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Modeling Asymmetric Volatility in the Nigerian Stock Exchange

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Abstract
This paper examines the response of volatility to negative and positive news using daily closing prices of the Nigerian Stock Exchange (NSE). By applying EGARCH (1,1) and GJR-GARCH (1,1) models to NSE daily stock return series from January 2nd 1996 to December 30th 2011, we find strong evidence supporting asymmetric effects in the NSE stock returns but with absence of leverage effect. Specifically, the estimates from EGARCH model show positive and significant asymmetric volatility coefficient. In the same way, results of the GJR-GARCH model show negative and significant asymmetric volatility coefficient, also supporting the existence of positive asymmetric volatility. Overall results from this study provide support for positive news producing higher volatility in the immediate future than negative news of the same magnitude in Nigeria.
Keywords: Returns volatility, Asymmetric effects, GARCH models, Nigerian Stock Exchange.

1. Introduction

An important assumption of the classical linear regression model is that the variance of all squared errors is homoscedastic; that is they all have the same variance (Gujarati, 2003: 387; Rachev et al., 2007: 279). Numerous empirical studies have however shown that stock return series exhibit heteroscedasticity, where the variances of the error term are not equal, and in which error terms may be expected to be larger for some observations or periods of the data than for others. For instance, Mandelbrot (1963) found evidence of the tendency of large changes in asset prices (either positive or negative) to be followed by large changes and small changes to be followed by small changes. The issue then became how to construct models that accommodate heteroscedasticity so that valid coefficient estimates are obtained for the variance of the error terms. Engle (1982) introduced the autoregressive conditional heteroscedasticity (ARCH) model to model volatility by relating the conditional variance of the error term to the linear combination of the squared error terms in the recent past. As a result of the long lag length and large parameters required to estimate ARCH model, Bollerslev (1986) introduced the GARCH model by modeling the conditional variance to depend on its lagged values as well as squared lagged values of the error terms. After the seminal ARCH paper by Engle (1982) and the generalization by Bollerslev (1986), the study of volatility has received substantial attention from researchers, practitioners and policy makers. This substantial interest is due to the fact that volatility, as a proxy for risk, is useful for risk management, pricing equity as well as option-type derivative instruments.

Although the ARCH and GARCH models have been very successful in capturing volatility clustering, there are some features of the financial time series data which they failed to capture. The most interesting feature not addressed by these models is the asymmetric effects, which considers the response of volatility to negative and positive news. Asymmetric effects are captured by asymmetric models such as the Exponential GARCH (EGARCH) of Nelson (1991), the GJR-GARCH model introduced by Glosten, Jagannathan, and Runkle (1993), Asymmetric Power ARCH (APARCH) of Ding, Engle and Granger (1993), and Threshold GARCH (TGARCH) model due to Zakoian (1994), and so many other models. The most celebrated asymmetric effect is the leverage effect. First documented by Black (1976), leverage effect implies that a negative shock to the conditional variance tends to cause volatility to rise by more than a positive shock of the same magnitude.

In his explanation of the leverage effect, Black (1976) notes that a fall in the value of a firm's stock will cause a negative return on its stock, and will usually increase the leverage of the stock which will cause a rise in the debt-equity ratio. This increase in leverage raises the riskiness of the firm as the shareholders perceive their future cash flow stream as being relatively more risky thereby leading to higher levels of volatility. Volatility feedback is another explanation for asymmetric effects offered by Campbell and Hentschel (1992). To them, volatility is a measure of risk; hence an increase in volatility signals a higher risk and also higher expected future risk. To bear this risk, investors will require higher returns and are thus inclined to pay less for the relevant equity. Avramov et al. (2006) explain that stock trading activity causes asymmetric effects. In this explanation, uninformed traders sell when stock prices fall, leading to an increase in stock returns volatility, while informed investors sell after stock price rises, which leads to a decline in volatility. So many other empirical works have also confirmed the existence of leverage effect in different stock markets across the globe (see, Black, 1976;

Christie, 1982; Nelson, 1991; Goudarzi and Ramanarayanan, 2011; Abdalla, 2012))

