the Mean and Conditional Volatility Models

The results of the best estimated asymmetric volatility models for the six stock returns are presented in table 6. The estimated model for NGSE30 returns shows that parameter estimates of the mean and variance equations are significant, except the asymmetric parameter, suggesting the absence of leverage effect. The ARCH and GARCH coefficients of the volatility model are 0.439 and 0.429, respectively. The value of ARCH coefficient has two important implications here. First, it shows that squared lagged error terms has positive and significant impact on the current period volatility of NGSE30 returns and secondly, it reveals that the speed of reaction of stock volatility to market events is high as the value is not close to zero.

Table 6 Parameter Estimates of the Best Fitted Asymmetric Models

Models/Error Distribution	Parameters	SB Models					NSB Model
		NGSE30	NSE20	NASDAQ	XETERA-DAX	JSEJ	SSE
		TGARCH-t	TGARCH-t	TGARCH-t	TGARCH-GED	EGARCH-t	EGARCH-t
Mean Equation	Intercept	0.000***	-0.000**	-0.000***	-0.000***	0.000**	0.000
	AR(1)	0.963***	0.968***	0.901***	0.904***	0.952***	0.945***
	Dummy	-0.000***	0.000***	0.000***	0.000***	-0.000**	na
Variance Equation	Intercept	0.000***	0.000***	0.000***	0.000***	-0.378***	-0.264***
	ARCH	0.439***	0.310***	0.003	0.018*	0.176***	0.155***
	Asymmetry	-0.026	-0.039	0.077***	0.083***	-0.066***	-0.020*
	GARCH	0.429***	0.608***	0.951***	0.933***	0.983***	0.989***
	Dummy	0.000***	0.000***	-0.000**	-0.000*	0.023***	na

***, ** and * imply significant at 1%, 5% and 10%, respectively.
na denotes not applicable.

Similarly, the GARCH coefficient suggests that previous period variance of NGSE30 returns has significant impact on the conditional volatility at the current period and it also shows that volatility persistence is relatively low as its value is not close to 1. This means that shock to conditional variance takes a relatively short time to decay. This result is similar to that obtained by Okpara and Nwezeaku (2009) who found less volatility persistence in the Nigeria stock market. The none significance and negative value of the asymmetric parameter indicates the absence of leverage effect, which contradicts the stylize fact of financial time series that equal magnitude of bad news and good news have differential effects on volatility of stock returns.

The estimated volatility model for NSE20 returns is relatively similar to that obtained from the NGSE30 returns. TGARCH-*t* model for NSE20 returns confirms that the estimated ARCH (0.310) and GARCH (0.608) parameters are highly significant. The ARCH parameter estimate suggests that the squared lagged error has positive and significant impact on the current period volatility of NSE20 returns; and the speed of reaction of volatility to market shock is high. Also, the GARCH coefficient suggests that previous period variance of NSE20 returns has significant impact on the conditional volatility and it also shows that volatility persistence is low. The result further reveals that asymmetric coefficient is negative and not significant, confirming the absence of leverage effect. This result conforms to the findings of Olweny and

Omondi (2011) who used TGARCH model to establish that Kenya returns is symmetric.

The selected model for estimating NASDAQ return series reveals that the parameters of the mean equation, including the dummy that accounted for structural breaks, are statistically significant. The TGARCH-*t* model for NASDAQ returns shows that the estimated ARCH coefficient is not significant at 10% level, while the GARCH parameter is significant at 1%. The ARCH and GARCH coefficients are 0.003 and 0.951, respectively. The ARCH coefficient shows that the tendency for volatility of the market to react to market events is insignificant. The GARCH coefficient suggests that previous period variance of NASDAQ stock returns has significant impact on the conditional volatility and it also shows that volatility persistence is very high as its value tends to unity. The test for leverage effect is positive and highly significant; suggesting that negative shock drives the volatility of the market more than equal amount of positive shock.

The chosen models for estimating XETERA-DAX returns indicate that parameters of the two equations are significant. The volatility estimate of XETERA-DAX returns with TGARCH-*GED* model shows that ARCH (0.018) and GARCH (0.933) parameters are significant 1% level. The ARCH parameter estimate indicates that the speed of reaction of volatility to market events is low compared NSE20 returns. However, the GARCH coefficient shows that the magnitude of volatility persistence in XETERA-DAX stock return series is very high given that the value of GARCH coefficient is close to unity. More so, the asymmetric parameter is positive and highly significance at 1% level, confirming the existence of leverage effect in the stock returns series.

The estimated ARCH (0.176) and GARCH (0.983) parameters in the EGARCH-*t* model for JESJ returns are highly significant. The facts presented indicate that the speed of reaction of volatility to market events is moderate and volatility persistence is relatively high. The result also confirms the existence of leverage effect, with the asymmetric parameter negative and highly significant. The effect of structural break on the estimated conditional variance model for JSEJ is higher than in the variance models for NGSE30, NSE20, NASDAQ and JSEJ returns.

