Streamlining Investors' Perceptions and the Behaviour of Capital Market Returns Around the World

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Abstract: This study adopted various econometric tools (Descriptive Statistics, Unit tests, Autocorrelation test, Pairwise Granger Causality test, Ordinary Least Square test, Normality/Random Walk test, Variance Ratio test and ARCH-GARCH models) to streamline the diverse investors' perceptions and behaviours of the capital market returns around the world. The study employed daily historical data from May 18, 2015 to June 6th, 2022, from prominent capital markets each from all the continents of the world: Nigeria, South Africa, USA, Germany, United Arab Emirate and China. Results of the analysis revealed that none of the market follows the random walk theory, hence investors cannot use the past data about the markets to predict their outcome. ARCH-GARCH models results showed that all the countries exhibited property of stock returns distribution known as volatility clustering or volatility pooling. The persistence parameter found that shocks to the conditional variance are persistent for all the capital markets under study. Asymmetric parameter results that all the countries except Nigeria corroborate the leverage effect theory; bad news create more volatility than good news of the same magnitude. Since all the markets under study do not follow random walk, demystifying the efficient market hypothesis, meaning that the behaviours of investors, heavily influenced by share prices deviated from the economic fundamentals or assumptions. This means that psychology of investors influence investment decision-making process and financial markets. Therefore, the researcher advises among others to place more emphasis on the theory of behavioural finance as a guide for decision concerning stock market investments.

Keywords: Stock market returns, Random walk, Behavioural finance, ARCH effects
JEL Classification: C32, C58, G14, G41.

1. INTRODUCTION

The stock market of any nation provides the needed mechanism that facilitates the flow of long-term fund, hence the engine that propels economic growth and development. It is unarguably, a veritable medium that facilitates the transaction of long-term claims and funds so transacted. There are two basic components of the stock market; the market for new or virgin issues (primary market) and market for existing or Tokunbo securities (secondary market) (Ogbulu, 2010; Forson &Janranttanagul, 2014; Ejem, 2021). Economic agents expect a market saddled with such important role to be efficient, which is the key to optimal allocation of resources. On the investor's perspective, an efficient stock market is expected where investors are involved in a fair game and the share price instantly reflects available information in the market; obeying the efficient market hypothesis (EMH) developed from the random walk theory (Fama,1976). This suggests that the market price is expected to be a good and correct guide for the share selection, implying that all known information is immediately discounted by all investors and reflected in share prices in the stock market. As such, no one has information edge to make abnormal profit. In the ideal efficient market, every investor knows all available information simultaneously, interprets it similarly, and believes rationally (Fama & French, 1993; Ogbulu, 2010; Forson & Janranttanagul, 2014; Ejem, 2021). Sequel to that, a good number of scholars have the belief that the market should always follow a random walk theory, where no investor usurps the information available to make abnormal profit since all information both from previous and current as well information available and knowable in the future have already reflected in the market price of the security (Ibenta, 2005). On the contrary, some scholars are of the opinion that the behaviour of investor could affect the performance of the market, hence the behavioural finance theory, that sees investors as both rational and exhibit behavioural biasness while evaluating and pricing securities and that financial markets are informationally inefficient (Kumar, 2017).

These diverse perceptions by investors and the trend or behaviour of the capital market returns, especially as the COVID-19 pandemic has ravaged and still traumatizing the global economy are not actually out of place. This is because a good number of investments are associated with finite amount of downside risk bounded by zero; hence investors are likely to lose entire investment (Ejem, 2021). Many scholarly articles abound to guide investors on the behaviour, performance and state of capital market around the world. For instance, on the efficiency of the Nigerian capital market, previous works on tests of efficiency forms have resulted to controversies; some scholars argued that the market is sensitive to past or historical information, hence weak form

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efficient such as Olowe, (1999); Keith & Graham, (2005); Ajao & Osayuwu, (2012); and Okpara, 2016). Other scholars have also found to be on the other extreme that the Nigeria capital market is weak form inefficient for instance, Okpara, (2010); Sabur & Vitali, (20110; Afego, (2012); Gimba, (2012); Ogbulu, (2016); Adebanjo et al, (20180; and Ejem, et al, (2020). Outside the shore of Nigeria, countries like South Africa, Morocco and Egypt stock markets were found to be weak form efficient (Keith & Graham, 2005), also countries like India and emerging markets (BRICS) were found not to follow random walk (Sabur& Vitali, 2011; Goudarzi, 2013; Gay, 2016). On the volatility and stock returns relationships, commensurate efforts have been made too to unravel the state of most developing and developed markets around the world. For instance, in Nigeria, capital market has been adjudged to have persistent volatility clustering (Okpara, 2010; Suleiman, 2011), presence of asymmetric effect (Okpara & Nwezeaku, 2009) Volatility persistent (Olowe, 2009; Emenike & Aleke, 2012). Outside, Nigeria, such as Kenya, USA, and emerging markets, the respective capital markets have been disclosed to be associated with asymmetric effect, volatility persistent, and volatility clustering (Ogun et al, 2005; Karmakar, 2005; Pandey, 2005; Leon, 2008; Kuhe & Chiawa, 2017).Of course, the perceptions of stock market volatility have become a heated discourse in the field of finance due to the insinuations that volatility discourages risk averse investors and savers, and the cost of capital market of firms could be raised as a result of fluctuations in the market. Besides, it is to ignite increase in value of option wait, delay in listing or investment, thereby becomes cog in the wheel of growth in the economy (De long et al, 1989; Akthan & Gbassan, 2000).

The performance indicators of the capital market, especially stock returns should be closely monitored and the capital market bulwarked appropriately by the authorities concerned around the globe. This is because the stock market as one of the environments of investment decisions has become a veritable avenue for the interactions among the surplus and deficit economic units of any economy (Okafor, 1983). The stock market facilitates economic growth by enhancing liquidity and providing funds for industrialization and economic development. They also act as interesting investment centers and avails long-term capital to the listed firms by pooling funds from different investors and allow them to expand in business by offering investors alternative investment avenues to put their surplus funds. It plays a crucial role in the economy of a nation, which transfers investment fund from stock investors to stock borrowers as already observed for healthy economy (Arodoye, 2012; Forson &Janrattanagul, 2014; Ilahi et al, 2015). The essence of monitoring the behaviour and the performance indicators of the stock market is as a result of rationality posture exhibited by investors to always get positive returns in investment. If otherwise, like a fall in stock prices, it weakens the investor's confidence and drives down the zeal to invest further. As expected, if the condition of the stock market is not timely disclosed, perceived volatility presence in the stock market would make investors to demand a higher risk premium, creating higher cost of capital (Ejem, et al, 2018), which impedes investment and slows economic development especially now the COVID-19 pandemic has posed as a global monster.

1.1. Statement of Problem

Explicitly, the existence of stock market is inextricably interwoven in the fabrics of country's economic life, thus the behaviour of such market should be keenly monitored by the handlers of the market and the economy in general. Though no clear consensus is reached about the behaviour of capital market, a good number of scholars around the world have the notion that they have not lived up to expectation of providing a convivial environment for investors and not reflecting economic fundamentals as required. As such, investors seem to have difficulties in processing available information correctly when forming future expectations concerning the behaviour of securities in the market. It is quite disturbing to observe how investors overreact and panic to recent events, for instance the COVID-19 pandemic ravaging the world economy. These of course result to over pricing of securities by majority of the participants, thereby drifting the perceptions and behaviour of investors towards the same direction, leading to persistence price deviation in the market. It is also perceived that the Nigerian and most nation's capital markets around the globe are not active, information not adequate or not instantly and widely disseminated, thus privileged investors do make abnormal profit. These overwhelming trepidations despite the past and current innovations in the capital markets around the world incited the researcher to probe further on the investors' perceptions and behaviour of capital market returns. Again, on the diverse perceptions of investors about the capital markets of various countries around the globe, for instance, one could intuitively adjudge the performance and behaviour of a particular capital market based on or commensurate with the level of development of such country. If one goes by such judgment in adherence to the rule of thumb, investors could be misguided. For that there is need to streamline the investors' perceptions and behaviour of the capital markets around the world by picking at least one in each continent of the world. On a specific note, the aim of this study is to determine the investors' perceptions and behaviour of capital markets with respect to the forms of market efficiency, presence of volatility, volatility clustering, volatility persistence and asymmetry effect.

The rest of this paper is decomposed as follows: Section 2 reviews some theoretical and empirical literature. Sections 3 provides the data, methods and description. Section 4 analyses and discusses the findings of the study. Section 5 concludes and recommends.

2. LITERATURE REVIEW

2.1. Theoretical Framework

This study is anchored on a number of theories to elucidate the investors' perceptions and behaviour of capital markets around the world, such as prospect theory, theory of Behavioural Finance and the Efficient Market Hypothesis (EMH).

