Monthly Stock Returns and Volatility: The Nigerian Capital Market

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Abstract
The fundamental role of stock market is to provide adequate guarantee to share holders for the existence of market for their second hand securities. Adequate knowledge about the volatility, performance and efficiency of stock returns remains vital and essential information to investors. These will guide not only investment decisions but also planning for economic growth and development. Given that the Nigerian Stock Exchange has existed, its ability to generate confidence is still in doubt given the recent crash witnessed in the market. It means the confidence the exchange is expected to in still in investors is still not commensurable. It was against the forgoing that this study examined the impact on stock market returns of liquidity and volatility in the Nigerian Stock market. The study adopted the ex-post facto research design and data were obtained from monthly reports of the Nigerian Stock Exchange from January, 2009 to December, 2015. The study used the Ordinary least square and ARCH/GARCH to test the hypotheses stated. The result from the hypotheses tested revealed that stock market returns measured by all shares index was positively and significantly impacted by liquidity measured by market capitalization value ratio and turnover ratio of the Nigerian Stock Exchange but was negatively and significantly impacted by volume of transaction ratio. The results also revealed that, there is a significant ARCH/GARCH (volatility) effect on stock market returns of the Nigerian Stock market. The study thus concludes that the Nigerian Stock Exchange should act to in still more confidence on investors. Thus, the study recommends amongst others that strategies need to be designed toward reaping abnormal returns by exploiting information and actions that enhance inefficiency in stock markets thus, firms and individuals should be encouraged to buy or sell securities outside their face values, as a means of encouraging business or economic activities in the economy.

1.0 INTRODUCTION

Recently, the volatility of stock market return on the Nigerian stock market has been of concern to investors, analysts, brokers, dealers and regulators. Stock return volatility which represents the variability of stock price changes could be perceived as a measure of risk. The understanding of the volatility in a stock market will be useful in the determination of the cost of capital and in the evaluation of asset allocation decisions. Policy makers therefore rely on market estimates of volatility as a barometer of the vulnerability of financial markets. However, the existence of excessive volatility, or “noise,” in the stock market undermines the usefulness of stock prices as a “signal” about the true intrinsic value of a firm, a concept that is core to the paradigm of the informational efficiency of markets (Karolyi, 2001).

Financial markets are well known for their uncertainty, especially the irregularity in the behaviour of certain financial indices, such as stock prices, exchange or interest rates, government bonds, treasury bills and so on, that are prone to constant variability. Such variability, otherwise known as volatility can generate very high frequency series of random variables which are stochastic in nature, the dynamics of which can best be described by means of models.

Numerous studies have documented evidence showing that stock returns exhibit phenomenon of volatility clustering, leptokurtosis and Asymmetry. Volatility clustering occurs when large stock price changes are followed by large price changes, of both signs, and small price changes are followed by periods of small price changes. Leptokurtosis means that the distribution of stock returns is not normal but exhibits fat-tails. In other words, Leptokurtosis signifies high probability for extreme values than the normal law predict in a series, also known as leverage effects, means that a fall in return is followed by an increase in volatility, greater than the volatility induced by an increase in returns. This implies that more prices wander far from the average trend in a crash than in a bubble because of higher perceived uncertainty (Mandelbrot, 1963; Fama, 1965; Black, 1976). These characteristics are perceived as indicating a rise in financial risk, which can adversely affect investors’ assets and wealth. For instance, volatility clustering makes investors more averse to holding stocks due to uncertainty. Investors in turn demand a higher risk premium in order to insure against the increased uncertainty. A greater risk premium results in a higher cost of capital, which then leads to less private physical investment.

