Gauging the Volatility Level of Stock Returns in the Nigerian Stock Market.

Samson Ogege, Ph.D.

University of Lagos, Faculty of Business Administration, Department of Finance, Akoka, Lagos, Nigeria.

E-mail: ogegesamson@yahoo.com
Telephone: 234 8036691036

ABSTRACT

Given the significance of assessing volatility in the subjects of pricing equity, risk management, and portfolio management, this study is designed to investigate the precarious nature of stock returns on the Nigerian Stock Exchange (NSE) using GARCH (1.1) monthly all share indices as a proxy for stock returns of the NSE from January 2003 to December 2014. The study provides the empirical sample for investigating volatility persistence and asymmetric properties of the series. The results of the GARCH (1.1) model indicate evidence of volatility clustering in the NSE return series as well as volatility persistence for the Nigeria stock returns data. Based on these findings, it is recommended that the government should create an awareness that discourages the acts of buying and restraining of investors.

(Keywords: GARCH, volatility, stock returns)

INTRODUCTION

Recently, the volatility of stock market returns on the Nigerian stock market has created a level of apprehension for investors, analysts, brokers, dealers, and regulators of the stock market as stock volatility which represents the variability of prices is perceived as a measure of risk. The understanding of the vitality in a stock market will be useful in determining the cost of capital and the evaluation of asset allocation decisions. Policy makers therefore rely on market estimates as a barometer for determining the vulnerability of financial markets. However, the existence of excessive volatility, or "noise", in the stock market undermines the suitability of stock prices as "signals" to the true intrinsic value of a firm, a concept that is core to the paradigm of the information efficiency of markets (Karolyi, 2001).

Stock market volatility has a number of negative implications on the economy, the central being 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 because as wealth increases it drives up consumer spending. However, a fall in the stock market will weaken consumer confidence thus pushing down consumer spending. Stock market volatility has the capability of directly affecting business investment (Zulium 1995) and economic growth (Levine and Zervos, 1996 and Arestis et al., 2001). A rise in the volatility of the stock market is equivalent to 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 from large, and well known firms.

While there is a general consensus as to what constitutes stock market volatility and, to a lesser degree on how it can be measured, there are discrepancies on the causes of changes in stock market volatility. Some economists see these causes of volatility in the arrival of new, unanticipated information that alter expected returns on a stock (Engle and Ng, 1993). Consequently, changes in market volatility would merely reflect changes in the local or global economic environment as 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 back drop, the aim of this study is to investigate the impulsive nature of stock returns in Nigeria which involves examining NSE return series for evidence of volatility clustering.

LITERATURE REVIEW AND THEORETICAL FRAME WORK

The studies of Madelbrot (1963), Fama (1965), and Black (1976) highlight volatility clustering, leptokurtosis, and the characteristics of leverage effect on 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.

Bollserlev (1986) generalized the ARCH model by modeling the condition 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 explain the subject of volatility. Some of these models include: EGARCH originally proposed by Nelson (1991), GJR-GARCH model promulgated by Glosten, Jagannathan, and Runkle (1993), Threshold GARCH (TGARCH) model propounded by Zakoian (1994).

Following the success of the ARCH family models in capturing the behavioral nature of volatility, stock returns have received a deal of attention from both the academics and practitioners as a measure and control of risk both in emerging and developed financial markets.

Concerning the effectiveness of the ARCH family models is capturing volatility of financial time series, Hsieh (1989) found that GARCH (1,1) model effectively captured most of the stochastic dependencies in the time series. Based on tests of standardized squared residuals, he discovered that the simple GARCH (1.1) model satisfactorily described the data than the previous ARCH (1.2) model estimated by Hsieh (1988). Similar conclusions were reached by Taylor (1994), Brook and Burke (2003), Frimpong and Oteng-Abayie (2006), and Olow (2009).

In like manner, the works of Bakaert and Harvey (1997) and Aggarwal et al (1999) which focused on the volatility of emerging markets, confirm the ability of asymmetric GARCH models in capturing asymmetry in stock return volatility. Thus, ARCH family models are suitable for modeling and estimating volatility in emerging stock markets. Further literature shows that the works of Campbell and Henstchel (1992), Braun et al. (1995), and LeBaron (2006) provide evidence that stock returns have time-varying volatility.

Although the GARCH model has had far reaching success in capturing financial data, particularly the symmetric effects of volatility, the same cannot be said of its impact in capturing extreme observations and skewedness 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 evidences suggest that the frequency of large magnitude events seem 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 consequently adopting the stable Paretian model, which has the uncomfortable property of infinite variance. Fama (1965) provides empirical tests of Mandelbrot’s idea on the 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 period in equilibrium (see Lai, 1991; Satchell, 2004). This has led to the use of non-normal distributions such as: Student-t, GED, asymmetric Student-t and asymmetric GED to model the empirical distribution on 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, Shwert, 1989; Eraker, 2004).