Although asymmetric volatility phenomenon is well documented in literature of developed and emerging stock markets, there are some evidence indicating lack of asymmetric behaviour particularly in emerging stock markets (see for example, Alagidede and Panagiotidis, 2009; Charlse, 2010; Cheng, Jahn-Paver and Rothman, 2010; Oskooe and Shamsavari, 2011). There are also studies that document evidence to show that positive returns are associated with higher volatility than negative returns of the same magnitude (see for example, Ogum, Beer and Nouyrigat (2005; Saleem, 2007; Aliyu (2011)

In Nigeria, literature on asymmetric volatility is still scanty but growing. Ogum, Beer and Nouyrigat (2005) reports, amongst others, that volatility clustering and asymmetric volatility found in the United States and other developed markets are also present in Nigeria. They also report positive and significant asymmetric volatility coefficient in Kenya, which suggests that positive shocks increase volatility more than negative shocks of the same magnitude. Olowe (2009) found, amongst others, evidence of volatility persistence and leverage effects. In contrast to olowe, Okpara and Nwezeaku (2009) argue 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. Emenike (2010) documents evidence to show asymmetric volatility, volatility clustering and volatility persistence in the NSE monthly returns data. More recently, Okpara (2011), provide evidence to support the findings of Okpara and Nwezeaku (2009). He reports that there is low persistence of volatility clustering and that there is a leverage effect in the Nigerian Stock Exchange. Aliyu (2011) shows weak support for leverage effect in Nigeria but document strong evidence to show that positive news increases volatility more bad news of the same magnitude in Ghana. Onwukwe, Bassey and Isaac (2011) found evidence of volatility clustering and leverage effect in the return series of UBA, Unilever, Guiness and Mobil. The empirical regularity in volatility literature from Nigeria is the existence of volatility clustering and asymmetric volatility, but volatility persistence is contended. It is also observed that most of the studies were conducted using monthly data.

In this study, our aim is to model and estimate the daily volatility of stock returns on the Nigerian Stock Exchange (NSE) by using symmetric and asymmetric GARCH models that capture asymmetry. This is to provide insight into the response of volatility to negative and positive news as well as extend existing literature on volatility in Nigeria. This paper is structured into four sections. Immediately preceding Introduction in Section 1 is Section 2, which outlines the nature of data and methodology. Section 3 presents the empirical results for the NSE, and Section 4 embodies the concluding remarks.

2. Data and Methodology

2.1 Data for Analysis

In order to examine the Nigeria stock returns volatility for asymmetric effect, we use daily closing prices of the Nigerian Stock Exchange weighted All-share index, from January 2, 1996 to December 30, 2011. This gives a total of 3930 observations. Market prices index are transformed to daily returns thus:

$$R_t = Log\left(\frac{p_t}{p_{t-1}}\right) \qquad (1)$$

Where: R_t is daily return of the All-share Index for day_t, P_t is current day index closing price, P_{t-1} is closing price of the previous day index, and Log is Natural Logarithm.

2.1.1 Descriptive Statistics

Descriptive statistics of daily returns are presented in Table 1 to aid our understanding of the nature and distributional characteristics of the NSE return series. The computed statistics include daily mean return (as well as minimum and maximum returns), standard deviation, skewness, kurtosis, and Jarque-Bera.

From Table 1, we observe that the average daily return is 0.04%. The daily standard deviation is 0.9%, reflecting a high level of dispersion from the average return in the market. The wide gap between the maximum (9.77%) and minimum (-6.73%) returns gives support to the high variability of price changes in the NSE. Another glaring characteristic of the statistics shown in Table 1 is high kurtosis coefficient. In a normally distributed series, kurtosis is 3. The high kurtosis value of 6.9665 suggests that big shocks of either sign are more likely to be present and that the return series is clearly leptokurtic. Similarly, zero (0) skewness coefficient indicates evidence of lack of asymmetry, while Positive or negative skewness indicate asymmetry in a series. The skewness coefficient of 0.1706 is positively skewed. Positive skewness implies that the distribution has a long right tail, implying that large positive movements in stock prices are not usually matched by equally large negative movements. The null hypotheses of zero (0) skewness and kurtosis coefficient of 3 were rejected at 1% *p*-value suggesting that the NSE daily returns series do not follow normal distribution. The rejection of normal distribution in the NSE daily series was confirmed with Jarque-Bera test as its associated marginal significance level is far below 1% confidence level.