1.1 STATEMENT OF THE PROBLEM

Stock market volatility also has a number of negative implications. One of the ways in which it affects the economy is through its effect on consumer spending (Campbell, 1996; Starr-McCluer, 1998; Ludvigson and Steindel 1999 and Poterba 2000). The impact of stock market volatility on consumer spending is related via the wealth effect. Increased wealth will drive up consumer spending. However, a fall in stock market will weaken consumer confidence and thus drive down consumer spending. Stock market volatility may also affect business investment (Zuliu, 1995) and economic growth directly (Levine and Zervos, 1996 and Arestis et al 2001). A rise in stock market volatility can be interpreted as a rise in risk of equity investment and thus a shift of funds to less risky assets. This move could lead to a rise in cost of funds to firms and thus new firms might bear this effect as investors will turn to purchase of stock in larger, well known firms.

While there is a general consensus on what constitutes stock market volatility and, to a lesser extent, on how to measure it, there is far less agreement on the causes of changes in stock market volatility. Some economists see the causes of volatility in the arrival of new, unanticipated information that alters expected returns on a stock (Engle and Ng, 1993). Thus, changes in market volatility would merely reflect changes in the local or global economic environment. Volatility is caused mainly by changes in trading volume, practices or patterns, which in turn are driven by factors such as modifications in macroeconomic policies, shifts in investor tolerance of risk and increased uncertainty. Against this background, this study seeks to answer some questions.

1.2 RESEARCH QUESTIONS

- What is the effect of stock return volatility on the performance of the Nigerian capital market?
- Is there stock return volatility persistence in Nigeria?

1.3 OBJECTIVES OF RESEARCH

The main objective of this paper is to investigate the behaviour of stock return volatility in Nigeria. This will involve examining NSE return series for evidence of volatility clustering. The specific objectives are as follows;

- To investigate the effect of stock return volatility on the performance of the Nigerian capital market.
- To ascertain stock return volatility persistence in Nigeria.

1.4 HYPOTHESES OF THE STUDY

- **HO_1:** Stock return volatility does not affect the performance of the Nigerian capital market.
- **HO_2** Stock return volatility is not persistence in Nigeria capital market.

2.0 LITERATURE REVIEW

The literature review is categorized into two main parts; the theoretical aspect and the empirical aspect of previous studies carried out by other scholars.

2.1 THEORETICAL LITERATURE REVIEW

The studies of Mandelbrot (1963), Fama (1965) and Black (1976) highlight volatility clustering, leptokurtosis, and leverage effects characteristics of stock returns. Engle (1982) introduced the Autoregressive Conditional Heteroscedasticity (ARCH) to model volatility by relating the conditional variance of the disturbance term to the linear combination of the squared disturbances in the recent past. Bollerslev (1986) generalized the ARCH model by modeling the conditional variance to depend on its lagged values as well as squared lagged values of disturbance. Since the works of Engle (1982) and Bollerslev (1986), various variants of GARCH model have been developed to model volatility. Some of the models include EGARCH originally proposed by Nelson (1991), GJR-GARCH model introduced by Glosten, Jagannathan and Runkle (1993), Threshold GARCH (TGARCH) model due to Zakoian (1994). Following the success of the ARCH family models in capturing behaviour of volatility, Stock returns volatility has received a great attention from both academies and practitioners as a measure and control of risk both in emerging and developed financial Markets.

Concerning the effectiveness of the ARCH family models in capturing volatility of financial time series, Hsieh (1989) found that GARCH (1,1) model worked well to capture most of the stochastic dependencies in the time series. Based on tests of the standardized squared residuals, he found that the simple GARCH (1,1) model did better at describing data than a previous ARCH(1,2) model also estimated by Hsieh (1988). Similar conclusions were reached by Taylor (1994), Brook and Burke (2003), Frimpong and Oteng-Abayie (2006) and Olowe (2009). In a like manner, Bekaert and Harvey (1997) and Aggarwal et al.(1999) in their study of emerging markets volatility, confirm the ability of asymmetric GARCH models in capturing asymmetry in stock return volatility. Thus, ARCH family models are good candidates for modelling and estimating volatility in emerging stock markets. In literature, also, studies like Campbell and Hentschel (1992), Braun *et al* (1995) and LeBaron (2006) provide evidence that stock returns has time-varying volatility.