2.1.1. The Efficient Market Hypothesis (EMH)

This is also known as the Random Walk theory (Kendall, 1953), is of the view that equity value of a listed firm reflects all data or information regarding the business value, indicating that market responds to all the available or possible-to-know information. Efficient market as presented by Eugene Fama in 1965, suggested that stocks always trade at fair value, implying that prices adjust rapidly and, on the average, without bias to new information (Fama, 1976). Numerous scholarly papers have been anchored on this theory since the presentation, in order to justify the assumptions inherent in the model. This has increasingly attracted reasonable attacks on the assumed deficiencies in the theory mostly as regards to return predictability (Rossi, 2016; Nasir et al, 2016). In practice, certain information may affect stock prices more quickly than other information, leading to discrepancies in the response rates and researchers have made frantic efforts to separate these responses rates or information into different types; information about past prices, publicly available information, and all information. There are the Weak Form (if it fully incorporates the information in the past stock prices); the Semi-Strong Form (if prices reflect (incorporate) all publicly available information, including information such as published accounting statement for firm as well as historical price information); and the strong Form (reflect all information relevant to the firm, including information available only to company insiders) (Fama, 1976; Brealey & Myers, 2003; Ross, Westerfield et al, 2009; Bhalla, 2011; Rossi & Guardi, 2018).

2.1.2. Behavioural Finance Theory

This is a new innovation in the field of finance; a departure from efficient market hypothesis. This theory believes that the pattern of behaviour, whether overconfidence, overreactions, over representation, perceptions of investors are the same, hence such attitude do heavily influence share price from reflecting the economic fundamentals or beliefs or assumptions. It borders about how psychology influences investment decision-making process and financial markets, hence deviation of investors from traditional economic assumptions (Shefrin, 2001; Sewell, 2007; Kumar, 2017). Contrary to the EMH that sees investors as trying to outsmart each other in the market to make abnormal profit thereby making prices of securities return to equilibrium market value, also does not see all investors to be rational, rather assume that markets make unbiased forecast for future (Copur, 2015; Kumar, 2017; Ogbulu, 2019), the behavioural finance theory adjudges investors as both rational and exhibit behavioural biasness while evaluating and pricing securities. The theory assumes that financial markets are informationally inefficient (Muradoglu & Harvey, 2012; Kumar, 2017). It seeks to explain certain psychological influences and biases that alter the logical reasoning of the people or investors. The biases of behavioural finance are that: it makes investors to totally adhere to the information that suites their beliefs (confirmation bias): investors experiences from previous or past trading influence them to take a position, even when such decision is not rational (experience bias): it makes investors to avoid taking risks completely even when it promises high returns (aversion bias); it makes investors to overestimate their capacity or marketing prowess, hence make decisions ignoring factual evidence (overconfidence); it gives investors the propensity to keep securities even when the prices are dwindling, hoping that the prices will definitely appreciate in future (disposition bias); it makes investors to always patronize or invest in familiar firms, firms they can attest to, rather than going into unfamiliar market (familiarity bias); investors making budget or spending could be at variance depending on the circumstances confronting them, thus not in permanent disposition (mental accounting) (Saba & Syed, 2014; Copur, 2015).

2.1.2. Prospect Theory

This is an aspect of behavioural finance developed by Amos Tversky and Daniel Kahneman in 1992 that emphasizes more on psychologically accuracy on how decisions are taken vis a vis the expected utility theory (Tversky & Kahneman,1992). The theory is of the opinion that losses and gains are evaluated separately, that individual investors take decisions relying on perceived gains rather than perceived losses. The theory also known as *loss aversion* theory, implies that if difference choices present themselves to an investor with equal magnitude; one based on potential benefits or gains, the other on possible losses, the former option will be preferred. Here, choices are independent and singular, the chances of gain or loss is assumed to be equal rather than probability being presented (Tversky & Kahneman, 1992; Barberis, 2012; Pahlevi & Oktaviani, 2018; Chen, 2021).

2.2. Empirical Review

There exists a number of studies on the behaviour of capital market returns and are still growing and the results have resulted to unending controversies on the efficiency of the market, existence of volatility, volatility persistence and asymmetry effect on stock markets around the globe.

For instance, in Nigeria, within the GARCH framework Okpara (2009) investigated on whether the Nigerian stock market follows a random work and found that Nigerian stock market follows a random walk, hence efficient in the weak form.

Onwukwe et al, (2011) investigated the behaviour of daily stock returns of four quoted firms in Nigeria using variants of ARCH and found evidences of volatility clustering, high volatility persistence among others.

Ogbulu (2016) used seven parametric tools; Autocorrelation test, the ADF and P-P unit root tests, Variance Ratio test, the Normality/Random test, the Granger Causality test ARCH-GARCH test and Regression test to investigate the perceptions of the Nigerian Stock Exchange (NSE) across different data estimation intervals (daily, weekly, monthly and quarterly aggregate stock price data using the NSE all share index series from 1999 to 2013. The results at balanced posture revealed that NSE is weak form inefficient. Employing Partial autocorrelation test among others, Adebanjo et al, (2018) examined the weak form efficiency of the Nigerian stock market and found that the movements of the stock prices in the stock market were not random.

Still on the perceptions of investors about the stock market in the face of the COVID-19 pandemic, Ejem (2021) did a work on harnessing the upside potentials of the stock returns volatility amidst the corona virus pandemic in Nigeria employing EGARCH model. The result of the analysis found that stock returns volatility was persistent within the scope of the study and the presence of asymmetric effect was not found. Ejem went ahead to advice investors that good potentials abound in the stock market despite the pandemic posing as a tsunami in the global economy.

Applying serial correlation technique and runs test, Ajao and Osayuwu (2012) investigated the efficacy of the weak form of efficient market hypothesis in the Nigerian capital market. The study covered all securities traded on the floor of the Nigerian Stock Exchange and the month end value of the All-Share Index from 2001-2010. The serial correlation technique was used to test for independence of successive price movement and the distributive pattern whereas runs test was applied to test for randomness of share price movement and found that the correlation coefficients did not violate the two-standard error test. Again, the Box-Ljung statistic revealed that none of the serial correlation coefficients was significant and the Box pierce Q-statistics indicated that the overall significance of the serial correlation test was poor while the result of the distribution pattern shows that stock price movements are approximately normal. On that premise, it was concluded that successive price changes of stocks traded on the floor of the Nigerian Capital Market are independent and random. Therefore, the Nigerian Capital Market is efficient in the weak-form.

Afego (2012) employed non-parametric runs test to examine the weak-form efficient market hypothesis for the Nigerian stock market with emphasis on random walks in the monthly index returns over the period 1984-2009. The results observed that index returns on the Nigerian Stock Exchange (NSE) exhibited a predictable component, indicating that traders can earn superior returns by employing trading rules. The statistically significant deviations from randomness also suggest sub-optimal allocation of investment capital within the economy. The results generally contradict the weak-form of the efficient market hypothesis.

Gimba (2012) used autocorrelation test to investigate the weak form EMH of the NSE using daily and weekly NSE All Share Index (ASI) and five most traded banks stock of NSE from January 2007 to December, 2009 for the daily and from June 2005 to 2009 for the weekly data. The results found that Nigerian Capital market is weak form is inefficient.

Outside Nigeria, Aktham and Gbassan (2000) employed GARCH, EGARCH and GJR to examine the volatility associated with two major dates associated with King Hussein; official denial that he may die within three months and the date of his death. The result of the analysis found that king Hussein health rumours and date of death led to very high volatility in the Jordan capital market.

Applying Box-Jenkins ARIMA models, Gay (2016) investigated the relationship between stock market prices and macroeconomic variables (exchange rate and oil price) and found no relationship between present and past stock returns, affirming that BRIC markets exhibited weak form efficiency within the scope of the study.

Keith and Graham (2005) engaged GARCH and time-varying parameters with data spanning from early periods of 1990s and ending of June 2001 to investigate the efficiency of seven African stock markets; South Africa, Egypt, Morocco, Nigeria, Zimbabwe, Mauritius and Kenya. The empirical results found that the Johannesburg stock market was weak form efficient throughout the period under study while Egypt and Morocco stock markets tested weak efficient from 1999. It was also discovered that Nigerian capital market was weak form efficient from early 2001, indicating that the market follows a random walk. Again, it was found that Kenya and Zimbabwe stock markets show no tendency towards weak form efficiency, while Mauritius market showed a slow tendency to eliminate inefficiency.

Sabur and Vitali (2011) examined weak-form efficiency in Africa using multi-approach such as unit root, autocorrelation, runs and variance ratio tests on the daily price indices of Egypt, Kenya, Mauritius, Morocco, Nigeria, South Africa and Tunisia over the period 1999-2009. The result obtained showed the rejection of the random walk hypothesis for all stock markets indices over the whole sample period except South Africa market.

Finally, in this review, Goudarzi (2013) employed ADF test and GARCH model to investigate market efficiency in India Stock Market through modeling one asset return series. The results found that underlying series is stationary, mean reverting, suggesting that the Indian stock market is weak form inefficient**.**

3. MATERIALS AND METHODS

To adjudge the investors' perceptions and behaviour of stock returns on select capital market around the world, this study adopted various econometric tools such as Descriptive statistics, Unit root tests (Augmented Dickey Fuller (ADF) and Philip-Perron (P-P)), Autocorrelation test, Pairwise Granger Causality test, Ordinary least square (OLS) test, Normality/Random Walk test, Variance ratio test (VRT) and ARCH-GARCH models. It employed daily historical data from May 18, 2015 to June 6th, 2022, from prominent capital markets each from all the continents around the world; Africa: Nigeria All Share Index (ASI-NG) and South Africa Johannesburg All Share (JSE-SA); America: USA Dow Jones Industrial Average (DJI-USA); Europe: Germany DAX (DAX-GER); Middle East: United Arab Emirate UAE) DFM General (DFM-UAE); Asia/Pacific: China CSI 1000 (CSI-CH).