EMPIRICAL LITERAURES

In Nigeria, the few published studies on modeling volatility of stock returns include: Ogum, Beer, and Nouyright (2005); Jayasuriya (2002); and Okpara and Nwezeaku (2009). Jayasuiya (2002) employs the asymmetric GARCH methodology to examine stock returns in the Nigerian stock market for the period December 1984 to March 2000. The study, among others reports that the positive (negative) changes in prices have been followed by negative (positive) changes indicating a cyclical feature in stock price changes rather than volatility clustering in Nigerian stock market.

Contrary to the stance of 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 in countries of the world is existent in the Nigerian market, but Kenya shows evidence of significant and positive asymmetric volatility, suggesting that positive shocks increase volatility more than negative shocks of an equal magnitude. Furthermore, they deduced 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, making the GARCH parameter (β) statistically significant as it indicates 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 procedure. Employing EGARCH (1,3) model to determine the impact of these risks on the stock market returns, a cross-sectional estimation produce is adopted. 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 an unexpected increase in price (good news); a trend similar in Nigeria.

Babikir et al.(2012) examines the unpredictable nature of stock returns using both the in-sample and out of sample tests applied to daily return of the Johannesburg Stock Exchange (JSE) Index and found a high level of persistence and variability in the parameter estimates of the GARCH(1,1) model across the sub-sample.

Zhou et al. (2012) analyzed the directional volatility between the Chinese and world equity markets and found that the Chinese market had a significant positive impact on other markets since 2005.

Tripathy and Rahman (2013) studied the conditional volatility of both the Bombay Stock Exchange (BSE) and the Shanghai Stock Exchange (SSE) based on the daily closing value of 23 years data and found that there was a significant ARCH effect in both the stock markets.

Makkar and Singh (2013) analyzed the stock return behaviors of two Indian commercial banks-SBI and ICICI during the period of financial crisis. He realized that the stock prices of the ICICI bank was more affected by the U.S subprime crisis compared to the SBI.

Singh and Kishor, (2014) examines the effect of macro-economic variables on stock market indices and found no inter linkages between gold price and Nifty indices.

Examining the relationship between the crisis and stock returns volatility in the Indian banking sector, Singh and Makkar (2014) adopts the GARCH model to capture the impact of the crisis on the volatility of banks. It was discovered that the crisis had a significant impact on the stock volatility of the Indian banking sector and stock return volatility has significantly changed during the pre and post crisis period.

METHODOLOGY

In financial and economic models, the future is always uncertain but over time we learn new information that enable us make feasible projections; such as when asset prices reflect the best forecasts of the future profitability of companies and countries, there would consistently be changes as long as new situations arises. ARCH/GARCH models can be interpreted as measuring the intensity of the news process which results in volatility clustering which is best understood as news clustering. Of course, many things influence the process involved in the arrival of news and its impact on prices such as the act of trades conveying news to the market and the macro economy which moderate the magnitude of the news. These can all be perceived as significant determinants of the volatility picked up by ARCH/GARCH which describe the time evolution of uncertainty in a complex system.

This study is descriptive and historical in nature as it seeks to describe the pattern of returns of the Nigeria Stock Exchange (NSE) in the past. Data collected was the monthly market share index of the NSE for the periods of trading-January 2003 to December 2014 (144 months). The periods were chosen based on the data available in the Cowry Asset Managers website which comprises of 757 observations. To enhance elucidation, the data was transformed by means of natural logarithm. The autoregressive conditional heteroskedasticity (ARCH) model introduced by Engle (1982) and its extension, the generalized autoregressive conditional heteroskedasticity (GARCH) model (Bollerslev, 1986), was used to estimate the conditional variance of Nigeria's daily stock return. This method permits an objective determination of the presence of volatility thus making the ARCH models and its extension, the GARCH models to be the most commonly employed class of time series models in the recent finance literature on the study of volatility.

MODEL SPECIFICATION

The forte of the models is its capability to 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:

$$STR_t = \beta 0 + \beta 1 STR_{t\text{-}}1 + \mu_t$$

Where; ST_t = Stock Market Return at time t
STR_t = Stock Market Return at time t – 1
β_0 = intercept
β_1 = coefficient of the Stock Marker Return at time t – 1
μ_1 = 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:

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

Where; ω = constant term,
$\beta\mu^2_{t-1}$ = ARCH term
$\psi\sigma_{2t-1}$ = GARCH term

EXPLANATORY VARIABLE

Stock Returns

The ratio of money gained or lost (whether realized or unrealized) on an investment is 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

RESULTS AND INTERPRETATION

Table1: Descriptive Statistics Results.