Although the GARCH model has been very successful in capturing important aspect of financial data, particularly the symmetric effects of volatility, it has had far less success in capturing extreme observations and skewness in stock return series. The Traditional Portfolio Theory assumes that the logarithmic stock returns are independent and identically distributed (IID) normal variables which do not exhibit moment dependencies, but a vast amount of empirical evidence suggest that the frequency of large magnitude events seems much greater than is predicted by the normal distribution (Harvey and Siddique, 1999; Verhoeven and McAleer, 2003; diBartolomeo, 2007). According to Mandelbrot (1963), extreme events are far too frequent in financial data series for the normal distribution to hold. He argues for a stable Paretian model, which has the uncomfortable property of infinite variance. Fama (1965) provides empirical tests of Mandelbrot's idea on daily US stock returns and finds fat- tails. Moreover, investors view upside and downside risks differently, with a preference for positively skewed returns, implying that more than the first two moments of returns may be priced in equilibrium (see Lai, 1991; Satchell, 2004). This has lead to the use of non-normal distributions such as: Student-*t*, GED, asymmetric Student-*t* and asymmetric GED to model the empirical distribution of conditional returns (Theodossiou, 1998, 2001; Olowe, 2009).

The pervasive daily return volatility in equity stock markets has attracted considerable attention in the literature in recent times (Galeotti and Schiantarelli, 1994; Mankiw et al 1991; Kumar and Makhija, 1986, Schwert, 1989; Eraker, 2004).

2.2 EMPIRICAL LITERATURE REVIEW

Mathematical models are usually employed to predict the future behavior of stock prices because most transactions in stocks, whether to buy or sell, are activities that take place in the future (Chauvin, 2006). In the past, much modelling attention had been focused on the predictable component of the stock return series. Later attention shifted to the error term whereby it is assumed that the latter is normally distributed. Schwart (1989) found that the amplitude of the fluctuations in aggregate stock volatility is difficult to explain using simple models of stock valuation and that there is a strong residual autocorrelation using least squares hence he applied ARMA (1, 3) model for the errors. Eraker (2004) developed an approach based on Markov Chain Monte Carlo (MCMC) simulation, which allows the investigation to estimate the posterior distributions of the parameters as well as the unobserved volatility and jump processes. Rydberg (2000) reviewed some models that have been used to describe the most important or stylized features of financial data. These include fact tools, asymmetry-symmetry, volatility clustering, aggregation Gaussianicity, quasi-long-range dependence and seasonality. Rydberg (2000) classified the models into two broad categories: mathematical finance models and econometric models. Since the goal of the latter is usually forecasting it requires less rigorous probability theory than the previous and tends to focus more on the correlation structure of the data.

Models that assume normally distributed log returns like the Black & Scholes model had been extensively used in the mathematical finance literature but this assumption has been disputed (Rydberg, 2000). More recently, attention has shifted towards modelling financial-market asset returns by processes other than normal error distribution. It has been established that the variances of the error terms in ordinary least square (OLS) estimates are not equal, and are indeed larger for some points or ranges of data than for others (Engle, 2001). This incidence of heteroskedasticity in which the usual procedures for estimating standard errors and confidence intervals fall short are best addressed by ARCH/GARCH models (Engle, 2001).

The ground breaking work of Engle (1982) introduced a means of capturing the property of time-varying volatility. Further research, however, has shown that in practical applications of the ARCH (q) model, large q's are usually required thereby necessitating the need for many parameters (Rydberg, 2000). To overcome this difficulty, Bollerslev (1986) and Taylor (1986) modified the basic ARCH model as Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. GARCH has since gained widespread acceptance in the literature and is often used for modelling stochastic risk volatility in financial time series. Floros (2007) used various GARCH models with bootstrapped out-of-sample period data to evaluate the performance of minimum capital risk requirement (MCRR) estimates. The models show that higher capital requirements are necessary for a short position, since a loss is then more likely.