The price data were converted into compound returns by taking logarithms:

$$R_t = \ln(\mathcal{P}_t/\mathcal{P}_{t\text{-}1})$$

where R_t, is the current market returns, p_t is the current market index price, $p_{t\text{-}1}$ is the previous market index price.

The choice of scope in this study is based on the belief of the researcher that from 2015, most viable capital markets around world are expected to have become relatively identical in terms of depth of trading and level of ICT compliance. For instance, to deepen and enhance efficient performance of the Nigerian stock market, in 2011 the regulatory bodies came up with an innovation for digital transformation known as the X-Era. This of course drifted into a monumental era and the launch of a historic and robust technology platform, X-GEN in 2013, thereby boosted and enhanced direct market access and mobile trading technologies. In 2021, the Nigerian Stock Exchange became fully demutualized transforming from a member-owned, not-for-profit entity into a shareholder-owned, for-profit entity. These remarkable transformations made the Nigerian Stock Exchange evolved into Nigerian Exchange Group Plc. ("NGX Group"), a non-operating holding company with three wholly-owned operating subsidiaries (Ogedengbe, 2020; Adonri, 2021)

3.1. Description of Tools Employed in this Study

3.1.1. Unit Root Test

Augmented Dickey Fuller (ADF) unit root test is a widely used to know the stationarity or non-stationarity of variables (Brooks, 2008). It handles bigger, more complex models (Gujarati, 2013). Deriving from AR (p) representation, the ADF test involves the following regressions:

No constant, no trend, (y_t is a random walk):

$$\Delta y_t = \gamma y_{t-1} + \nu_t \qquad (1)$$

Constant, no trend, (y_t is a random walk with drift):

$$\Delta y_t = \alpha + \gamma y_{t-1} + \nu_t \qquad (2)$$

Constant and trend, (y_t is a random walk with drift around a deterministic trend):

$$\Delta y_t = \alpha + \gamma y_{t-1} + \lambda_t + \nu_t \qquad (3)$$

According to Gujarati (2013), ADF is conducted by augmenting the missing links inherent in the Dickey Fuller unit root test by adding the lagged values of the dependent variable, ΔY_t

The Augmented Dickey Fuller adds lagged differences to these models:

No constant, no trend:

$$\Delta y_t = \gamma y_{t-1} + \sum_{s=1}^{m} \alpha_s \Delta y_{t-s} + \nu_t \qquad (4)$$

Constant, no trend:

$$\Delta y_t = \alpha + \gamma y_{t-1} + \sum_{s=1}^{m} \Delta\alpha_s y_{t-s} + \nu_t \qquad (5)$$

Constant and trend:

$$\Delta y_t = \alpha + \gamma y_{t-1} + \lambda_t + \sum_{s=1}^{m} \Delta\alpha_s y_{t-s} + \nu_t \qquad (6)$$

Let y_t be a time series.

Where ν_t is a pure white noise error term and where $\Delta y_{t-1} = (y_{t-1} - y_{t-2})$. $\Delta y_{t-2} = (y_{t-2} - y_{t-3})$ and so on with numbe of lagged difference included so that the error term is serially uncorrelated to enable the researcher obtain an unbiased estimate γ, the coefficient of lagged y_{t-1} in the above eqns (4,5,6) (Gujarati, 2013).

Another unit test is the Philip-Perron (P-P); a nonparametric statistical method that takes of the serial correlation in the error term without lagged difference terms. The asymptotic distribution of the PP test is the same with that of ADF test (Gujarati, 2013).

Decision: In unit root test, the null and alternative hypotheses are presented as follows

H_o : η = 0 (unit root exists and series is non-stationary) as against H_1 : η = 0 (no unit root series is stationary)

Here, non-rejection of null hypothesis implies that stock market prices follow a random walk and is weak form efficient, whereas rejection of the null hypothesis means that there is no unit root in the series, suggesting that the series is stationary. That indicates that stock market prices support weak form inefficiency and do not follow random walk (Ogbulu, 2016; Ejem et al, 2020).

3.1.2. The Granger Causality Test

This is a special test tool engaged in examining the short run direction of causality between variables, say X and Y (Granger, 1969). The test is based on estimating the following bivariate regression (Ogbulu, 2016), as presented below:

$$Y_t = \sum_{i=1}^{n} \alpha_i X_{t-i} + \sum_{j=1}^{n} \beta_j \gamma_{t-i} + u_{1t} \qquad (1)$$

$$X_t = \sum_{i=1}^{n} \delta_i Y_{t-i} + \sum_{j=1}^{n} \lambda_j \chi_{t-j} + u_{2t} \qquad (2)$$

Where, Y_t and X_t = variables of interest; u_{1t} and u_{2t} = disturbance terms assumed to be correlated.

From previous finance studies, Granger causality test as a veritable tool for testing weak form efficiency examines the lead lag or predictability associated in financial time series. In this case, this tool is used to estimate the degree of causality between stock returns (Brooks, 2008).

3.1.3. The Variance ratio Test

The variance ratio technique tests the null hypothesis that a given time series is independent and identically distributed, thus, if the series follows a random walk with uncorrelated changes in the series, p_t, then the variance of its q-difference would be q times the variance of its first differences. The variants of ratio test are Chow and Denning (1993) multiple variance ratio test, Wright (2000) test, and the Lo and Macinlay (1988) variance ratio test (Ogbulu, 2016). The variance ratio is presented below as follows;

$$Z(q) = \text{Var}\,(R_{(q)}\text{-}1))/\sqrt{Q_{(q)}} \rightarrow N(0,1) \qquad (1)$$

$$Z^*(q) = \text{Var}\,(R_{(q)}\text{-}1))/\sqrt{Q^*_{(q)}} \rightarrow N(0,1) \qquad (2)$$

Meanwhile, under the null hypothesis of homoscedasticity Z(q) and $Z^*(q)$ have an asymptotic standard distribution with mean zero and standard deviation, one. if the computed variance ratio Z(q) or $Z^*(q)$ is greater than the critical value of a predetermined significance level, then the random walk hypothesis is rejected, implying the market is weak form inefficient (N'dri, 2015; Ogbulu, 2016).

3.1.4. The Autocorrelation tests

Autocorrelation as suggested by Gujarati (2013) is correlation between numbers of series of observation ordered in time as in the case of time series or spaced as seen in cross sectional data. It is seen as a special case of correlation where the relationship is not actually in between two or more variables, rather between successive values of the same variables (Koutsoyiannis, 1973). As a measure of the linear relationship between successive values of the same variables, it is also applied to investigate the relationship between past and present prices of securities and their current levels, thus the predictability of future prices given current or historical prices. The autocorrelation function (ACF) likewise at lag k is applied to test for weak form efficiency forms of the Efficient Market Hypothesis (EMH) under the assumption that prices of securities is efficient market follow the random walk and non-stationary. According to Gujarati and Porter (2009), the sample autocorrelation function (p_k) is normally presented as:

$P_K = \gamma_k/\gamma_0$= (covariance at lag k)/variance (1)

$\gamma_k = \sum(p_{jt}$-E(p_{jt})) (p_{t+k}-E(p_{jt}))/N-K and $\gamma_o = \sum(p_{jt}$-E(p_{jt}))^2/N-K (2)

Where, p_{jt} = stock market at period t; E(p_{jt}) = sample mean of stock price series; N = sample size

Decision rule: For lags of k periods, if and only if the probability values are significantly different from zero at the chosen level of significance which supports the weak efficiency, do not reject the null hypothesis, P_k. Then reject null hypothesis, if the probability values are not significantly different from zero at the selected level of significance; suggesting the market is weak form inefficient, hence does not follow random walk (Gujarati & Porter, 2009).

3.1.5. Volatility Modeling

Modeling and forecasting volatility inherent in stock market has over the decades occupied empirical and theoretical investigations by finance and economics experts. This academic excursion has a lot of motivations due to the prime place taken by volatility in the field of finance. Brooks (2008) volatility as measured by the standard deviation or variance of returns, is sometimes applied as a crude measure of the total risk of financial assets. However, volatility models for evaluating market risk need the estimations or forecast of volatility parameters. From previous study the mostly used stationarity models are original Autoregressive Conditional Heteroskedastic (ARCH) presented by Engle (1982) permits the conditional variance to change over time as a function of past errors leaving the unconditional variance constant. Furthermore, Engle et al (1987) introduced the ARCH-M model, an extension of ARCH model which allows the conditional variance to be determining factor of the mean. Engle et al model was applied to three different data sets of bond yields; hence came out to opine that risks are not time invariant; instead risks vary systematically with the assumptions of underlying uncertainty. Other models are improvement of ARCH model, such as Generalized Autoregressive Conditional Heteroskedasticity (GARCH), introduced by Bollerslev (1986). This generalized ARCH model allows for a longer memory and a more permissible and flexible lag structure at the same time. It provides a relatively long lag in the conditional variance equation and negates the problems associated with negative variance parameters in a fixed lag structure. The difference between the ARCH and GARCH is that in ARCH model, the conditional variance is specified as a linear function of past sample variance only, while, the GARCH process permits lagged conditional variances to also enter in the model. ARCH and GARCH family models is to provide a volatility measure applied in in financial decisions with about risk analysis, portfolio selection and derivative pricing (Bollerslev 1986, Bollerslev et al, 1992; Engle & Nelson, 1993; Bera & Higgins, 1993). Another is the Exponential GARCH (EGARCH) model which according to Brook (2008) is an improvement of the GARCH which imposes a non-negativity constant on market variable, and permits for conditional variance to respond asymmetrically to returns innovations of different signs. The EGARCH used to describe the behavior of return volatilities by Nelson (1991) was proposed to test the hypothesis that the variance of return was affected differently by positive and negative excess returns, and that excess returns were negatively related to stock market variance. In order to avoid the imposition of a symmetric response of volatility to positive and negative shocks in GARCH model, Glosten et al (1993) presented the Threshold GARCH (TGARCH) models and came out boldly that there is a positive and significant relation between the conditional mean and conditional volatility of the excess return on stocks when the standard GARCH-M framework is used to model the stochastic volatility of stock returns, they also found that positive and negative unexpected returns have vastly different effects on conditional variance (Christie ,1982; Schwert ,1990; Pagan &Schwert ,1990).