	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	144

Source: E-view Results

The meaning 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 skewedness of this study is 5.259328 and the Kurtosis is 45.70597, suggesting non-normality of the market.

Table 2: Unit Root Result.

VAR	ADF	1%	5%	10%	TREND	CONSTANT	LAG
STR	-6.396476	-40.0250	-3.4419	-3.1453	YES	YES	1

Source: E-view Results

Jarque-Bera's test rejects the normal state of the data at 5% level (11606.60) as being higher than the χ^2-value of 5.99. Overall, the non-normality of the stock return series revealed in this study suggests the use of the non-linear model.

The stationarity test of the data (STR) indicates 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%, the unit root test 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. 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	0.408839	-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 the GARCH (1.1) model is thus:

$$\sigma^2_t = 6.80E{+}08 + 0.90314u^2_{t-1} - 0.015991\sigma^2_{t-1}$$

The ARCH coefficient is 0.903147 and significant at 1% level implying 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 thus implying a non-persistent shock 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 $\beta + \psi$ 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.

SUMMARY AND CONCLUSIONS

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 the GARCH model, it reveals that the NSE is not only volatile but existent in the market, are persistence shocks just as is similar to other emerging markets. The study employed monthly data of large sample size which reveals the risk return characteristics and volatility persistence shocks in the emerging stock market of Nigeria indicating an 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 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.

The results as discussed above indicate high volatility presence in the conditional variance. Therefore, the market returns depend on their own shocks and confirm the volatility clustering phenomenon for the inefficient market as also discovered by Rizwan and Khan (2007) that volatility clustering exists in Pakistani stock market signifying inefficiency in the stock market. These results clearly explain the volatile nature of emerging markets and provide clear evidences 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 in the stock market of Nigeria. This may be the cause of frictions in the securities market trading. This result also indicates that the participants may have limited access to the market information regarding the firms' performance either because the firms do not provide a prompt financial statements or investors do not seek financial advice in stock dealings due to lack of a professional financial community who analyzes 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) attributed the non-synchronous trading to negative autocorrelation in portfolio returns. Furthermore, 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 making the investors lose confidence in the stock market.

There is need for the modernization of the Nigeria Stock Exchange which will improve the trading system by permitting a prompt dissemination of information to investors as well as ensure the development of specialized financial institutions (portfolio managers) who can analyze stock market data for the investors so as to speed up adjustment to new information arrival. Finally, timely disclosure and appropriate dissemination of company's specific information to the investors will improve the efficiency of the stock market in Nigeria.

REFERENCES

1. Aggarwal, R., C. Inclan, and R. Leal. 1999. "Volatility in Emerging Stock Markets". *Journal of Financial and Quantitative Analysis*.34:33-35.

2. Amin, K.I. and V.K. Ng. 1997. "Inferring Future Volatility from the Information in Implied Volatility in Eurodollar Options: A New Approach". *The Review of Financial Studies*.10(2):333-367.

3. Arestis, P., P.O. Dometriades, and K.B. Luintel. 2001. "Financial Development and Economic Growth: The Role of Stock Markets". *Journal of Money, Credit and Banking*. 33(2):16-41.

4. Baillie, R.T. and R.O. DeGennaro. 1990. "Stock Returns and Volatility". *The Journal of Financial and Quantitative Analysis*. 25(2):203-214.

5. Batra, A. 2004. "Stock Return Volatility Patterns in India". Indian Council for Research on International Economic Relations, Working Paper No.124.

6. Bekaert, G. and C. Harvey. 1997. "Emerging Equity Market Volatility". *Journal of Financial Economics*.43:29-78.

7. Black, F. 1976. "Studies of Stock Market Volatility Changes". *Proceedings of the American Statistical Association*, Business and Economic Statistics Section. 177-181.

8. Bollerslev, T. 1986. "Generalized Autoregressive Conditional Heteroskedasticity". *Journal of Econometrics*. 51:307-327.

9. Bratun, P.A., D.B. Nelson, and A.M. Sunier. 1995. "Good and News, Bad News, Volatility and Betas". *Journal of Finance*. 1(5):1575-1603.

10. Brook, C. and S.P. Burke. 2003. "Information Criteria for GARCH Model Selection: An Application to High Frequency Data". *European Journal of Finance*. 9:6:557-580.

11. Campbell, J. 1996. "Consumption and the Stock Market: Interpreting Interantional Experience". NBER Working Paper. 5160.