Since NSE return series do not follow normal distribution, the asymmetric GARCH models are estimated with the Generalized Error Distribution (GED) which takes into account the fat tail characteristic of stock returns distribution.

Figure 1 shows the daily logarithmic returns of the NSE All-share index for the period January 2, 1996 to December 30, 2011 – 3930 observations in all. A visual inspection of Figure 1 shows that returns fluctuate around the mean value. The fluctuations are both in positive and negative region with clustering in volatile periods alternated by periods of calm. This behaviour of stock returns series suggests volatility clustering in the NSE, where large returns tend to be followed by large returns and small returns following small returns. The implication of volatility clustering is that volatility shocks today will influence the expectation of volatility in the immediate future periods. On the other hand, Figure 2, shows the plot of the log level data of the NSE for the sample period. It is easy to see the great growth of the series and its subsequent decline as a result of the effect of global economic crises on Nigeria. It is trending.

2.1.2 Unit Root Tests for the NSE Daily Index

To test for possible unit roots in the NSE returns series, Table 2 presents results of the unit root tests on the logarithmic level and stock return. Testing methodology is the Augmented Dickey-Fuller (ADF). The critical value is 5% level of significance to avoid the problem of accepting a false null hypothesis. The critical value of the ADF test is -2.863. The ADF test accepts the null hypothesis of unit roots in logarithmic level (i.e., logindex ~ $I(1)$, but reject it in the return series ($R_t \sim I(0)$). In the return series, the computed tau values of the ADF (-31.2496) exceeds the critical value in the NSE returns series, thereby confirming the alternative hypothesis of no unit root for return series as the computed tau values far exceed the critical values. This result supports earlier findings that the NSE return series is stationary (Olowe, 2009; Emenike, 2009).

2.2 Methodology

In order to examine the presence of asymmetric volatility in the Nigerian Stock Exchange, we first analyze the dynamics of stock returns volatility. To this end, we apply the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. In the volatility modeling process using GARCH models, the mean and variance of the series are estimated simultaneously. GARCH (1,1) model for stock returns, assuming that the distribution of the return series for period$_t$, conditional on all previous returns (or information), is normal can be estimated as:

$$R_t = \theta + \varepsilon_t \qquad (2)$$

$$\varepsilon_t \sim (0, \sigma_t^2)$$

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \qquad (3)$$

Where R_t represents the return at day$_t$, θ is the mean return, and ε_t is the error term. Equation 3 specifies that the conditional variance (σ^2_t), which represent volatility at day$_t$, is the weighted average of three different variance forecasts: ω is the constant variance that correspond to the long run average, α_1 refers to a first order ARCH term which transmits news about volatility from the previous period and β_1, the first order GARCH term, is the new information that was not available when the previous forecast was made (Engle, 2003). The non-negativity restrictions of GARCH (1,1) are $\omega > 0$, $\alpha_1 > 0$ and $\beta_1 \geq 0$. Statistical significance of the parameters is tested using marginal significance level and t-statistics. Under the null hypothesis of no GARCH effects (i.e. no volatility clustering in the NSE daily series), marginal significance level of parameter β_1 should be greater than the critical level (0.05) and computed t-statistics will be lesser than theoretical t (±1.96). The sum of α_1 and β_1 indicate persistence in volatility clustering and varies from 0 to 1. The closer ($\alpha_1 + \beta_1$) to 1, the more persistent is volatility clustering.