David (1997) classified the models for describing the properties of stock market returns into two – the fast learning model and the slow learning model. Exploring the properties of exponential GARCH model for measuring the asymmetry between returns and volatility, David (1997) found that the fast learning model generates a negative relationship while the slow model generate returns that exhibit greater excess kurtosis. Other ARCH/GARCH based studies include Amin and Ng (1997); Baillie and DeGennaro (1990); Chahal and Wang (1998) and Chan et al (1991). Amin and Ng (1997) argue that implied volatility dominates the GARCH terms and therefore include an entire lag structure through GARCH persistence terms in their study. However, as Rydberg (2000) had observed, neither the ARCH nor the GARCH models consider both asymmetry and leverage (the fact that volatility negatively correlated with changes in stock returns). Although GARCH (p, q) models give adequate fits for most equity-return dynamics, these models often fail to perform well in modeling the volatility of stock returns because GARCH models assume that there is a symmetric response between volatility and returns. GARCH models are thus unable to capture the "leverage effect" of stock returns. For equities, it is often observed that downward movements in the market are followed by higher volatilities than upward movements of the same magnitude.

To account for this, Zakoian (1990) and Glostan, Jagannathan, and Runkle (1993) introduced the threshold GARCH (TGARCH) to take care of existing leverage effect. During the same period Nelson (1991) proposed the Exponential GARCH (EGARCH) models in order to model asymmetric variance effects. In Nigeria, the few published studies on modelling volatility of stock returns, include:Ogum, Beer and Nouyrigat (2005), Jayasuriya (2002), Okpara and Nwezeaku (2009). Jayasuriya (2002) use asymmetric GARCH methodology to examine the effect of stock market liberalization on stock returns volatility of fifteen emerging markets, including Nigeria, for the period December 1984 to March 2000. The study reports, among others, that positive (negative) change in prices have been followed by negative (positive) changes indicating a cyclical type behavior in stock price changes rather than volatility clustering in Nigeria. In contrast to Jayasuriya (2002), Ogum, Beer and Nouyrigat (2005) investigate the emerging market volatility using Nigeria and Kenya stock return series. Results of the exponential GARCH model indicate that asymmetric volatility found in the U.S. and other developed markets is also present in Nigerian, but Kenya shows evidence of significant and positive asymmetric volatility, suggesting that positive shocks increase volatility more than negative shocks of an equal magnitude. Also, they show that while the Nairobi Stock Exchange return series indicate negative and insignificant risk-premium parameters, the NSE return series exhibit a significant and positive time-varying risk premium.

Finally, they report that the GARCH parameter (β) is statistically significant indicating volatility persistence in the two markets. Okpara and Nwezeaku (2009) examine the effect of the idiosyncratic risk and beta risk on the returns of 41 randomly selected companies listed on the NSE from 1996 to 2005. They employed a two-step estimation procedures, firstly, the time series procedure is used on the sample data to determine the beta and idiosyncratic risk for each of the companies; secondly, a cross–sectional estimation procedure is used employing EGARCH (1,3) model to determine the impact of these risks on the stock market returns. Their results reveal, among others, that volatility clustering is not quite persistent but there exists asymmetric effect in the Nigerian stock market. They concluded that unexpected drop in price (bad news) increases predictable volatility more than unexpected increase in price (good news) of similar magnitude in Nigeria.

3.0 METHODOLOGY OF RESEARCH

In financial and economic models, the future is always uncertain but over time we learn new information that helps us forecast this future. As asset prices reflect our best forecasts of the future profitability of companies and countries, these change whenever there is news. ARCH/GARCH models can be interpreted as measuring the intensity of the news process. Volatility clustering is most easily understood as news clustering. Of course, many things influence the arrival process of news and its impact on prices. Trades convey news to the market and the macroeconomy can moderate the importance of the news. These can all be thought of as important determinants of the volatility that is picked up by ARCH/GARCH; both of which also describe the time evolution of uncertainty in a complex system.