ARCH, GARCH, TGARCH and EGARCH models with associated mathematical formulations are seen below.

Volatility Models of Stationarity: Volatility model is generally stated as

$\chi_t = \mu_t(\theta) + \varepsilon_t$ (1)

$\varepsilon_t = \sigma_t(\theta) Z_t$ (2)

Here, volatility is explained as a precise function of a set of variables, where, χ_t = the return, $\mu_t(\theta)$ = conditional means, ε_t= residual term

ARCH Model: Engle (1982) presented ARCH model as the behaviour of conditional variance $\sigma_t(\theta)$ as seen in eqn (2). According to Engle (1982), the ARCH model assumed that the conditional variance, $\sigma_t(\theta)$ is a linear function of the past or previous 'p' squared innovation, viz;

$\sigma_t^2(\theta) = \omega + \alpha_t \varepsilon_{t-1}^2 + \ldots + \alpha_p \varepsilon_{t-p}^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2$ (3)

In this case, the conditional volatility (variance) is assumed as a moving average of squared innovation, and ω>0 and $\alpha_i > 0$, i = 1,…,p. However, the conditional variance of innovation, is designated as $\sigma^2$and computed thus,

$\sigma^2 = \omega/(1-\sum_{i=1}^{p} \alpha_i)$ (4)

Besides, ε_t is serially uncorrelated, where, $\varepsilon_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-1}^2 + V_t$ (5)

Jondeau, et al (2006) observed that forecasts of ARCH model are arrived recursively as seen below;

The 1-step ahead forecast for σ_{t+1}^2 is $\sigma_t^2(1)$ =$\hat{\omega}$ +$\hat{\alpha}_1\hat{\varepsilon}_t^2$ +…+$\hat{\alpha}_p\hat{\varepsilon}_{t+1-p}^2$= $\hat{\omega}$+ $\sum_{i=1}^p \hat{\alpha}_i\,\hat{\varepsilon}_{t+1-i}^2$

The k-step ahead forecast for σ_{t+k}^2 is σ_k^2(k) = $\hat{\omega}$ + $\hat{\alpha}_i\sigma_t^2(k-1)$ +…+ $\hat{\alpha}_i\sigma_t^2(k-p)$ = $\hat{\omega}$ + $\sum_{i=1}^p \hat{\alpha}_i\sigma_t^2(k-1)$ with $\sigma_t^2(k-i) = \hat{\varepsilon}_{t+k-i}^2$ if k-i ≤ 0

Therefore, the unconditional distribution for ϵ_t comes with fatter tails, hence the normal distribution. Given the null hypothesis, the error term ϵ_t is assumed to be a normal white noise process; whereas the alternative hypothesis is that error term for an ARCH (p) model is seen as;

$\epsilon_t = \sigma_t z_t$, and σ_t^2= ω+ $\sum_{i=1}^p \alpha_i\varepsilon_{t-i}^2$ while, the rest for ARCH (p) effects is based on the null hypothesis: H_0: α_1= … = α_p= 0 vs H_a: $\alpha_1 \geq 0, \dots \alpha_p \geq 0$

With at least one strict inequality, the ARCH test is expected to be formulated as a one-sided test. In the same vein, Lagrange-Multiplier (LM) test, and the Ljung and Box (1978) Statistics is also applied for the test of already stated hypothesis above, ε_t^2.

GARCH family Models: Under normal condition, volatility clustering is seen in financial log returns data, where changes in the log returns are possibly followed by further large changes. Bollerslev (1986) presented the GARCH model for been consistent with volatility clustering.

Fundamentally, GARCH (1,1) specification sees the mean equation as below:

$Y_t = X_t^I\theta + \varepsilon_t$ (6)

However, the mean equation in eqn (5) is a function of endogenous variables with associated error term. In order to monitor the presence of autocorrelation in financial data series, the mean equation id modified to include Autoregressive (AR) and Moving Average (MA) terms.

Therefore, the GARCH (p, q) takes the following

$Y_t = X_t^I\theta + \sum_{i=1}^p \alpha_i Y_{t-i} + \sum_{i=1}^q \beta_i\varepsilon_{t-i}$ (7)

Where, P and q are selected to capture significant spikes in the autocorrelation function, hence the conditional variance of the GARCH (p,q) is presented in the following equation:

$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2$ (8)

Where, ω = constant term, ε_{t-1}^2 = the ARCH term; as stated above in eqn (8) is the first lag of the squared residual from the mean equation, representing an update about the volatility from the past period and the GARCH term σ_{t-1}^2 above in eqn (8) is the last periods forecast variances.

Contributing further, Thomas and Mitchel (2007) are of the view that forecasting of the GARCH models are recursively obtained in the same way as seen in ARCH models. Jondeaus, et al (2006) as suggested in the estimation of GARCH (p,q) model under normality assumption, the maximum likelihood (ML) estimation procedure is applied. This estimation of GARCH model is expected to follow as stated below:

A. *Estimate the mean equation* $X_t = \mu_t + \varepsilon_t$. Deduce $\hat{\varepsilon}_t = X_t - \mu_t$ and $\hat{\sigma}^2 = \frac{1}{T}\sum_{t=1}^T \hat{\varepsilon}_t^2$

B. *Select initial values for θ, say* θ^0 = $(\omega^0, \alpha_1^0, \beta_1^0, \dots \beta_q^0)$ and set $\hat{\varepsilon}_1^2 = \dots = \hat{\varepsilon}_m^2 = \hat{\sigma}_1^2 = \dots = \hat{\sigma}_m^2 = \hat{\sigma}^2$ with m = max (p,q)

C. *Compute the conditional variance* $\hat{\sigma}_t^2 = \hat{\omega}^0 + \sum_{i=1}^p{}' \alpha_i^0\hat{\varepsilon}_{t-1}^2 + \sum_{j=1}^p + \beta_j^0\hat{\sigma}_{t-j}^2$(9)

for t = m + 1, …, T

D. *Compute the log likelihood* $L_T(\theta^0) = \sum_{t=m+1}^T \ell_t(\theta^0)$,

Where, $\ell_t(\theta^0) = -\frac{1}{2}\log(2\pi) - \frac{1}{2}\log(\hat{\sigma}_t^2) - \frac{\hat{\varepsilon}_t^2}{2\hat{\sigma}_t^2}$ (10)

any change in the value of parameters, for instance, θ^1, the log likelihood will increase, thus $L_T(\theta^1) > L_T(\theta^0)$.

Iterate steps (c) and (d) until convergence of the log likelihood to a fixed value. The covariance matrix of ML estimator is given by the inverse of the information matrix. The ML estimator is consistent and has the following asymptotic distributions

$\sqrt{T}\,(L_T(\hat{\theta} - \theta) \rightarrow N(0, 1(\theta)^{-1}$ (11)

In sum, to test the null hypothesis that process is homoscedastic against the alternative that the variance follows a GARCH (1,1) process. Then, the null is H_o:$\alpha_1 = \beta_1$ = 0, against H_a:$\alpha_1 \geq \beta_1 \geq 0$ with least one strict inequality.

3.1.5.1. Methodology for ARCH Model

In the words of Hojatallah et al (2010), the ARCH model is seen as a diagnostic model that examines the ARCH effects and autocorrelation of a financial data. It remains the veritable model that is used to test in a volatility model the presence of ARCH effects and autocorrelation and where a model of no ARCH effects is a good model. Here, two pertinent tests must be carried out for ARCH model; test of stationary with unit roots test in the residuals, and ARCH effects test. Already discussed, unit root in a time series is checked using Augmented Dickey- Fuller test (ADF), which incorporates regressing the first difference of the series against the series lagged k times (Brooks, 2008; Gujarati, 2013). Here, the series is assumed to be stationary if the ADF test rejects the null hypothesis of a unit root in the return series. Furthermore, Engle (1982) gave a process of testing for the presence of ARCH effects in a residual as seen below;

$LM = n.R^2 \sim \chi_{(p)}^2$ (12)

Where, n = sample size and $R^2$is arrive by regressing $\varepsilon_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \dots + \alpha_p\varepsilon_{t-p}^2 + u_t$

Whenever the sample is seen to be large nR^2 follows the Chi-square distribution with *df* equal to the number of auto-regressive terms in the auxiliary regression model. Here, whenever there is non-rejection of the null hypothesis, it shows no volatility clustering and the rejection of same null hypothesis indicates the presence of ARCH effects. According to Engel (1982), to test for heteroscedasticity, the linear ARCH (q) model for heteroscedasticity is used.

$$h_t^2 = \beta_0 + \sum_{i=1}^{q} \beta_1 \varepsilon_{t-p}^2 \quad (13)$$

If $\beta_1 = 0$, then there is no volatility clustering. The AIC (Akaike Information Criterion) and SBIC (Schwartz Bayesian Information Criterion) are applied to determine the ARCH model order (the value of q) where the model with the minimum value of information criterion is to be preferred.

