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RESEARCH ARTICLE

VOLATILITY MODELING AND THE NIGERIAN STOCK RETURN RELATIONSHIP IN EGARCH –IN –MEAN FRAMEWORK

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ABSTRACT

This study investigated the relationship between the stock market returns and volatility in Nigerian stock market using the EGARCH – in–mean framework. To carry out this investigation, end of the month stock price data were sourced from the Nigerian stock Exchange Fact Book. The result reveals that the forecast of variance cannot be used to predict expected returns in the Nigerian stock market. The Nigerian stock market is volatile implying that there exists a high level of risk in stock trading. The market demonstrates a greater probability of large decreases in market portfolio returns than increases. The result however, indicates a low persistence of volatility clustering suggesting that increase in volatility is not likely to remain high over several periods. Thus, investors in this market are not rewarded for their exposure to risk. The study also reveals that there exists a leverage asymmetric effect in the Nigerian stock market during the period of study. That is an unexpected drop in price (bad news) increases predictable volatility more than unexpected increase in price (good news) of similar magnitude.

INTRODUCTION

A statistical measure of the dispersion of returns for a given security or market index is called volatility. Volatility can either be measured by using the standard deviation or variance between returns from that same security. Stock volatility refers to the potential for a given stock to experience a drastic decrease or increase in value within a predetermined period of time. In other words, volatility refers to the amount of uncertainty or risk about the size of changes in a security's value. A higher volatility means that a security's value can potentially be spread out over a larger range of values. This means that the price of the security can change dramatically over a short time period in either direction. Stock return volatility which represents the variability of stock price changes could be perceived as a measure of risk. Commonly, the higher the volatility, the riskier the security. Investors evaluate the volatility of stock before making a decision to purchase a new stock offering, buy additional shares of a stock already in the portfolio, or sell stock currently in the possession of the investor. 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 on the other hand 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). The traditional measure of volatility as represented by variance or standard deviation is unconditional and does not recognize that there are interesting patterns in asset volatility; e.g., time-varying and clustering properties (Ayodeji, 2009). Researchers have introduced various models to explain and predict these patterns in volatility. Engle (1982) introduced the autoregressive conditional heteroskedasticity (ARCH) to model volatility. Engle (1982) modeled the heteroskedasticity 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, which is called generalized autoregressive conditional heteroskedasticity (GARCH). Some of the models include IGARCH originally proposed by Engle and Bollerslev (1986), GARCH-in-Mean (GARCH-M) model introduced by Engle, Lilien and Robins (1987) and other models introduced by other researcher. The relationship between expected returns and expected volatility have been extensively examined over the past years. Theory generally predicts a positive relation between expected stock returns and volatility, if investors are risk averse. That is, equity premium provides more compensation for risk when volatility is relatively high. In

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other words, investors require a larger expected return from a security that is riskier. 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 (Emenike, 2010). Asymmetry, also known as leverage effects, means that a fall in return is followed by 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. This work sets to investigate the behavior of stock returns volatility in the Nigerian Stock market using most current data sourced from the Nigerian stock Exchange. Precisely, it seeks to find out if the conditional variance can be used to predict expected returns in the market and also to investigate whether leverage effect and volatility clustering exist in NSE return series.

2. Review of related Literature

Volatility of prices and returns in financial markets can be an impediment for attracting investment in a developing economy. The presence of high degree of volatility indicates that investors will demand for much premium thereby creating high cost of capital which is inimical to the growth of the economy. A rise in stock market volatility is an indication of a rise in risk of equity investment and thus a shift of funds to less risky assets. Stock market volatility has a number of negative implications such as impairing the smooth functioning of the financial system, adversely affecting economic performance (Mala and Reddy 2007). Many empirical papers have related the behaviour of stock market volatility with business cycle (Hamilton and Gang, 1996, Casarin and Trecroci 2007), while others relate stock volatility with upward and downward trend - bull and bear stock markets (Maheu and McCurdy 2002 and Cunado *et al.,* 2007).