One of the significant weaknesses in the GARCH (1,1) model is its premise of symmetric response of stock returns volatility to positive and negative shocks. This weakness is due to the fact that conditional variance in the basic model is a function of the (squared) magnitudes of the lagged residuals, regardless of their signs ((Oskooe and Shamsavari, 2011)). In order to capture asymmetric effect in the volatility of stock returns, two extensions of the basic GARCH model were estimated, among other possibilities: the Threshold Autoregressive Conditional Heteroskedasticity (GJR-GARCH) and the Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH)

Nelson (1991) introduced a number of refinements on the GARCH model in using EGARCH to detect asymmetric volatility in the stock return series. The first of these refinements was to model the log of the variance, rather than the level. This ensures that the estimated conditional variance is strictly positive, thus non-negativity constraints of the ARCH and GARCH models are not necessary. The second is that the γ parameter typically responds asymmetrically to positive and negative values. In this method, asymmetric effects are estimated using the following equation:

$$\log \sigma_t^2 = \omega + \alpha_1 \left(\left| \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} \right| - \sqrt{\frac{2}{\pi}} \right) + \beta \log \sigma_{t-1}^2 + \gamma \left| \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} \right| \qquad (4)$$

Here, the γ coefficient signifies asymmetric effects of shocks on volatility. The presence of asymmetric effects can be tested by the hypothesis that $\gamma=0$. A zero γ coefficient would imply that positive and negative shocks of the same magnitude have the same effect on volatility of stock returns. The effect is asymmetric if $\gamma\neq0$. If the γ coefficient is negative, then negative shocks tend to produce higher volatility in the immediate future than positive shocks. The opposite would be true if γ were positive.

Similarly, Glosten, Jagannathan and Runkle (1993) proposed a modification of the original GARCH model using a dummy variable to capture asymmetric effects in financial time series. In GJR-GARCH model, there are two types of news: there is squared return and there is a variable that is the squared return when returns are negative and zero otherwise. The coefficients are now computed in the long run average (ω), the previous forecast (α_1), symmetric news (β_1), and negative news (γ). On this basis, Glosten, Jagannathan and Runkle (1993) introduced the following GJR-GARCH model for the conditional variance:

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \gamma \mu_{t-1}^2 \mathrm{I}_{\mu<0} (\mu_{t-1}) \qquad (5)$$

Where, *I* is an indicator function. In this formulation, the effects of positive and negative news on the conditional variance are completely different. The news effect is asymmetric if $\gamma \neq 0$. If the γ coefficient is positive, then negative shocks tend to produce higher volatility in the immediate future than positive shocks. The opposite would be true if γ were negative. β_1 measures clustering in the conditional variance and $\alpha_1 + \beta_1 + \gamma/2$ measures persistence of shocks on volatility. If the sum is less than one the shock is not expected to last for a long time but if it is close to one then volatility can be predicted for some time. However, if the sum of the coefficients is one then shock is going to affect volatility for indefinite future.

3. Empirical Results and Discussion

In this section, we present the estimates of different GARCH models as well as brief discussion of the results. The GARCH models are estimated using Maximum Likelihood estimators assuming Normal Distribution for symmetric GARCH models and Generalized Error Distribution (GED) for asymmetric GARCH models. The choice of GED is due to the presence of excess kurtosis in the NSE daily return series. The Broyden, Flectcher, Goldfarb and Shanno (BFGS) iterative algorithm was used to obtain optimal parameter estimates and relevant standard errors. The analysis is done using RATS version 7.0 econometric software.

The maximum likelihood estimates for the GARCH (1,1) model for the NSE return series are presented in Table 3. The coefficients of all the three parameters in the conditional variance equation (ω, α_1 and β_1), are highly significant, at 1% confidence levels, as measured by their *t*-statistics; and all satisfy the non-negativity restrictions of the model. The significance of ARCH parameter (α_1) indicates that the news about volatility from the previous day has explanatory power on current volatility. In the same way, statistical significance of the GARCH parameter (β_1) does not only indicate explanatory power on current volatility but also suggests volatility clustering in the daily returns of the NSE. The lagged conditional variance estimate (β_1) has coefficient 0.75, implying that 75% of a variance shock remains the next day. Volatility persistence, like we noted in section 3.2, is measured by the sum of α_1 and β_1. From the estimates in Table 3, the NSE daily returns have high persistence in volatility with $\alpha_1 + \beta_1 = 1.066$. High persistence implies that average variance will remain high since increases in conditional variance due to shocks will decay slowly (Rachev et al., 2007: 296). Evidence of persistence in volatility shocks abound in literature (see, Emenike, 2010; Oskooe and Shamsavari, 2011; Abdalla, 2012)