3.1.5.2. Methodology for GARCH Family

Here, some of the models in GARCH family to be considered are GARCH, EGARCH and TGARCH. As already stated, GARCH (p,q) specifies the conditional variance to represent linear combination of (q) lags of the squared residuals ε_t^2 from the conditional return equation and (p) lags from the conditional variance σ_{t-j}^2. This GARCH (p,q) conditional variance is expressed as;

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \qquad (14)$$

This is estimated under the constraints; $\alpha_1\beta > 0$ and $(\alpha + \beta) < 1$. It's (GARCH model) adequacy is examined by standardized residual $\frac{\varepsilon}{\sigma}$. Where (σ) = conditional standard deviation. Arrived by the GARCH (p,q) model as seen in eqn (14).

(ε) = residuals of the conditional return equation, and the standardized residuals are assumed to be independently and identically distributed (IID). To test for independence of the error term, a two- step is needed: First, according to Ljung and Box (1978), calculate the Liung-Box statistics on the squared observation of the raw data. This test is normally applied to test for the remaining serial correlation in the mean equation; if the mean equation is correctly specified; all Q-statistics is expected not be significant. Second, this one is a diagnostic test, also known as post hoc analysis step; it examines the specification of the variance equation. It involves the calculation of the Q- statistics of squared standardized residuals, again if the variance equation correctly specified, all Q-statistics should not be significant. It is a Chi-square statistic, χ_{m-p-q}^2. Here the rejection of null hypothesis signifies that there are no autocorrelation and that the series under examination signposts volatility clustering. Moreso, the adequacy of the GARCH model and selection criteria are examined or tested using the same method as of the ARCH model. For that, since the standard GARCH model cannot take account of leverage effects, and does not permit for any direct feedback between the conditional variance and the conditional mean, hence the postulations of two popular GARCH models; Threshold GARCH (TGARCH) model or according Glosten, Jagannathan and Runkle in1993 called GJR model, and the Exponential GARCH (EGARCH) model (Nelson, 1991). Meanwhile, the TGARCH or GJR model is a simple extension of GARCH with additional feature or term to account for possible asymmetries. Here, the conditional variance is given below as;

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \gamma \varepsilon_{t-1}^2 d_{t-1} + \beta \sigma_{t-1}^2 \qquad (15)$$

Where $d_{t-1} = 1$, if $\varepsilon_{t-1} < 0$, = 0, otherwise. However, the conditional variance of the basic GARCH model in eqn (7) is simply extended to include a threshold term, $\varepsilon_{t-1}^2 d_{t-1}$. In this model, $d_1 = 1$, if $\varepsilon<0$, and 0 otherwise. For leverage effect, γ should be greater than zero, and for non-negativity, the following should be: $\alpha_0 > 0$, $\alpha_1 > 0$, $\beta \geq 0$, and $\alpha_1 + \gamma \geq 0$.

Therefore, the model is still admissible, even if $\gamma < 0$, given that $\alpha_1 + \gamma \geq 0$. According Brooks (2008), for EGARCH, model, the conditional covariance is given by:

$$\ln(\sigma_t^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \gamma \frac{\mu_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left(\frac{|\mu_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right) \qquad (16)$$

ω = the mean level, β = persistence parameter, α = volatility clustering coefficient, Log (σ_{t-1}^2) = the past variance, γ = the leverage effect.

The above model ensures that even when the parameters are negative, σ_t^2 will be positive and the asymmetry or the leverage effect measure, γ, will be negative even when the relationship between volatility and log returns is negative. The EGARCH is symmetric when = 0, when $\gamma < 0$ then positive shocks (good news) generate less volatility than bad news (negative shocks); in other way round, bad news or negative shocks magnify more volatility than good news or positive shock of the same magnitude. When $\gamma > 0$, it implies that positive innovations or shocks are more destabilizing than negative innovations or shocks (Black, 1976; Christie, 1982). In other words, negative value of γ is called the 'sign effect'. The choice of EGARCH framework is to accommodate examination of conditional variance (volatility), asymmetric effect and volatility persistence. According to Alexander (2009), the $\propto$ parameter represents the symmetric effect of the model, if $\propto$ is positive, then the conditional volatility tends to rise (fall) when the absolute value of the standardized residuals is larger (smaller), hence magnitude effect'. The GARCH effect β measures the persistence in conditional volatility, when β is relatively large, then volatility takes a long time to fizzle out or decay or die out following a mayhem in the market or economy in general. Succinctly, EGARCH model has good number advantages over the normal GARCH specification. First, since the log (σ_t^2) is modeled, then even the parameters σ_t^2 will be positive. There is thus no need to artificially impose non-negativity constraints on the model parameters. Second, asymmetries are allowed

Table 1. Descriptive Statistics for Stock of Select Countries Under Study.

	ASI_NG	JSE_SA	DJI_USA	DAX_GER	DFM_UAE	CSI_CH
Mean	0.000285	0.000118	0.000348	0.000165	-5.44E-05	-0.000123
Median	-0.000100	0.000000	0.000700	0.000600	0.000200	0.000900
Maximum	0.062300	0.071900	0.113700	0.109800	0.073200	0.066200
Minimum	-0.049100	-0.090400	-0.129300	-0.122400	-0.082900	-0.087900
Std. Dev.	0.009662	0.012676	0.011929	0.012986	0.011510	0.018312
Skewness	0.373743	-0.515504	-0.633512	-0.401560	-0.513715	-0.882702
Kurtosis	7.491546	9.277415	24.47933	13.27723	11.70983	6.611110
Jarque-Bera	1515.216	3107.676	34433.15	7956.694	5672.606	1161.268
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Observations	1754	1843	1785	1797	1770	1725

Table 2. Unit Root Test.

Unit Root Stat & Prob.	ASI_NG	JSE_SA	DJI_USA	DAX_GER	DFM_UAE	CSI_CH
ADF Test	-31.90581 (0.0000)	-42.30078 (0.0000)	-18.3469 (0.0000)	-42.85463 (0.0000)	-21.60995 (0.0000)	-37.85180 (0.0000)
P-P Test	-32.73587 (0.0000)	-42.36418 (0.0000)	-364.9594 (0.0001)	-42.86291 (0.0000)	-38.19370 (0.0000)	-37.94114 (0.0000)

for under the EGARCH formulation, since if the relationship between volatility and returns is negative, γ, will be negative (Brooks, 2008).

4. ANALYSIS AND DISCUSSION

Table **1** above shows the descriptive statistics explaining the distributional features of stock returns for the select countries in this study. The results for respective countries suggest low average daily stock returns series. The standard deviations recorded are 0.9%, 1.2%, 1.1%, 1.2%, 1.1% and 1.8% for Nigeria, South Africa, USA, Germany, UAE and China respectively, which are closely related suggesting relatively high volatility in each country. The difference between the values of the minimum and maximum are also relatively high in various countries suggesting high volatility in price changes in each country. The values of the skewness and kurtosis are greater than normal (for null hypothesis, Skewness = 0 and Kurtosis = 3) for respective countries. For Kurtosis which is greater than 3 showing leptokurtic distribution (the tendency of financial asset returns to have distribution that exhibit fat tails and excess peakness at the mean) which is as a result of volatility clustering in the return series for the select countries in this study. Positive skewness recoded in all the countries indicate that all their returns distribution is skewed to the right of their mean with long right tail, suggesting there are tendencies that large positive returns occur more than large negative returns in the various markets. This shows that large movements in stock returns do not follow with the same magnitude of negative movement. In sum, skewness greater than zero and kurtosis greater than 3 are sufficient evidences supporting presence of asymmetry and volatility clustering in the stock return series of respective countries, also the deviation from normality support weak form inefficiency. Jarque-Bera values are expected to be zero under null hypothesis, but the results here revealed that the values for all the countries in this study are greater than zero, also the associated probability values are highly significant at 1%; sufficient evidences of abnormal distribution, supporting deviation from random walk, hence weak form inefficient for the respective countries. It is worthy to clarify that the difference in the observations from May 18, 2015 to June 6^{th}, 2022 is as result of differences in trading days in the select countries.

Next is unit root test, a popular macroeconomic technique used for the test of stationarity of time series data due to the dependent nature of most economic variables. This study used ADF and P-P unit root tests as shown below;

Results of ADF and P-P unit root tests on table **2** revealed rejection of null hypothesis at 1 % significant level, supporting deviation from random walk which is consistent with most financial time series data. The results affirm the weak form inefficiency in the stock return series of all the countries.

The researcher then proceeded to Autocorrelation (AC) and Partial Autocorrelation (PAC) tests; a special correlation test that examines the relationship between successive values of the same variable and not necessarily between two or more variables. The test is shown in table **3** below;

Table 3. Autocorrelation Test.

AC & PAC Test (1-36)	ASI_NG	JSE_SA	DJI_USA	DAX_GER	DFM_UAE	CSI_CH
Q-Statistics range	123.17 to 195.23	432.32 to 519.09	50.313 to 426.57	50.313 to 426.57	498.26 to 662.44	14.714 to 107.13
Probability	0.000	0.000	0.000	0.000	0.000	0.000
AC &PAC Coefficient. Range	-0.002 to 0.265	-0.012 to 0.078	-0.001 to 0.080	-0.001 to 0.206	-0.002 to 0.080	-0.008 to 0.092

Table 4. Variance Ratio Test (VRT).