This study is both descriptive and historical in nature as it seeks to describe the pattern of returns of the Nigerian Stock Exchange (NSE) in the past. Data collected was the monthly market share index of the NSE for the period of trading January 1998 to December 2009 (144 months). The period was chosen base on the data available in the Cowry Asset Managers website and comprises of 757 observations. To improve interpretability the data was transformed by means of natural logarithm. The autoregressive conditional heteroskedasticity (ARCH) model introduced by Engle (1982) and its extension, the generalised autoregressive conditional heteroskedasticity (GARCH) model (Bollerslev, 1986), was used to estimate the conditional variance of Nigeria's daily stock return. This method allows for an objective determination of the presence of volatility. ARCH models and its extension, the GARCH models have been the most commonly employed class of time series models in the recent finance literature for studying volatility.

3.1 MODEL SPECIFICATION

The appeal of the models is that it captures both volatility clustering and unconditional return distributions with heavy tails. The estimation of GARCH model involves the joint estimation of a mean and a conditional variance equation. According to the GARCH (p, q) model, the conditional variance of a time series depends on the squared residuals of the process. In this study the model were based on autoregressive AR(1) estimation of the residuals.

The autoregressive model is thus

$$STR_t = \beta_0 + \beta_1 STR_{t-1} + \mu_t$$

Where; STR_t = Stock Market Return at time t

STR_{t-1} = Stock Market Return at time t – 1

β_0 = intercept

β_1 = coefficient of the Stock Market Return at time t - 1

μ_t = stochastic error term

In the model the value of STR at time t depends on its value in the previous time period and a stochastic error term. Both ARCH and GARCH models were based on the regression of squared error term. Under the ARCH model, the 'autocorrelation in volatility' is modeled by allowing the conditional variance of the error term, σ^2_t, to depend on the immediately previous value of the squared error.

$$\sigma^2_t = \omega + \beta_1\mu^2_{t-1}$$

The GARCH model allows the conditional variance to be dependent upon conditional variance lags, so that the conditional variance equation is now

$$\sigma^2_t = \omega + \beta\mu^2_{t-1} + \psi\sigma^2_{t-1}$$

where; ω = constant term,

$\beta\mu^2_{t-1}$ = ARCH term

$\psi\sigma^2_{t-1}$ = GARCH term

3.2 ESTIMATION PROCEDURE

ARCH and GARCH models have been applied to a wide range of time series analysis, but applications in finance have been particularly successful (Engle, 2001). This study employs GARCH (1,1), type model. The model will be computed with the aid of E-views software. The study hold the views of Engle and Bollerslev (1986), Chou (1988), and Bollerslev et al. (1992) where they show that the persistence of shocks to volatility depends on $\alpha + \beta$ parameters. Where $\alpha + \beta < 1$ imply a tendency for the volatility response to decay over time, $\alpha + \beta = 1$ imply indefinite volatility persistence to shocks over time, and $\alpha + \beta > 1$ imply increasing volatility persistence over time and covariance stationarity is violated. In addition, Hasan et. al (2000) indicate that significance of [alpha] parameter signals the tendency of shock to persist.

3.3 EXPLANATORY VARIABLE

Stock Returns

The ratio of money gained or lost (whether realized or unrealized) on an investment relative to the amount of money invested. The amount of money gained or lost may be referred to as interest, profit/loss, or net income/loss. The money invested may be referred to as the asset, capital, principal, or the cost basis of the investment. In this study, stock returns are measured as:

ST = P1-P0/P0

where:

ST	=	stock returns
P1	=	price of stock at time today
P0	=	price of stock yesterday

3.4 SOURCE OF DATA

The data for this study are from monthly indices of stocks traded on the floor of the Nigerian Stock Exchange (NSE). The time series data cover twelve years starting from January, 1998 to December, 2009 and coincidentally the period corresponds to Nigeria's recent stable market economy and civil democratic governance. The data are sourced from Central Bank of Nigeria (CBN) statistical bulletin (special edition) 2009.