Also given in Table 3 are estimates obtained from EGARCH and GJR-GARCH asymmetric volatility models. These estimates are used to examine the existence of asymmetry in stock returns volatility of the NSE. According to reported EGARCH results, the γ coefficient, which measures asymmetric effect, is greater than zero. The positive γ coefficients are shown by the marginal significance level. Marginal significance level less than the critical level lead to rejection of the null hypothesis of zero coefficients. The marginal significance level for the γ coefficient of the EGARCH model (**0.00635**) is clearly significant at 1% confidence level. More so, the *t*-statistics also rejects $\gamma=0$ hypothesis. The computed t-value (2.7286) is far greater than the theoretical t-value

(1.96) for a two-tailed test with asymptotic degrees of freedom, thereby rendering the γ coefficient statistically significant. Statistically significant γ coefficient indicates that the null hypothesis of no asymmetric effect in the volatility of NSE is false. In other words, there is asymmetric effect in the volatility of stock returns of the Nigerian stock market. In contrast to leverage effect, the γ coefficient is positive, suggesting that positive shocks tend to produce higher volatility in the immediate future than negative shocks of the same magnitude in the Nigerian stock market. This result agrees with the positive skewness of our descriptive statistics in section 2.1.1.

Furthermore, the GJR-GARCH model estimates in Table 3 also confirm the evidence of asymmetry in the stock returns volatility of the NSE. This is confirmed by a marginal significance level (**0.01941**) lesser than the confidence levels (i.e., 0.05) and a *t*-statistics (-2.3374) greater than table t-statistics in absolute value (1.960). As noted in section 3.2, positive (negative) γ coefficient indicate that negative (positive) shock tends to produce higher volatility in the immediate future than positive (negative) shocks. According to results given in Table 4, the γ coefficient is negative, indicating that positive shock tends to produce higher volatility in the immediate future than negative shock of the same magnitude, thereby suggesting absence of leverage effect in Nigeria. Evidence of volatility clustering given in GARCH (1,1) estimates above is also confirmed by high statistical significance of the GARCH term (β_1) and ARCH term (α_1). Similarly, sample evidence shows that volatility clustering is persistent in Nigeria stock returns on the basis of sum of $\alpha_1 + \beta_1 + \gamma/2 = 1.0796$. This implies that volatility shocks can be predicted for several days in the NSE. The rejection of leverage effect is consistent with some of the prior studies (see for example, Ogum, Beer and Nouyrigat, 2005; Saleem, 2007; Surya, 2008, Aliyu, 2011); but disagrees with others (see, Nelson, 1991; Olowe, 2009; Okpara, 2011).

4. Conclusion

In this study, we examined the volatility of Nigerian Stock Exchange return series for evidence of asymmetric effects by estimating GARCH (1,1), EGARCH and GJR-GARCH models. Asymmetric model (EGARCH and GJR-GARCH) were fitted to the daily returns data ranging from 3rd January 2006 to 30th December 2011. The results obtained from GARCH (1,1) model show evidence of volatility clustering and volatility persistence in Nigeria. Similarly, estimates from asymmetric models indicate that there is asymmetric volatility effect in Nigeria. Contrary to leverage effect theoretical sign, result of EGARCH model estimate is positive suggesting that positive news increases volatility more than negative news. In the same way, estimated results from the GJR-GARCH model show the existence of a negative coefficient for the asymmetric volatility parameter thereby providing support to the EGARCH result of positive news producing higher volatility in immediate future than negative news of the same magnitude in Nigeria.

Overall results from this study provide strong evidence that positive shocks have higher effect on volatility than negative shocks of the same magnitude. The results also show volatility clustering and high volatility persistence in Nigeria.