VRT Prob	ASI_NG	JSE_SA	DJI_USA	DAX_GER	DFM_UAE	CSI_CH
Joint Tests	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Individual Test 2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
4	0.0000	0.0000	0.0002	0.0000	0.0000	0.0000
8	0.0000	0.0000	0.0037	0.0000	0.0000	0.0000
16	0.0000	0.0000	0.0201	0.0000	0.0000	0.0000

Table 5. Causality Test.

Select Countries	Null Hypothesis	Prob
NIGERIA ASI	ASI_NG does not Granger Cause ASI_NIG_1	0.0000
SOUTH AFRICA JSE	FTSE_SA does not Granger Cause JSE_SA_1	0.0000
USA DJI	DJI_USA does not Granger Cause DJI_USA_1	0.0000
GERMANY DAX	DAX_GER does not Granger CauseDAR_GER_1	0.0000
UAE DFMG	DFM_UAE does not Granger Cause DFM_UAE_1	0.0000
CHINA CSI 1000	CSI_CH does not Granger Cause CSI_CH_1	0.0000

Table 6. OLS Test.

OLS test	ASI_NG	JSE_SA	DJI_USA	DAX_GER	DFM_UAE	CSI_CH
Ass. Prob	0.0000	0.5853	0.0000	0.6193	0.0000	0.0001
Prob -F-Stat	0.000000	0.585310	0.000000	0.619317	0.000004	0.000124
Dw -Stat	2.001903	1.996761	1.963779	1.997929	1.991151	1.999530

Table **3** above revealed that the individual AC and PAC coefficients at different lags from 1-36 are significantly different from zero for all price series in the selected countries, also the associated probability values suggest that successive autocorrelation of the prices are very significant from 1-36, showing rejection of serial correlation for series in the select countries. This suggest that there is existence of volatility clustering in the price series, also that the price series in all the markets do not follow random walk.

Table **4** above shows the test of random walk using the Variance Ratio test (VRT) done under the null hypothesis of stock returns (Martingale process) for all the six countries under study. The results revealed that both joint and individual (lags 2-16) variance tests were rejected at 1% significant level, suggesting that price series do not follow a martingale process, hence do not follow random walk, or is not weak form efficient.

Granger Causality tests for all the select countries in table **5** above reject the null hypotheses of no causal direction found between successive variables (prices regressed on their lagged value), suggesting deviation from random walk assumption for the return series; meaning that the various markets are not efficient in the weak form.

Then the researcher moved to check the relationship between the successive variables using Ordinary Least Square (OLS) Model as shown below;

Table **6** above reveals significant relationship between the successive variables (prices regressed on their lagged value), i.e., the coefficients of the regression are significantly differ-

Table 7. ARCH Effect Test.

ARCH Test	ASI_NG	JSE_SA	DJI_USA	DAX_GER	DFM_UAE	CSI_CH
F-statistic	0.0000	0.0000	0.0000	0.0096	0.0000	0.0000
Obs*R-squared	0.0000	0.0000	0.0000	0.0096	0.0000	0.0000

ent from zero for all the price series for all the countries under study except South Africa and Germany. These suggest that there is significant relationship between the price series and their lagged values; indicating that historical prices for the affected countries can be used to predict current and future prices in the stock markets, hence weak form inefficiency is affirmed for the countries.

Table **7** above shows that the F-version and the LM-statistics are very significant, indicating presence of ARCH effects in the returns all capital markets of the countries under study.

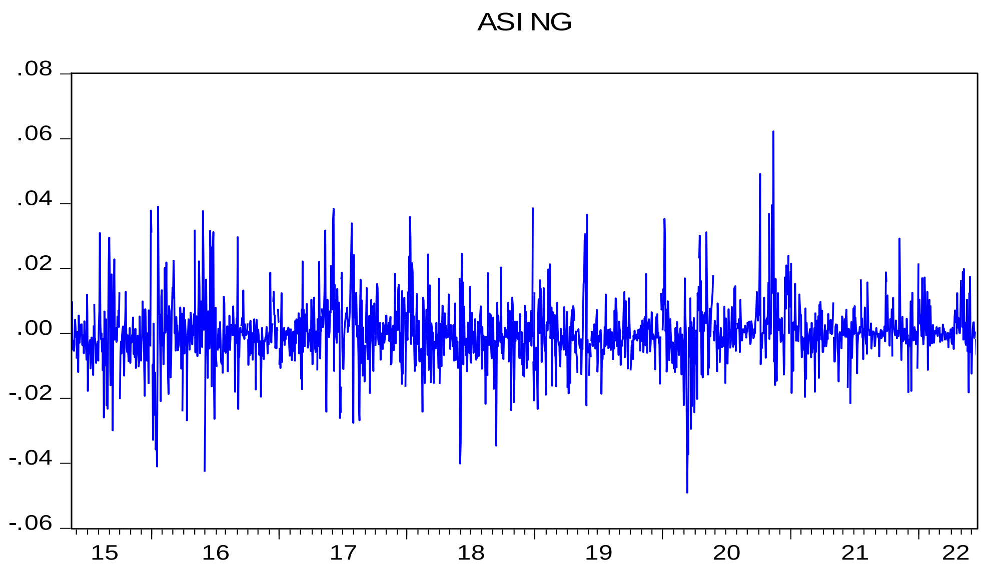

Fig. (1). Volatility Clustering Test for Nigeria Capital Market returns.

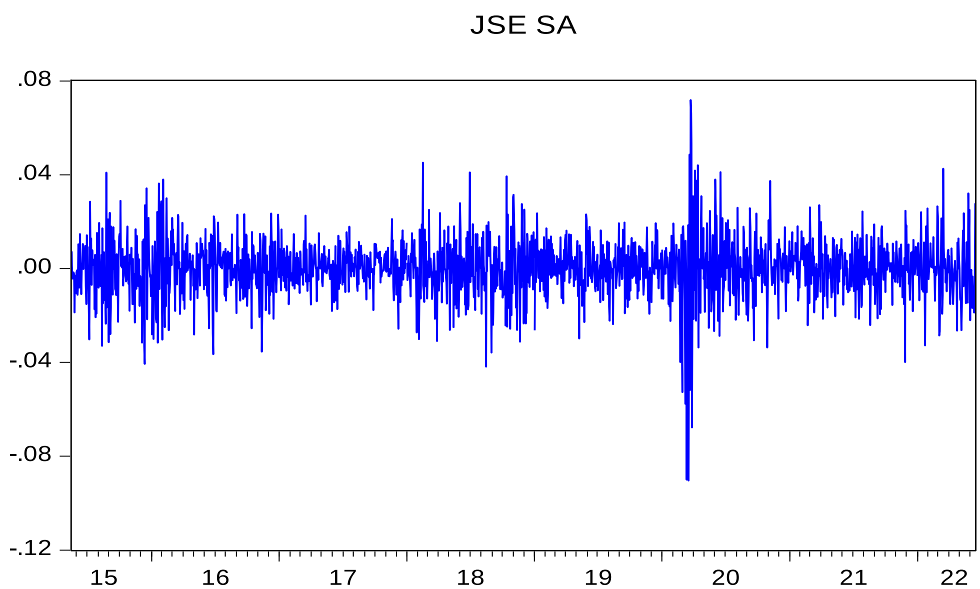

Fig. (2). Volatility Clustering Test for South Africa Capital Market returns.

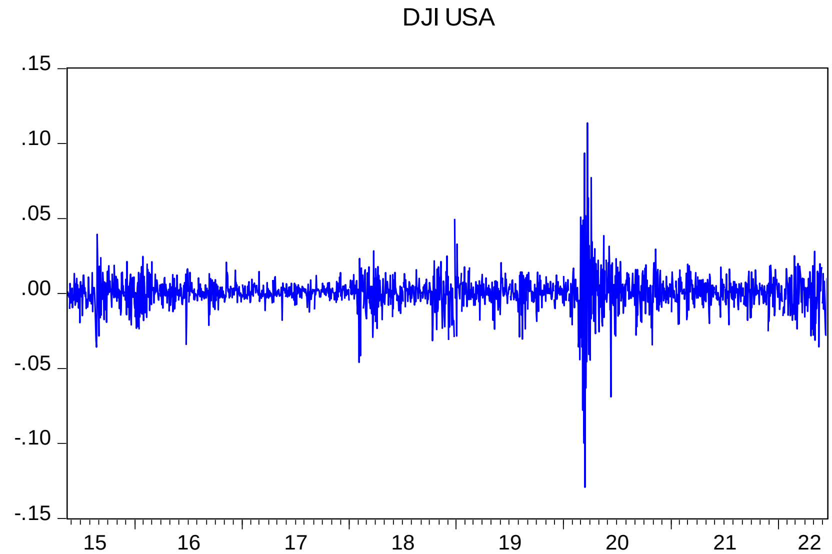

Fig. (3). Volatility Clustering Test for USA Capital Market returns.