In an emerging economy with financial "shallowness", the volatility of the stock market may lead to portfolio adjustments which change other asset prices and their returns. In addition to the prices of other financial assets being bid up, the prices of real goods and services will also rise and this may induce a high rate of inflation emanating from supply shortages. However, the workings of this mechanism will depend on how investors are rewarded for risk bearing on the economy. Mala and Reddy (2007), campball (1996), Starr-Mecluer (1998), Ludvigson and Steindel (1999) and Poterba (2000), noted that the impact of stock market volatility on consumer spending is related through the wealth effect. An increased stock market prices will strengthen confidence on the investors through the wealth effect and hence beef up consumers spending while a fall in the stock market will weaken consumer confidence and drive down consumer spending. Investment decisions as characterized by asset pricing model strongly depend on the assessment of future returns and risk of various assets. Moreover, the expected volatility of a security return plays an important role in option pricing theory. According to Leon (2008) the relationship between expected returns and expected volatility have been extensively examined over the past years. Theory generally predicts a positive relation between expected stock returns and volatility if investors are risk averse. That is equity premium provides more compensation for risk when volatility is relatively high. In other words, investors require a larger expected returns from a security that is riskier. Yet empirical studies that attempt to test this important relation yield mixed results. Researchers such as French et al (1987), Chou (1988), Baillie and DeGennero (1990), Campbell and Hentschel (1993), Scruggs (1983) and Bensal and Lundblad (2002) got positive results while Nelson (1991), Glosen et al (1993), Campbell (1987) and Pegan and Hong (1991) found negative relationship.

Olowe(2009) has it that few studies have been done on stock market volatility. According to Emenike(2010), in Nigeria, the few published studies on modeling volatility of stock returns, include Ogun, Beer and Nouyrigat (2005), Jayasuriya(2002), Okpara and Nwezeaku (2009). Jayasuriya (2002) used 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) investigated 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 an positive asymmetric volatility, suggesting that positive shocks increase volatility more than negative shocks of an equal magnitude. Also, they showed that the Nairobi Stock Exchange return series indicate negative and insignificant risk-premium. Finally, they reported that the GARCH parameter (β) is statistically significant indicating volatility persistence in the two markets. Okpara and Nwezeaku (2009) examined 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 was used on the sample data to determine the beta and idiosyncratic risk for each of the companies; secondly, a cross-sectional estimation procedure was used employing EGARCH (1,3) model to determine the impact of these risks on the stock market returns. Their results revealed, 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. Engle, Lilien and Robins (1987) introduced the GARCH-in-Mean to examine relation between stock return and volatility to enable risk-return tradeoff to be measured. Other researchers following Engle, Lilien and Robins (1987) did the same study. However, there is mixed evidence on the nature of this relationship. It has been found to be positive as well as negative (Kumar and Singh, 2008). French, Schwert and Stambaugh (1987) used daily and monthly returns on the NYSE stock index to investigate the relation between risk and return. They found evidence that expected market risk premium is positively related to predictable volatility of stock returns.