References

Alagidede, P. and Panagiotidis, T. (2009). Modelling Stock Returns in Africa's Emerging Equity Markets. *International Review of Financial Analysis*, 18, 1-11. http://dx.doi.org/10.1016/j.irfa.2009.02.001

Aliyu, S.U.R. (2011). Does inflation has an impact on Stock Returns and Volatility? Evidence from Nigeria and Ghana. *International Conference on Economics and Finance Research Singapore.* [Online] Available: http://www.csae.ox.ac.uk/conferences/2011-EDiA/papers/054-Aliyu.pdf (May 11, 2012)

Avramov, D., Chordia, T. and Goyal, A. (2006). The Impact of Trades on Daily Volatility. *The Review of Financial Studies*, 19 (4), 1214-1277. http://dx.doi.org/10.1093/rfs/hhj027

Black, F. (1976). Studies of Stock Market Volatility Changes. *Proceedings of the American Statistical Association, Business and Economic Statistics Section*, pp. 177–181.

Bollerslev, T. (1986). A Generalized Autoregressive Conditional Heteroscedasticity. *Journal of Econometrics*, 31, 307-327.

Campbell, J.Y. and Hentschel, L. (1992). No News is Good News: An Asymmetric Model of Changing Volatility in Stock Returns. *Journal of Financial Economics*, 31, 281-318. http://dx.doi.org/10.1016/0304-405X(92)90037-x

Charlse, A. (2010). The Day-of-the-week Effects on the Volatility: The Role of Asymmetry. *European Journal of Operational Research*, 202, 143-142. http://dx.doi.org/10.1016/j.ejor.2009.04.022

Cheng, A. R., Jahn-Paver, M. R. and Rothman, P. (2010). An Empirical Investigation of Stock Market Behaviour in the Middle East and North Africa. *Journal of Empirical Research*, 17, 413-427. http://dx.doi.org/10.1016/j.jempfin.2009.11.002

Christie, A A (1982). The Stochastic Behaviour of Common Stock Variance - Value, Leverage and Interest Rate Effects. *Journal of Financial Economics*, 10(4), 407-432. http://dx.doi.org/10.1016/0304-405X(82)90018-6

Ding, Z., Engle, R.F. and Granger, C.W.J. (1993). Long Memory Properties of Stock Market Returns and a New

Model. *Journal of Empirical Finance,* 1, 83-106.

Emenike, K. O. (2009). An Empirical Test for Weak-form Efficient Market Hypothesis of the Nigerian Stock Exchange. *Journal of Business Administration and Management*, Vol. 4 (4), 118-133. [Online] Available: http://ssrn.com/abstract=1291273 (May 11, 2012)

Emenike, K. O. (2010). Modelling Stock Returns Volatility in Nigeria Using GARCH Models. *African Journal of Management and Administration*, Vol. 3 (1), 8-15. [Online] Available: http://mpra.ub.uni-muenchen.de/22723/ (May 11, 2012)

Engle, R.F. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of the United Kingdom Inflation. *Econometrica*, 50,987-1008. http://dx.doi.org/10.2307/1912773

Engle, R.F. (2003), "Risk and Volatility: Econometric Models and Financial Practice", *Noble Lecture* (December 8), Salomon Centre New York

Glosten, L., R. Jagannathan, and D. Runkle (1993). On the Relation between Expected Value and the Volatility of the Nominal Excess Return on Stocks. *Journal of Finance*, 48(5), 1779–1801. http://dx.doi.org/10.2307/2329067

Goudarzi, H. and Ramanarayanan, C.S. (2011). Modeling Asymmetric Volatility in the Indian Stock Market. *International Journal of Business and Management*, Vol. 6 (3): 221-231. [Online] Available: www.ccsenet.org/journal/index.php/ijbm/article/download/9714/6964 (June 04, 2012)

Gujarati, D.N. (2003). *Basic Econometrics* (4th Ed), Delhi: McGraw Hill Inc., (Chapter 11).

Henry, O. (1998). Modelling Asymmetry of Stock Market Volatility. *Applied Financial Economics*, Vol. 8: 145-153.