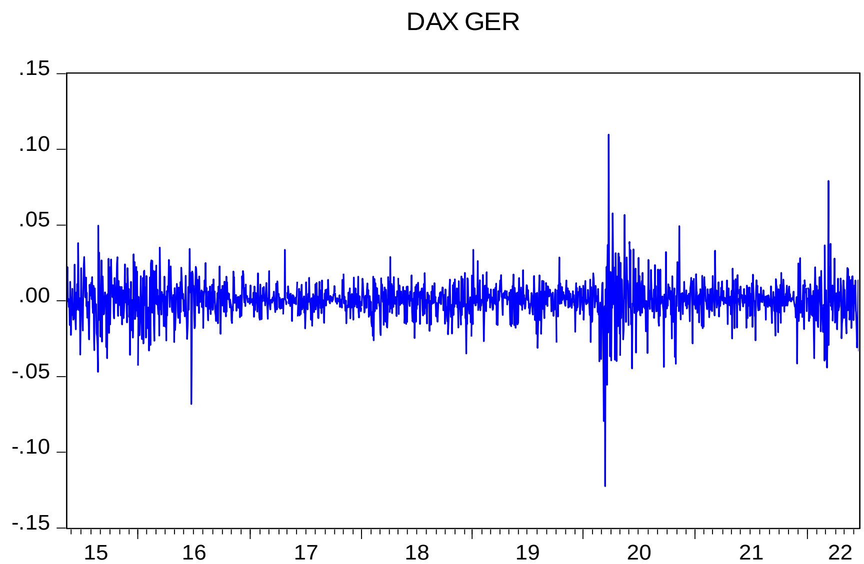

Fig. (4). Volatility Clustering Test for Germany Capital Market returns.

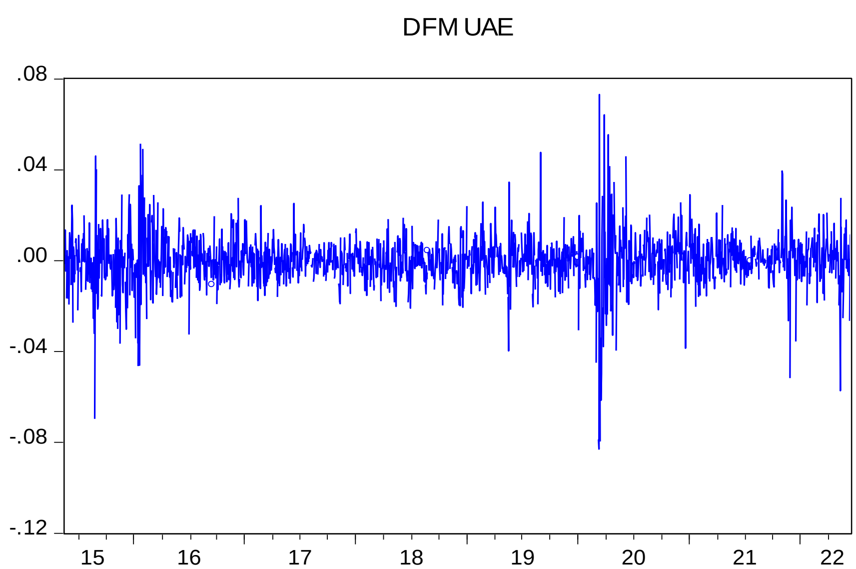

Fig. (5). Volatility Clustering Test for UAE Capital Market returns.

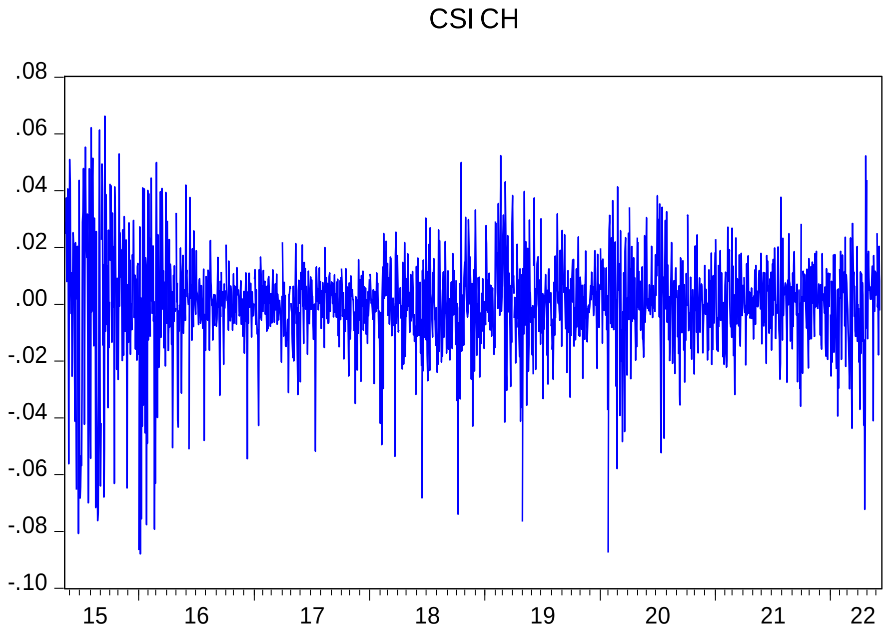

Fig. (6). Volatility Clustering Test for China Capital Market returns.

A cursory look at Figs. (**1-6**) revealed as follows; that Nigeria and South Africa exhibited wide swings for almost all the period under study though at a reduced rate in South Africa, suggesting that in the two African countries, periods of high volatility are followed be the same magnitude of volatility for a prolonged period. For USA market, it exhibited period of relative tranquility from May 2015 to last quarter of 2019, intercepted with high volatility close to the end of 2019 to 2020. It then witnessed another calmness from 2020 to 2022. Germany and UAE appear to be relatively calm in their respective markets, though with seemingly very low volatility in UAE as indicated in the small positive and negative returns. It followed with high volatility occasioned by large positive and negative returns close to end of 2019 (short and long) then return to period of calmness from 2020 to 2022. China showed period of high volatility from 2015 to 2016, then at a reduced rate from 2016 to 2017. Thereafter China market exhibited a prolonged period with high volatility due to large positive and negative from 2017 to 2022.The implication of the above stylized movements is that all the countries under study exhibited property of stock returns distribution called volatility clustering or volatility pooling; a kind of heteroscedasticity. This means that volatility shocks at the current period influence the expectation of volatility in some periods in the future.

Finally, to parameterize the suspected ARCH effects, the researcher employed variants of ARCH (ARCH, GARCH and EGARCH) to capture the effect of serial correlation of volatility in time series data. This expresses conditional variance as distributed lag of past squared as shown below.

Table **8** below, the estimation using ARCH reveals that the results of the estimated parameters and associated probability values for all the countries under study. The lags (α_1 to α_5) are the conditional volatility dynamics, revealing all lags from α_1 to α_5 are significant at 5% level, implying that the ARCH (5) model is properly fitted. In table 9, the model is estimated based on the assumption that errors have a Generalized Error Distribution (GED). The essence of using GED for the asymmetric GARCH model is because of the excess kurtosis discovered in the return series of all countries in the descriptive statistics. It was then found that GED tail parameter, r is less than 2 and significant for all the countries under study, suggesting that the errors have a fat-tailed distribution. Under the theoretical assumption, GED is normally distributed if r = 2, otherwise a fat-tailed distribution if r < 2. The outputs of the GARCH models in Table **9** shows that the coefficients of conditional variance equations parameters (ω, α, β) are found to be significant at 1% significance level as measured by t-statistic, thereby satisfy the non-negativity restrictions of the models. However, the ARCH effect (α_i) for all the select countries are significant at 1% level, suggesting that news about volatility from past has the capacity to predict current volatility. The coefficient of β (lagged conditional variance) are significantly different from zero for all countries under study, suggesting volatility clustering in all the market return series. It is worthy to note that since GARCH output for all returns series coefficients of variance equations are statistically significant, it means weak form inefficiency and presence of volatility clustering. In sum, the variance equation, both ARCH (α) and GARCH (β) terms are positive and highly significant, indicating that conditional variance for all the countries under study are generated by an ARCH/GARCH process. It is also observed that the persistence parameter, which the sum of the ARCH and GARCH parameters (α +β) are very close to unity or 1, indicating shocks to the conditional variance are highly persistent (volatility is highly persistent) and shocks die or fizzle out very slowly in all the markets under study. This therefore confirms the long memory characteristics of the capital markets, though eventually reverts back to its long run average. That means that prolonged changes in returns tend to be followed by prolonged changes and mild changes are also tend to be followed by mild changes, implying that volatility in stock returns occur in clusters and are predictable, hence persistent of volatility clustering. Table **10** shows that the leverage effect or asymmetry parameter γ are negative and significant for USA. South Africa, Germany, UAE and China markets, suggesting presence of leverage effects in the markets, implying that bad or negative news cause more volatility than good or positive news of the same magnitude. For Nigeria, the asymmetric coefficient γ is positive and significant, indicating that good news has more impact on volatility than bad news of equal magnitude. This contradicts or invalidates the leverage effect theory which states that effect of bad news on volatility is higher than the effect of good news of the same magnitude. Furthermore, the persistent parameter β are positive and significant, also are relatively large for all the markets under study, indicating that the various capital market volatility is persistent, confirming that volatility takes a long time to die following the crisis in the respective markets. Magnitude effect ($\propto$) (volatility clustering) coefficient of EGARCH is positive and significant. That means the conditional volatility will rise or fall when the absolute value of the standardized residual is larger (smaller). However, since the lagged values of the return series are positively and significantly different from zero and the error terms (by the rule of thumb, DW<2) are not independently distributed. The researcher affirms that the various capital stock markets are weak form inefficient. Tables 8, 9 and 10 above found that the ARCH- LM tests for the serial correlations were insignificant at 5% critical level for all the countries under study, suggesting that the asymmetry models are sufficient in modeling the serial correlation structure in the conditional mean and variance. This indicates there is no further ARCH effect in the estimated ARCH-GARCH models, as well suggest that the models are correctly specified. The AIC and SIC were found to maintain small criterion value for all the variants of ARCH in the countries under study, affirming the suitability of the models, hence are best fit models.