Chou (1988) and Baillie and DeGennaro (1990) also found a positive relation between the predictable components of stock returns and volatility. Glosten et al.(1993) used data on the NYSE over April 1851 to December 1989, and found negative relationship between expected stock market return and volatility. However, Glosten , Jagannathan , Runkle (1993) used the data on the New York Stock Exchange to find negative relationship between expected stock market return and volatility. Bekaert and Wu (2000) reported asymmetric volatility in the stock market and negative correlation between return and conditional volatility. There are other studies on the relation between stock return and risk using other framework other than GARCH-in-Mean model., Campbell (1987) used an instrumental variables specification for conditional moments and founds negative risk-return tradeoff, Pagan and Hong (1991) used non-parametric techniques and found a weak negative relationship between risk and return. Harrison and Zhang (1999) found that the relationship between risk and return is significantly positive at longer horizons. Few studies have been done on stock market volatility in emerging markets. Leon (2007) investigated the relationship between expected stock market returns and volatility in the regional stock market of the West African Economic and Monetary Union called the BRVM. Using weekly data over the period 4 January 1999 to 29 July 2005, he found that expected stock return has a positive but not statistically significant relationship with expected volatility. They also found that volatility is higher during market booms than when market declines. Aggarwal, Inclan and Leal (1999) analyzed volatility in emerging stock markets during 1985-95. They identified the points of sudden changes in the variance of returns and examined the nature of events that cause large shifts in stock return volatility in these economies. Aggarwal et al found that mostly local events cause jumps in the stock market volatility of the emerging markets. Kim and Singal (1997) and De Santis and Imorohoroglu (1994) studied the behavior of stock prices following the opening of a stock market to foreigners or large foreign inflows. They found that there is no systematic effect of liberalization on stock market volatility. Hussain and Uppal (1999) examined stock returns volatility in the Pakistani equity market. He finds a strong evidence of persistence in variance in returns implying that shocks to volatility continue for a long period. However, after accounting for the structural shift due to opening of the market, the persistence was found to decline significantly. Barta (2004) examined the time variation in volatility in the Indian stock market during 1979-2003. He found that the period around the BOP crisis and the subsequent initiation of economic reforms in India is the most volatile period in the stock market. Sudden shifts in stock return volatility in India are more likely to be a consequence of major policy changes and any further incremental policy changes may have only a benign influence on stock return volatility. Olowe (2009) investigated the relation between stock returns and volatility in Nigeria using E-GARCH-in-mean model in the light of banking reforms, insurance reform, stock market crash and the global financial crisis. Volatility persistence, asymmetric properties and risk-return relationship are investigated for the Nigerian stock market. It was found that the Nigerian stock market, returns show persistence in the volatility and clustering and asymmetric properties. This similar result was found for other emerging market (Karmakar ,2005; Karmaka, 2006; Pandey, 2005; Leon, 2007; Kumar and Singh, 2008). The result also shows that volatility is persistent and there is leverage effect supporting the work of Nelson (1991) .The study found little evidence on the relationship between stock returns and risk as measured by its own volatility. The study found positive but insignificant relationship between stock return and risk. This positive relationship is consistent with most asset-pricing models which postulate a positive relationship between a stock portfolio's expected returns and volatility. Thus, the knowledge of a stock market volatility can help policy makers, investors and economic forecasters to predict the path of economy's growth while its structure can guide the investors on the quantity of stock to hold to achieve diversification (Krainer, 2002:1).

According to Badshar (2010), there are two existing hypotheses that characterize asymmetric volatility: the leverage and the volatility feedback hypotheses. The leverage hypothesis proposed by Black (1976) and Christie (1982) attributes asymmetric volatility to the leverage of the firm; when the financial leverage of a firm increases, the value of the firm declines, and the value of its equity declines further. Because the equity of a firm has the maximum exposure to the firm's entire risk, the volatility of the equity should increase as a result. On the other hand, the volatility feedback hypothesis proposed by French et al. (1987), Campbell and Hentschel (1992) and Bakaert and Wu (2000) attributes asymmetric volatility to the volatility feedback effect. Contrary to the leverage-based justification, the volatility feedback hypothesis states that increases in volatility trigger negative stock returns. For instance, an increase in volatility implies that the required expected future returns will also increase, thereby triggering declines in current stock prices. However, both hypotheses empirically fail under the daily frequency data, being unable to fully characterize the asymmetric return-volatility relationship; in that respect, Schwert (1990) argued that it is too strong for the leverage hypothesis to fully characterize asymmetric volatility. Furthermore, it is also empirically found that the feedback hypothesis is not always consistent, and this has become a controversial subject; some studies have found that there are not always positive correlations between current volatility and expected future returns (e.g., Breen *et al.,* 1989), but others support the hypothesis (e.g., French *et al.,* 1987; Campbell and Hentschel, 1992; Ghysels *et al.,* 2005). Badshah(2010) maintained that Nonetheless, the economic and accounting explanations might be important for characterizing the asymmetric return-volatility relationship at lower frequencies, for instance, monthly or quarterly data, but not for daily or higher frequencies. Many prior studies have documented very strong negative asymmetric return-volatility relationships at higher frequencies, contrary to the explanations of the two hypotheses (see, e.g., Fleming *et al.,* 1995; Whaley, 2000; Giot, 2005; Simon, 2003; Skiadopoulos, 2004; Low, 2004; Dennis *et al.,* 2006; Hibbert *et al.,* 2008). Poterba and Summers (1986) characterized the volatility feedback effect through economic explanation. The main underlying factor that induces the volatility feedback effect is the existence of time-varying risk premia, which serve as the link between fluctuations in volatility and returns.