12. Campbell, J.Y., A.W. Lo, and A.C. Mackinlay. 1997. *The Econometrics Financing Markets* Princeton University Press: Princeton, NJ.

13. Campbell, J.Y. and L. Hentschel. 1992. "No News is Good News: An Asymmetric Model of Changing Volatility in Stock Returns". *Journal of Financial Economics*. 31:281-318.

14. Chahal, S. Mandeep, and J. Wang. 1998. "Jump Dffusion Processes and Emerging Bond and Stock Markets: An Investigation Using Daily Data". *Multinational Finance Journal*. 1(3):169-197.

15. David, A. 1997. "Fluctuating Confidence in Stock Markets: Implications for Returns and Volatility". *The Journal of Financial and Quantitative Analysis*. 32(4):437-462.

16. DiBartolomeo, D. 2007. "Fat Tails, Tale Tails and Puppy Dog Tail". Annual Summer Seminar Newport, RI, June

17. Emenike, K.O. 2010. "Modelling Stock Returns Volatility in Nigeria Using GARCH Models", MPRA Paper No.23432, posted 05. July 2010/19:53

18. Engle, R. 2001. "Garch 101: The use of Arch/Garch Models in Applied Econometrics". *Journal of Economic Perspectives*. 15:157-168.

19. Engle, R. and V. Ng. 1998. "Measuring and Testing the Impact News on Volatility". *Journal of Finance*. 48:1748-1778.

20. Engle, R. and V. Ng. 1982. "Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of the United Kingdom Inflation". *Econometricia*, 50:987-1007.

21. Engle, R.F. and T. Bollerslev. 1986. "Modeling the Persistence of Conditional Variances". *Econometric Reviews*.5:81-87.

22. Engle, R.F., S.M. Forcard, and F. Fabozzi. 2005. "ARCH/GARCH Models in Applied Financial Econometrics". *Journal of Econometrics and Financial*.

23. Eraker, B. 2004. "Do Stock Prices and Volatility Jump? Reconciling Evidence from Spot and Option Prices". *The Journal of Finance..* 59(3): 1367-1403.

24. Fame, E. 1965. "The Behavior of Stock Market Prices". *Journal of Business*. 38(1):34-105.

25. Floros, C. 2007. "The use of GARCH Models for Calculation of Minimum Capital Risk Requirements: International Evidence". *International Journal of Managerial Finance*. 3(4): 360-371.

26. Floro, C. 2008. "Modeling Volatility using GARCH Models: Evidence from Egypt and Israel". *Middle Eastern Fin. Econ*., ISSN: 1450-2889 Issue 2.

27. French, K.R., W.G. Schwert, and R.F. Stambugh. 1987. "Expected Stock Return and Volatility". *Journal of Financial Economics*.19:3-29.

28. Frimpong, J.M. and E.F. Oteng-Abayie, 2006. "Modeling and Forecasting Volatility of Returns on the Ghana Stock Exchange using GARCH Models". *Munich Personal RePEc Archive*. 593:1-21.

29. Galeotti, M. and S. Fabio. 1994. "Stock Market Volatility and Investment: Do only Fundamentals Matter?". *Economica*. 61(241):147-165.

30. Glostan, L., R. Jagannathan, and D. Runkle. 1993. "On the Relationship between the Expected Value and the Volatility of the Nominal Excess Return on Stocks". *Journal of Finance.* 48:1779-1802.

31. Harvey, C.R. 1995a. "Predictable Risk and Return in Emerging Markets". *The Review of Financial Studies*, 8:773-816.

32. Harvey, C.R. 1995b. "The Cross-Section of Volatility and Auto-correlation in Emerging Markets". *Finanzmarkt and Portfolio Management*. 9:12-34.

33. Harvey, C.R. and A. Siddique. 1999. "Autoregressive Conditional Skewness". *Journal of Financial and Quantitative Analysis*, 34(4):465-477.

34. Hongyns, P. and Z. Zhichao. 2006. "Forecasting Financial Volatility: Evidence from Chinese Stock Market". Working paper in Economics and Finance Conference. 2:63-86.

35. Hsieh, D. 1989. “Modeling Heteroskedasticity in Daily Foreign Exchange Rates”. *Journal of Business and Economic Statistics*. 7:307-317.

36. Hsieh, D. 1991. “Chaos and Nonlinear Dynamics: Application to Financial Markets”. *Journal and Finance*. 46:1839-1877.

37. Jayasuriya, S. 2002. “Does Stock Market Liberalization Affect the Volatility of Stock Returns: Evidence from Emerging Market Economies”. Georgetown University Discussion Series, August.