4.0 DATA ANALYSIS

DESCRIPTIVE STATISTICS RESULT

	STR
MEAN	22551.57
MEDIAN	19990.38
MAXIMUM	230783.3
MINIMUM	4890.800
STD.DEV.	23273.40
SKEWNESS	5.259328
KURTOSIS	45.70587
JARQUE-BERA	11606.60
PROBABILITY	0.000000
OBSERVATION	84

Source: E-view results

The mean of the data – Stock Market Return (STR) using descriptive statistics in the Nigerian Stock Exchange (NSE) during the period of the study [appendix] is 22551.57 while the standard deviation of the series is 23273.40. However, the Skewness of this study is 5.259328 and the Kurtosis is 45.70587, suggest non-normality of the market. Jarque-Bera test also reject the normality of the data at 5% level (11606.60) being higher than the χ^2-value of 5.99. Overall, the non-normality of the stock return series revealed in this study suggests using non-linear model.

TABLE 2: UNIT ROOT RESULT

VAR	ADF	1%	5%	10%	TREND	CONSTANT	LAG
STR	-6.396476	-4.0250	-3.4419	-3.1453	YES	YES	1

Source: E – view results

The stationarity test of the data (STR) indicate the absence of unit root in the level form as shown by the Augmented Dickey Fuller ADF -6.396476 showing stationarity at both 1% and 5% [appendix] The unit root test was conducted using trend and constant at lag 1. Equally, correlograms and Q-statistics first difference tests further shows stationarity in the residuals and are serially correlated (appendix). The correlogram test the presence of ARCH effect in the data.

Autocorrelation is the measure of persistence and/or predictability of the market returns based on past market returns. The coefficient of the first order auto-correlation AR(1) is 0.578431 (appendix) indicating that market returns in the NSE are predictable on the basis of past returns. Accordingly, this rejects the Efficient Market Hypothesis. The departure from the efficient market hypothesis of the NSE suggests that relevant market information is only gradually reflected in stock price changes. This arises from frictions in the trading process, limited provision of information of firm's performance to market participants.

MODEL RESULT

TABLE 3: Dependent Variable: STR

Variable	Coefficient	Std. error	z-statistics	Prob. Value
CONSTANT	6.80E+08	2.27E+08	2.991695	0.0028
ARCH(1)	0.903147	0.395068	2.286054	0.0223
GARCH(1)	-0.015991	0.048839	-0.327420	0.7434

R – Squared = -0.945498
Adjusted R – Squared = -0.973094
Durbin-Watson stat = 0.578431
Result is shown in Appendix
The result above shows that GARCH (1,1) model is thus,

$$\sigma^2_t = 6.80E{+}08 + 0.903147u^2_{t-1} - 0.015991\sigma^2_{t-1}$$

The ARCH coefficient is 0.903147 and significant at 1% level implies the tendency of the shock to persist. The ARCH coefficient is significantly positive and close to one and indicates an integrated ARCH process in which shocks have a persistent effect on volatility. The ARCH term shows that the current period volatility is dependent on the lagged error terms. The GARCH coefficient for the model -0.015991 is highly insignificant in the Nigeria stock market and implies non-persistent shocks in the NSE. This shows that the past variance terms have a weak impact on the current conditional variance and exhibit that the last period's volatility has an insignificant impact on the current period conditional volatility. The residual graph (appendix IV) depicted volatility in the residuals, showing clustering in the monthly percentage change of NSE stock return. The results support the evidence of volatility clustering in Nigeria similar to findings by Ogum, et al., (2005) and Emenike (2010).French et al. (1987), Harvey (1995), Li (2002) and Batra (2004)

Despite the significance of β and insignificance of ψ coefficients and volatility persistence parameter β + ψ is close to 1 (0.887156). In GARCH-type model that indicates the tendency for volatility response to shocks to display a long memory in the NSE.The high persistence (0.887156) shows that the volatility of the stock returns dies down slowly.

5.0 SUMMARY OF FINDINGS

This study investigates the time-varying risk return relationship within GARCH framework and the persistence of shocks to volatility in the stock market of Nigeria. Using GARCH type models, it reveals that NSE is volatile and there is a persistence shocks in the market like in other emerging markets. The study employed monthly data of large sample size and reveals the risk return characteristics and volatility persistence shocks in the emerging stock market of Nigeria indicating inefficient market.