Table 8. Estimation of Models Using ARCH.

Parameter Estimates	ASI_NG	JSE_SA	DJI_USA	DAX_GER	DFM_UAE	CSI_CH
μ	0.195804	0.042117	-0.022626	-0.021080	0.115433	0.063318
	*0.0000	*0.1134	*0.4165	*0.4180	*0.0000	*0.0292
ω	-0.000216	0.000303	0.000783	0.000616	1.72E-05	8.71E-05
	*0.2439	*0.2254	*0.0000	*0.0091	*0.9334	*0.8220
α_1	9.84E-05	0.000147	0.000135	0.000158	0.000119	0.000259
	*0.0000	*0.0000	*0.0028	*0.0000	*0.0000	*0.0000
α_2	0.959170	0.976374	0.986523	0.993259	0.971357	0.990688
	*0.0000	*0.0000	*0.0000	*0.0000	*0.0000	*0.0000
α_3	0.092847	0.048906	0.088749	0.033636	0.086856	0.031950
	*0.0000	*0.2788	*0.0101	*0.0012	*0.0000	*0.0000
α_4	0.192122	0.059707	0.142776	0.109422	0.088691	0.103477
	*0.0000	*0.1538	*0.0000	*0.0000	*0.0000	*0.0000
α_5	0.377435	0.851491	0.766790	0.787184	0.499691	0.659318
	*0.0000	*0.0000	*0.0000	*0.0000	*0.0026	*0.0000
$\sum_{i=1}^{5} \alpha_i$	1.6216724	1.936625	1.984973	1.923659	1.646714	1.785692
Log likelihood	5887.949	5659.102	5993.015	5545.780	5699.390	4715.248
Dw Stat	1.856918	2.053812	2.281545	1.976133	2.001835	1.940846
AIC	-6.705757	-6.133589	-6.707020	-6.164474	-6.432079	-5.458838
SIC	-6.683928	-6.112626	-6.685501	-6.143073	-6.410411	-5.436710
ARCH-LM Test	0.6936	0.2390	0.6489	0.3767	0.4996	0.6379

*Probability values.

Table 9. Estimation of Models Using GARCH.

Parameter Estimates	ASI_NG	JSE_SA	DJI_USA	DAX_GER	DFM_UAE	CSI_CH
Mean Eqn						
ω	-0.000224 *0.2368	0.000306 *0.2210	0.000782 *0.0000	0.000597 *0.0109	6.70E-05 *0.7486	-0.000123 *0.7532
Variance Eqn						
ω	9.70E-06 *0.0000	6.25E-06 *0.0000	4.27E-06 *0.0000	5.02E-06 *0.0000	5.43E-06 *0.0000	5.98E-06 *0.0000
α	0.210046 *0.0000	0.103485 *0.0000	0.220380 *0.0000	0.125493 *0.0000	0.129695 *0.0000	0.069066 *0.0000
β	0.689903 *0.0000	0.854064 *0.0000	0.749774 *0.0000	0.845758 *0.0000	0.825359 *0.0000	0.909665 *0.0000
α + β	0.899949	0.957549	0.970154	0.971251	0.955054	0.978731
GED r	0.948095 *0.0000	1.363753 *0.0000	1.264118 *0.0000	1.180170 *0.0000	1.274960 *0.0000	1.171746 *0.0000
Log likelihood	5880.044	5658.327	5989.692	5537.324	5696.154	4704.295
Dw Stat	1.880344	2.054063	2.282321	1.981417	2.001464	1.940878
AIC	-6.699024	-6.134918	-6.690167	-6.157289	-6.430683	-5.448458
SIC	-6.683432	-6.119945	-6.699861	-6.142002	-6.415206	-5.432652
ARCHLM Test	0.6936	0.2390	0.6489	0.3767	0.4996	0.6379

*Probability values.

Table 10. Estimation of Models Using EGARCH.

Parameter Estimates	ASI_NG	JSE_SA	DJI_USA	DAX_GER	DFM_UAE	CSI_CH
Mean Eqn						
ω	-3.38E-05 *0.8581	-0.000159 *0.5014	0.000456 *0.0082	8.27E-05 *0.7191	-0.000245 *0.2556	-0.000232 *0.5339
Variance Eqn						
ω	-1.414485 *0.0000	-0.470631 *0.0000	-0.665371 *0.0000	-0.321961 *0.0000	-0.581535 *0.0000	-0.332935 *0.0000
α	0.347470 *0.0000	0.140742 *0.0000	0.266303 *0.0000	0.110266 *0.0000	0.229345 *0.0000	0.156009 *0.0000
γ	0.064907 *0.0000	-0.127483 *0.0000	-0.156859 *0.0000	-0.140435 *0.0000	-0.076695 *0.0000	-0.048037 *0.0000
β	0.877592 *0.0000	0.959430 *0.0000	0.951391 *0.0000	0.973487 *0.0000	0.955486 *0.0000	0.973788 *0.0000
Log likelihood	5896.634	5685.763	6017.993	5588.811	5698.353	4709.026
Dw Stat	1.879809	2.079733	2.301931	2.001128	2.011089	1.933793
AIC	-6.716801	-6.163606	-6.736127	-6.213480	-6.432037	-5.452784

SIC	-6.698091	-6.145638	-6.717682	-6.195136	-6.413465	-5.433817
ARCH LM Test	0.6936	0.2390	0.6489	0.3767	0.4996	0.6379

*Probability values.

Where, ω, β, α, γ are constant parameters, Log (σ_t^2) = the one period ahead volatility forecast,

5. CONCLUSION AND RECOMMENDATIONS

There is plethora of studies on random walk theory or efficient market hypothesis and the modeling of volatility on the capital market returns, yet no consensus has been reached on the behaviour of a typical capital market around the world rather diverse opinions abound. Greater emphasis is always made on the random walk theory that opines that no investor usurps the information available to make abnormal profit, since the market is efficient; all information both from previous and current as well information available and knowable in the future have already reflected in the market price of the security. For that, this study tried to streamline the diverse investors' perceptions and behaviour of the global capital markets by employing various tools that are suitable for financial time series. From the results of these tools employed, none of the market under study follows the random walk theory within the scope of the study, hence rational investors cannot use the past data or information about the market to predict the outcome of the market. This makes the global market to be dynamic and unpredictable. This deviation from the random walk theory of all the markets under study signposts that investors are rational and unpredictable; they are the same all over the world. Investors are always expected to do good analysis and keep abreast of the factors responsible for stock market behaviour which is a sine qua non for maximizing the reward of investing in the stock market (Ibenta, 2005). These results demystify the overemphasis placed on the efficient market hypothesis, paving way for behavioural finance theory reviewed under theoretical literature. That means the behaviours of investors heavily influenced share prices to deviate from the economic fundamentals or assumptions, suggesting that psychology or mind sets or emotions of investors influence investment decision-making process and financial markets. Again, the essence of employing ARCH and GARCH family models in this study is to guide volatility measurement for financial decisions that bothers about risk analysis, derivative price and portfolio selection (Engle, 1982; Bollerslev, 1986). Therefore, results of ARCH and GARCH family models revealed as follows; the test for volatility clustering unveiled that all the countries under study exhibited property of stock returns distribution called volatility clustering or volatility pooling; a kind of heteroscedasticity. This means that volatility shocks at the current period influences the expectation of volatility in some period in the future. The persistence parameter shows that shocks to the conditional variance are highly persistent, confirming long memory characteristics of the capital markets under study. This suggests that prolonged changes in returns tend to be followed by prolonged changes and mild changes are also tend to be followed by mild changes. Magnitude effect parameter (volatility clustering) on its own discloses that conditional volatility will rise or fall when the absolute value of the standardized residual is larger (smaller). The results of the asymmetric parameter for the countries under study except Nigeria confirm that bad news create more volatility than good news of the same magnitude, this corroborates features of market volatility known as leverage effect (Black, 1976; Christie, 1982; Engle & Ng, 1993). In the light of the above findings, the researcher makes the following recommendations;

I. Since the various capital market do not follow random work or are inefficient at weak form, investors and other economic agents are advised to be proactive when evaluating the values of securities.

II. Having found that all the markets under study do not follow random walk, demystifying the efficient market hypothesis, a suggestion that the behaviours of investors heavily influence share prices to deviate from the economic fundamentals or assumptions. This means that emotions of investors influence investment decision-making process and financial markets, hence there is need to place more emphasis on the theory of behavioural finance as a guide for decision on stock market investments.

III. The nature of the capital markets around the globe are volatile, with volatility clustering and persistence. These rightly inform the regulatory authorities to offer timely interventions whenever any economic mayhem is perceived in order to avert loss in investments.

IV. The presence of asymmetry effect as reported in all the markets under study informs need for timely disclosure and appropriate dissemination of related information by the stock market operators to the public or investors in order to avert escalation of bad news which increases volatility.

V. Results will go a long way in closing the gap between theory and practice as well guide future policy direction.

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