Mandelbrot, B. (1963). The Variation of Certain Speculative Prices. *Journal of Business*, 36 (4), 394-419. [Online] http://web.williams.edu/Mathematics/sjmiller/public_html/341Fa09/econ/Mandelbroit_VariationCertainSpeculativePrices.pdf

Nelson, D. (1991). Conditional Heteroscedasticity in Asset Returns: A New Approach. *Econometrica*, 59 (2), 347-370. http://dx.doi.org/10.2307/293826

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

Okpara, G.C. and Nwezeaku, N.C. (2009). Idiosyncratic Risk and the Cross-Section of Expected Stock Returns: Evidence from Nigeria. *European Journal of Economics, Finance and Administrative Sciences*, 17, 1-10. [Online] Available: http://www.eurojournal.com/ejefas_17_09.pdf (May 28, 2012)

Okpara, G. C. (2011). Volatility Modeling and the Nigerian Stock Return Relationship in EGARCH-in-Mean Framework. *International Journal of Current Research*, Vol. 3 (8), 176-185. [Online] Available: http://www.journalcra.com/?q=node/758 (May 11, 2012)

Olowe, R.A. (2009). Stock Return, Volatility And The Global Financial Crisis In An Emerging Market: The Nigerian Case. *International Review of Business Research Papers,* Vol. 5(4), 426-447. [Online] Available: http://www.bizresearchpapers.com/35.olowe-.pdf (June 04, 2012)

Onwukwe, C. E., Bassey, B.E.E & Isaac, I. O. (2011). On Modeling the Volatility of Nigerian Stock Returns Using GARCH Models. *Journal of Mathematics Research*, Vol. 3(4), 31-43. http://dx.doi.org/10.5539/jmr.v3n4p31

Oskooe, S. A. P. and Shamsavari, A. (2011). Asymmetric Volatility in Emerging Stock Markets: A Case of Iran. *International Journal of Economics and Finance*, Vol. 3 (6): 15-24. http://dx.doi.org/10.5539/ijef.v3n6p16

Rachev, S. T., Mittnik, S., Fabozzi, F. J., Focardi, S. M. and Jasic, T. (2007). *Financial Econometrics: from Basics to Advanced Modeling Techniques*, New Jersey: John Wiley & sons Inc

Saleem, K. (2007). Modelling Time Varying Volatility and Asymmetry of Karachi Stock Exchange. [Online] Available: http://ssrn.com/abstract=964898 (May 17, 2012)

Surya, B.G.C. (2008). Volatility Analysis of Nepalese Stock Market. *The Journal of Nepalese Business Studies*, V (1), 76-85. http://ssrn.com/abstract=1565603 (April 06, 2012)

Zakoian, J.M. (1994). Threshold Heteroscedastic Models. *Journal of Economic Dynamics and Control*, 18, 931–955.

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Appendices

Table 1: Descriptive Statistics of the NSE Daily Returns Series

Skewness	0.170607 (0.000013)	**Kurtosis**	6.966491 (0.000000)	**Jarque-Bera**	7964.1525 (0.000000)
Mean	0.000357	**Variance**	0.000082	**Std Dev**	0.0090
Minimum	-0.067254	**Maximum**	0.097660	**Observations**	3929

Note: Marginal Significance Levels displayed as (.). Skewness and Kurtosis are tests for zero skewness and excess kurtosis. Jarque-Bera is for normality.