Overall results from this study provide evidence to show volatility clustering, leptokurtic distribution and leverage effects for the Nigeria stock returns data. These results are in tune with international evidence of financial data exhibiting the phenomenon of volatility clustering, fat-tailed distribution and leverage effects. The results also support the evidence of volatility clustering in Nigeria provided by Ogum, et al. (2005); existence of leverage effects in Nigeria stock returns provided by Okpara and Nwezeaku (2009), but disagree with their conclusion that stock returns volatility is not quite persistent in Nigeria.

5.1 CONCLUSIONS

The results as discussed in chapter four indicate high volatility presence in the conditional variance therefore market returns depend on their own shocks and confirm the volatility clustering phenomenon for the inefficient market as also found by Rizwan and Khan (2007) that the volatility clustering exists for Pakistani stock market, which signifies inefficiency in the stock market. These results clearly explain the volatile nature of emerging markets and provide clear evidence of time varying risk in the emerging stock market of the NSE.

The significance of the conditional variance coefficient revealed by GARCH (1, 1) model implies long-term volatility persistent in the stock market of Nigeria. This may be the cause of frictions in the securities market trading. This result also indicate that the participants may have limited access to the market information regarding the firms performance either because the firms do not make available their financial statements timely or investors do not seek financial advice in stock dealings due to lack of professional financial community who can analyze stock market data for the investors. Persistency in volatility is normally due to the inefficiency in the market.

In addition, market inefficiency may be the result of non-synchronous effects, which implies that information in the stock market is processed with a lag. The study presented a positive autocorrelation which may implies non-enforcement of regulations and/or weak supervision by the Securities and Exchange Commission (SEC), however, Cambell et al. (1997) noted that non-synchronous trading is caused by negative autocorrelation in portfolio returns. Further, the findings might has implications on investors in Nigeria as volatility in the stock return of a firm stems from the fact that stock returns may no longer be seen as the true intrinsic value of a firm and thus the investors might start losing confidence in the stock market.

Sequel to the above findings the study have shown strong evidence to reject the null hypothesis stated below;

HO_1: Stock return volatility does not affect the performance of the Nigerian capital market.

HO_2 Stock return volatility is not persistence in Nigeria capital market.

5.2 RECOMMENDATIONS

There is need for the modernization of the Nigerian Stock Exchange to improve the trading system to permit immediate information dissemination to investors and there is need for the development of specialized financial institutions (portfolio managers) who can analyze stock market data for the investors so as to speed off adjustment to new information arrival. Finally, timely disclosure and appropriate dissemination of company specific information to the investors will also improve the efficiency of the stock market in Nigeria.

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APPENDIX
DESCRIPTIVE STATISTICS RESULT

Dependent Variable: STR
Method: ML – ARCH
Date: 08/17/16 Time: 14:14
Sample: 2009:01 2015:12
Included observations: 84
Convergence not achieved after 100 iterations

	Coefficient	Std. Error	z-Statistic	Prob.
		Variance Equation		
C	6.80E+08	2.27E+08	2.991695	0.0028
ARCH(1)	0.903147	0.395068	2.286054	0.0223
GARCH(1)	-0.015991	0.048839	-0.327420	0.7434
R-squared	-0.945498	Mean dependent var		22551.57
Adjusted R-squared	-0.973094	S.D. dependent var		23273.40
S.E. of regression	32691.41	Akaike info criterion		23.40167
Sum squared resid	1.51E+11	Schwarz criterion		23.46354
Log likelihood	-1681.920	Durbin-Watson stat		0.578431

	STR
Mean	22551.57
Median	19990.38
Maximum	230783.3
Minimum	4890.800
Std. Dev.	23273.40
Skewness	5.259328
Kurtosis	45.70587
Jarque-Bera	11606.60
Probability	0.000000
Observations	84