3. Methodological Framework

The appropriate method(s) for the estimation of the models was necessary since misconception of this could lead to a result that would be fatal when invoked for policy making. In this study therefore**,** the researcher though followed the Worthington and Higgs (2004) approach of using several different tests to avoid spurious result which might arise from any of the tests from affecting the conclusions, relied heavily on the EGARCH in –mean.

Variance test, tests the null hypothesis that the variance of a series x is equal to a specified value σ^2 against the two-sided alternative that it is not equal to σ^2:

H_0: var(x) = σ^2

H_0: var(x) ≠ σ^2

Eviews reports a X^2 –statistic α computed β as

$$X^2 = \frac{(N-1)s^2}{\sigma^2}, \quad \sigma^2 = \frac{1}{N-1}\sum_{i=t}^{N}(R_{mt} - \bar{R}_{mt})^2$$

Where N is the number of observations and R is the sample mean of R. Under the null hypothesis and the assumption that R is normally distributed, the R^2 –statistic has a R^2 –distribution with N-1 degrees of freedom. The probability value is computed as min {p, 1 – p}, where p is the probability of observing a R^2 –statistic as large as the one actually observed under the null hypothesis. The summary statistics of the market returns were examined in order to determine the normality, autocorrelation and homoscedasticity condition of the market. The skewness statistic and the kurtosis of the summary statistics would enable us to determine the normality condition while the Ljung-box test statistics Q and Q^2 provided tests for the absence or presence of autocorrelation and hetroscedasticity. Skewness is a measure of asymmetry of the distribution of the series around its mean. Skewness is computed as:

$$sk = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{\sigma}{R_i - R}\right)^3$$

where σ is based on the biased estimator for the variance (Bickel and Doksum 1977:388). The Skewness of a symmetric distribution, such as the normal distribution, is zero. Positive skewness means that the distribution has a long right tail and negative skewness implies that the distribution has a long left tail. Kurtosis measures the peakedness or flatness of the distribution of the series. Kurtosis is computed as

$$K = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{R_i - \bar{R}}{\sigma}\right)^4$$

Where σ is estimator for the variance (Bickel and Doksum 1977, p.388). The kurtosis of the normal distribution is 3. if the kurtosis exceeds 3, the distribution is peaked (leptokurtic) relative to the normal; if the kurtosis is less than 3, the distribution is flat (platykurtic) relative to the normal. Jarque-Bera is a test statistic for testing whether the series is normally distributed. The test statistic measures the difference of the skewness and kurtosis of the series with those from the normal distribution. The statistic is computed as:

$$JB = \frac{N-K}{6}\left(S^2 + \frac{1}{4}(K-3)^2\right)$$

Where S is the skeweness, K is the kurtosis, and K represents the number of estimated coefficients used to create the series.

3.1. Model for Volatility of the Nigerian Stock Market

In the traditional finance literature, the expected volatility is approximated by σ_t^2, the conditional variance of R_t. The statistical measure that accomplishes this purpose is the variance of returns which is determined by the formula

$$\sigma^2_t = \sum_{t=1}^{\infty}\{R_t - E(R)\}P_j \qquad (1)$$

Equation 1 defines the variance as the weighted average of the squared deviations of the returns from their means. Assuming that there is an equal probability of each return occurring, the conditional variance method becomes

$$\sigma^2_t = \sum_{t=1}^{n}[R_t - E(R)]^2/n \qquad (2)$$

The greater the variance of a security return, the higher the security's total risk level and this is the volatility measure (French, 1987). With this formula in mind, one used the summary statistics to determine the variance/standard deviation of the returns. The traditional measure of volatility as represented by variance or standard deviation is unconditional and does not recognize that there are interesting patterns in asset volatility; e.g., time-varying and clustering properties (Olowe, 2009). In the light of the foregoing note, it is pertinent to explain the Generalized Autoregressive Conditional Hetroscedasticity (GARCH) model introduced by Bollerslev (1986) widely used in financial time series analysis as an alternate method. The estimation of the GARCH model involves the estimation of two distinct specifications, one for the conditional mean and the other for the conditional variance. The standard GARCH (1,1) model, specification is stated as follows.