Figure 1: Logarithmic Daily Returns of the NSE

02/01/1996 - 30/12/2011

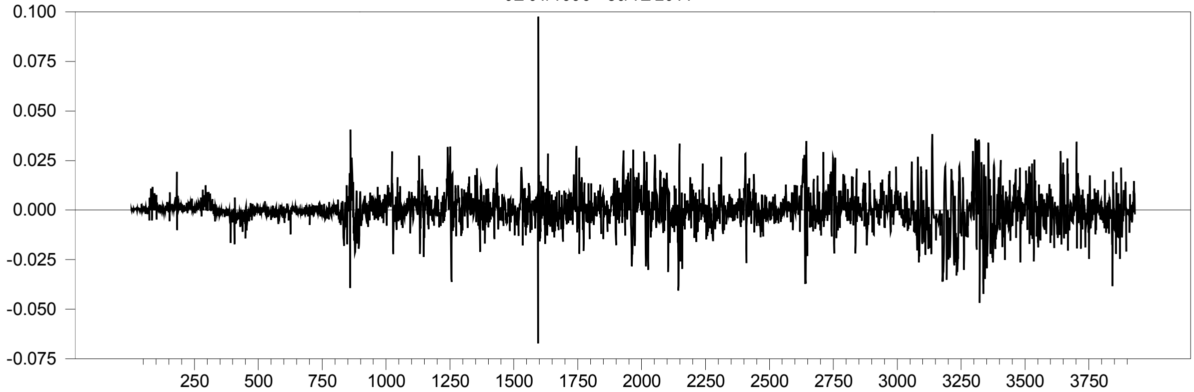

Figure 2: Logarithmic Level Series of the NSE Index

02/01/1996 - 30/12/2011

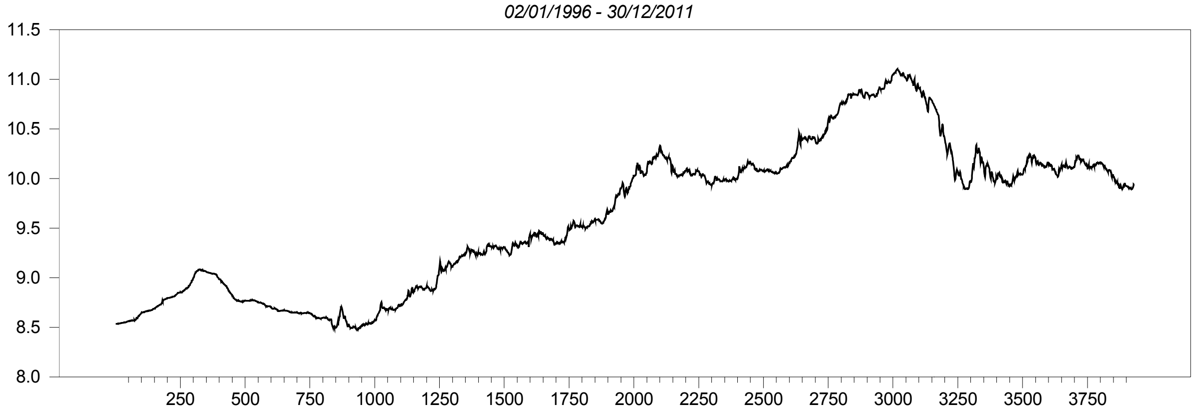

Table 2: Stationary Test for Log Level and First Difference of the NSE Daily Index

	Critical Value at 10%	Critical Value at 5%	Critical Value at 1%	Computed Value	Unit Root Test
Log Level	-2.567	-2.863	-3.435	-1.41589	ADF Test
Stock Return	-2.567	-2.863	-3.435	-31.24962	

Table 3: Estimates of the Parametric Volatility Models

Parameters	GARCH	EGARCH	GJR-GARCH
Mean	1.29640e-04	0.000087	0.00013
	(0.0789)	**(0.00000)**	**(0.02306)**
	{1.7568}	{12.6106}	{2.2723}
Constant (α_0)	4.05488e-07	-0.83050	0.0000003
	(0.00003)	**(0.0000)**	**(0.00348)**
	{4.1329}	{-2485.42}	{3.1355}
ARCH (α_1)	0.3116	0.52986	0.37650
	(0.0000)	**(0.0000)**	**(0.0000)**
	{14.8822}	{21.6016}	{10.6887}
GARCH (β_1)	0.7545	0.95610	0.73944
	(0.0000)	**(0.0000)**	**(0.0000)**
	{57.6493}	{568.1571}	{42.6176}
Asymmetry (γ)	________	0.037447	-0.07250
		(0.00635)	**(0.01941)**
		{2.7286}	{-2.3374}
($\alpha_1 + \beta_1$)	1.0661	1.4859	
($\alpha_1 + \beta_1 + \gamma/2$)			1.0796
Shape (c)	________	1.66294	1.71178
		(0.0000)	**(0.0000)**
		{29.8044}	{30.0857}
Log Likelihood	14096.48	14294.22	14276.38

Notes: Marginal significance level displayed as (.) and t-statistics displayed as {.}.