UNIT ROOT TEST FOR STR

ADF Test Statistic	-6.396476	1%	Critical Value*	-4.0250
		5%	Critical Value	-3.4419
		10%	Critical Value	-3.1453

*MacKinnon critical values for rejection of hypothesis of a unit root.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(STR)
Method: Least Squares
Date: 08/17/16 Time: 15:47
Sample(adjusted): 2009:03 2015:12
Included observations: 84 after adjusting endpoints

Variable	Coefficient	Std. Error	t-Statistic	Prob.
STR(-1)	-0.694396	0.108559	-6.396476	0.0000
D(STR(-1))	-0.141074	0.085018	-1.659343	0.0993
C	430.7602	3280.072	0.131326	0.8957
@TREND(1998:01)	212.8566	52.37406	4.064161	0.0001

R-squared	0.414258	Mean dependent var	101.4155
Adjusted R-squared	0.401525	S.D. dependent var	24863.14
S.E. of regression	19234.41	Akaike info criterion	22.59455
Sum squared resid	5.11E+10	Schwarz criterion	22.67782
Log likelihood	-1600.213	F-statistic	32.53292
Durbin-Watson stat	2.026754	Prob(F-statistic)	0.000000

Date: 08/17/16 Time: 16:04
Sample: 2009:01 2015:12
Included observations: 84

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	-0.008	-0.008	0.0100	0.920
.|. |	.|. |	2	-0.008	-0.009	0.0205	0.990
.|. |	.|. |	3	-0.008	-0.008	0.0308	0.999
.|. |	.|. |	4	-0.008	-0.009	0.0415	1.000
.|. |	.|. |	5	-0.008	-0.008	0.0517	1.000
.|. |	.|. |	6	-0.008	-0.008	0.0603	1.000

.|. |	.|. |	7	-0.007	-0.007	0.0680	1.000
.|. |	.|. |	8	-0.007	-0.008	0.0763	1.000
.|. |	.|. |	9	-0.008	-0.008	0.0858	1.000
.|. |	.|. |	10	-0.008	-0.009	0.0971	1.000
.|. |	.|. |	11	-0.008	-0.009	0.1078	1.000
.|. |	.|. |	12	-0.009	-0.009	0.1197	1.000
.|. |	.|. |	13	-0.009	-0.010	0.1328	1.000
.|. |	.|. |	14	-0.009	-0.010	0.1463	1.000
.|. |	.|. |	15	-0.009	-0.010	0.1602	1.000
.|. |	.|. |	16	-0.009	-0.011	0.1748	1.000
.|. |	.|. |	17	-0.009	-0.011	0.1895	1.000
.|. |	.|. |	18	-0.009	-0.011	0.2041	1.000
.|. |	.|. |	19	-0.009	-0.010	0.2176	1.000
.|. |	.|. |	20	-0.009	-0.011	0.2318	1.000
.|. |	.|. |	21	-0.009	-0.011	0.2461	1.000
.|. |	.|. |	22	-0.009	-0.011	0.2604	1.000
.|. |	.|. |	23	-0.009	-0.011	0.2755	1.000
.|. |	.|. |	24	-0.009	-0.011	0.2906	1.000
.|. |	.|. |	25	-0.009	-0.011	0.3047	1.000
.|. |	.|. |	26	-0.009	-0.011	0.3191	1.000
.|. |	.|. |	27	-0.009	-0.011	0.3327	1.000
.|. |	.|. |	28	-0.009	-0.011	0.3466	1.000
.|. |	.|. |	29	-0.009	-0.012	0.3615	1.000

.|. |	.|. |	30	-0.009	-0.012	0.3769	1.000
.|. |	.|. |	31	-0.009	-0.012	0.3933	1.000
.|. |	.|. |	32	-0.010	-0.013	0.4106	1.000
.|. |	.|. |	33	-0.010	-0.013	0.4283	1.000
.|. |	.|. |	34	-0.010	-0.013	0.4465	1.000
.|. |	.|. |	35	-0.010	-0.014	0.4656	1.000
.|. |	.|. |	36	-0.010	-0.014	0.4849	1.000