The volatility estimate of China stock returns with EGARCH-*t* model with no structural break shows that ARCH (0.1550) and GARCH (0.989) parameters are highly significant. The reaction of volatility to market events and the magnitude of volatility persistence in SSE stock return series are similar to that obtained in the Jo'burg stock returns. Also, the significance of the asymmetric parameter at 10% level confirms the presence of leverage effect in the stock returns series.Table 5 below presents the comprehensive comparison of volatility persistence of selected stock returns and their conditional volatility reaction to market shock.

Table 7: Volatility Persistence[4] and Conditional Volatility Reaction to Market Shock[5]

Stock Returns	Volatility Reaction to Market Shocks/1	Ranking	Volatility Persistence/2	Ranking	Asymmetric Property
NGSE30	High	1	Low	6	No Levergae Effect
NSE20	High	2	Low	5	No Levergae Effect
NASDAQ	Low	6	High	3	Leverage Effect Exists
XETERA-DAX	Low	5	High	4	Leverage Effect Exists
JSEJ	Moderate	3	High	2	Leverage Effect Exists
SSE	Moderate	4	High	1	Leverage Effect Exists

In Nigeria, the NGSE30 returns volatility reaction to market shocks is higher than that of other countries under consideration (see table 7), meaning that the Nigerian stock market would react faster than the other five, in the event of simultaneous fluctuations caused by disequilibrium in the world stock market. Such developments are usually traced to two reasons. First, where investment in the local stock market is significantly controlled by foreign investor and secondly, where the local market is not fully developed in terms of market infrastructure, quality of instrument traded on the floor and regulatory practices. A clear example was the 2007/2009 financial crisis when the Nigeria stock market recorded a significant drop in the all share index due to the massive investment withdrawal by foreign portfolio (equity) investor. The Kenyan stock market is expected to have similar experience to that of Nigeria. The Jo'burg and Chinese stock markets are most likely to record moderate reaction to market shocks. The more developed markets like the US stock and German stock markets would record a low reaction to such market fluctuations.

[4] ARCH < 0.09, Reaction is Low; from 0.09 to < 0.29, Reaction is Moderate and from 0.29 to < 0.49, Reaction is high

[5] GARCH from 4.09 to < 0.69 is Low; from 0.69 to <0.89 is Moderate and from 0.89 to < 1.00 is High

In terms of volatility persistence, which measure the time it takes for volatility in stock market to dissipate or decay, again, the Nigeria and Kenya stock markets are found to be low compared to other markets under consideration. This result could also be traced to the level of development in these markets, as the two markets had experienced various interventions by the fiscal authorities during crisis instead of allowing the market forces to even-out the fluctuations. Such interventions usually have much impact on market development, thus calming the volatility within a shorter time period. It takes more time for fluctuations in the stock returns to fizzle out in more developed markets such as XETERA-DAX, NASDAQ, SSE and JESJ.

5.0 Summary and Conclusion

This study used the daily all share index (ASI) of Nigeria, Kenya, South Africa, China, United State of America and Germany obtained from *www.reuters.com* spanning from February 14, 2000 to February 14, 2013 to estimate TGARCH and EGARCH models under Student's *t* and generalized error distribution (GED) assumptions with the view to obtaining the best fit volatility models (one for each market) for comparing volatilities in their stock returns. With the aid of Zivot and Andrew's unit root technique, structural break date was endogenously identified, which was incorporated in the estimated mean and conditional variance equations. Using AIC, TGARCH on student-*t* is best fit for estimating the volatility in NGSE30, NSE20, and NASDAQ stock returns, while EGARCH on student-*t* is the best model for estimating the volatility in JESJ and SSE stock returns. TGARCH on GED is most suitable for modeling the volatility of XETERA-DAX returns. The comparison of the selected volatility models is based on the speed of reaction of volatility to market shocks and volatility persistence alongside the asymmetric properties.

From the results obtained, the NGSE30 and NSE20 returns volatility reaction to market shock is higher than that of other countries considered in the study. The Jo'burg and Chinese stock markets volatility are found to record moderate reaction to market shocks. The volatility of more developed markets (US and Germany) responds slowly to market fluctuations. Volatility persistence of the Nigeria and Kenya stock returns is low compared to other markets. It takes more time to fizzle out from XETERA-DAX, NASDAQ, SSE and JESJ. The results also suggest the absence of leverage effect in NGSE30 and NSE20, but confirm existence of leverage effect in NASDAQ, XETERA-DAX, JESJ and SSE stock returns. The positive sign of the asymmetric coefficient of TGARCH model and negative sign of the asymmetric coefficient of EGARCH model confirms that negative market shock has higher impact on volatility of stock returns than positive market shock of equal magnitude. Estimated parameters of the conditional variance model for NGSE30 and NSE20 returns revealed marked similarities between the Nigeria and Kenya stock markets.

In conclusion, the study recommended that less developed stock markets, particularly the Nigeria and Kenya stock markets, should make its market more robust by enhancing market infrastructure, regulatory practices and quality of instrument traded on the floor of the exchanges as such efforts could help build against fast reaction to market fluctuations.

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