38. Karolyi, G.A. 2001. “Why Stock Return Volatility Really Matters”. Paper Prepared for Inaugural Issue of Strategic Investor Relations, Institutional Investor Journals Series, February.

39. Kumar, R. and A.K. Makhija. 1986. “Volatility of Stock Prices Market Efficiency”. *Managerial and Decision Economics*. 7(2):119-122.

40. Lai, T. 1991, “Portfolio Selection with Skewness: A Multi-Objective Approach”. *Review of Quantitative Finance and Accounting*. 1(3):293-306.

41. Levine, R. and S. Zervos. 1996. “Stock Market Development and Long-Run Growth”. *World Bank Economic Review*. 10(1):323-339.

42. Li, K. 2002. “Long-Memory versus Option-Implied Volatility Prediction”. *Journal of Derivatives*. 9(3):9-25.

43. Ludvigson, S. and C. Steindel. 1999. “How Important is the Stock Market Effect on Consumption” .*Federal Reserve Bank of New York Economic Policy Review*. 5(1):29-51.

44. Mandelbrot, B. 1963. “The Variation of Certain Speculative Prices”. *Journal of Business*. 36(4): 394-419.

45. Mankiw, G.N., D. Romer, and M.D. Shapiro. 1991. “Stock Market Forecastability and Volatility: A Statistical Appraisal”. *The Review of Economic Studies*. 58(3):455-477.

46. Nelson, D.B. 1991. “Conditional Heteroskedasticity in Asset Returns: A New Approach”. *Economietrica*. 59(2):347-370.

47. Ogum, G., F. Beer, and G. Nouyright. 2005. “Emerging Equity Market Volatility: An Empirical Investigation to Markets in Kenya and Nigeria”. *Journal of African Business*. 6(1/2):139-154.

48. Okpara, G.C. and N.C. Nwezeaku. 2009. “Idisoyncratic Risk and the Cross-Section of Expected Stock Returns: Evidence from Nigeria”. *European Journal of Economics, Finance and Administrative Sciences*. 17:1-10.

49. Olowe, R. A. 2009. “The Impact of the Announcement of the 2005 Capital Requirement for Insurance Companies on the Nigerian Stock Market”. *The Nigerian Journal of Risk and Insurance*. 6(1):43-69.

50. Poterba, J.M. 2000. “Stock Market Wealth and Consumption”. *Journal of Economic Perspectives*. 14(2):99-118.

51. Rizwan, M.F. and S. Khan. 2007. “Stock Return Volatility in Emerging Equity Market (Kse): The Relative Effects of Country and Global Factors”. *Int. Rev. Bus. Res. Papers*. 3(2):362-375.

52. Rydberg, T.H. 2000. “Realistic Statistic Modelling of Financing Data”. *International Statistical Review*. 68(3):233-258.

53. Satchell, S. 2004. ”The Anatomy of Portfolio Skewness and Kurtosis”. Trinity College Cambridge Working Paper.

54. Schwert, G.W. 1989. “Why does Stock Market of Volatility Change Overtime?”. *The Journal of Finance*. 44(5):1115-1153.

55. Starr-McCluer, M. 1998. “Stock Market Wealth and Consumer Spending”. Board of Governors of the Federal Reserve System, Finance and Economics Discussion Paper Series, 98/20.

56. Taylor, S. 1994. “Modeling Stochastic Volatility: A Review and Comparative Study”. *Mathematical Finance*. 4:183-204.

57. Thoedoiou, P. 2001. “Skewed Generalized Error Generalized Error Distribution of Financial Assets and Option Pricing”. Working Paper, School of Business, Rutgers University, New Jersey.

58. Verhoeven, P. and M. McAleer. 2003, “Fat Tails and Asymmetry in Financial Volatility Models”, CIRJE-F-211 Discussion Paper, March.

59. Zakoian, J.M. 1994. “Threshold Heteroscedastic Model”. *Journal of Economic Dynamic and Control*. 18.

60. Zuliu, H. 1995: “Stock Market Volatility and Corporate Investment”. IMF Working Paper, 95/102.

ABOUT THE AUTHOR

Dr. Samson Ogege, is a Lecturer in the Department of Finance, Faculty of Business Administration, University of Lagos, Nigeria. He has B.Sc. in Banking & Finance, an M.Sc. in Finance, and a Ph.D. in Finance.

SUGGESTED CITATION

Ogege, S. 2016. “Gauging the Volatility Level of Stock Returns in the Nigerian Stock Market”. *Pacific Journal of Science and Technology*. 17(1):120-128.

Pacific Journal of Science and Technology