$$Y_t = X_t\theta + \varepsilon_t \qquad (3)$$

$$\sigma_t^2 = \omega + \alpha\varepsilon^2_{t-1} + \beta\sigma^2_{t-1} \qquad (4)$$

Where (3) is the conditional mean equation with X_t as a vector of exogeneous variable with an error term ε_t. Equation (4) is the conditional variance σ_t^2 equation with

ω = the mean (constant)

ε^2_{t-1} = news about volatility from the previous period, measured as the lag of the squared residual from the mean equation (the ARCH term). σ^2_{t-1} = last period's forecast variance (the GARCH term) (1,1) in parenthesis refers to the presence of a first order GARCH and the first order ARCH term. If the conditional variance is introduced into the mean equation, the ARCH in mean (ARCH-M) model is derived. That is,

$$Y_t = X^1_t \gamma_1 + \gamma_2 \sigma^2_{t-1} + \varepsilon_t$$

which is often used in financial applications where the expected returns on an asset is related to the expected asset risk. It is however often the case that the conditional variance, σ^2_t is not an even function of the past disturbances, U_{t-1}, U_{t-2},…U_{t-n}, an important feature which is often observed when analyzing stock market returns (Koulakiotis, Papasyriopuolos and Molyneux, 2006). In order to arrest this important feature, Nelson (1991) proposed the exponential GARCH model with the assumption that ε follows a generalized error distribution. In his model, the log of conditional variance implies that the leverage effect is exponential, rather than quadratic and that forecast of the conditional variance are guaranteed to be nonnegative.

The model is specified as follows.

$$\text{In}\sigma^2_t = \omega + \beta\text{In}\sigma^2_{t-1} + \propto\left(\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} - \sqrt{\frac{2}{\pi}}\right) + \gamma\frac{\varepsilon_{t-1}}{\sigma_{t-1}} \qquad (7)$$

Where :- $\omega, \beta, \propto, \gamma$ are constant parameters,
$\text{In}\sigma^2_t$ = the one period ahead volatility forecast
ω = the mean level
β = persistence parameter
$\propto$ = volatility clustering coefficient
$\text{In}\sigma^2_{t-1}$ = the past period variance
γ = the leverage effect

Unlike the GARCH model, the EGARCH model allows for leverage effect. If γ is negative, leverage effect exists. That is unexpected drop in price (bad news) increases predictable volatility more than an unexpected increase in price (good news) of similar magnitude (Black, 1976; Christie, 1982). If α is positive, then the conditional volatility tends to rise (fall) when the absolute value of the standardized residuals is larger (smaller). In the analysis of the relationship between expected returns and expected volatility in the Nigerian stock market, the augmented version of the EGARCH-in-mean model following Leon (2008), Kulakiotis *et al.* (2006) is employed. The choice of this method stems from the fact that in a developing economy, the market consists of risk-averse investors as the opportunity to invest and diversify the investment is not much. Thus, the expected returns on asset should significantly move in the same direction with the expected risk of the asset. The return equation could therefore be stated as follows

$$R_t = b_0 + b_1R_{t-1} + b_2\sigma^2_t + \varepsilon_t \qquad (8)$$

Where

R_t = stock market returns at time t
R_{t-1} = last period return accounting for autocorrelation
σ^2_t = the conditional variance
$b_2\sigma^2_t$ = market rise premium for expected volatility
ε_t = the usual idiosyncratic term with zero mean and conditional variance σ^2_t.

This expected volatility which is approximated by the conditional variance σ^2_t is related to information set up such that

$$\sigma^2_t = \text{var}(R_t/\psi_{t-1}) \qquad (9)$$

Where

ψ_{t-1} is the information set at time, t-1 containing observations on lagged values of R_t and σ_t. That is $\psi_{t-1} = (\sigma_{t-1}, \sigma_{t-2}\ldots\ldots R_{t-1}, R_{t-2}\ldots\ldots)$

If the estimated variance can be used to predict expected returns in equation 1, then the value of b_2 should be positive and significant for a risk averse investor. That is to say that the higher the risk of an investment, the higher the reward accruable for having undertaken such a risky investment. The EGARCH-M model, a refinement of the GARCH model imposes a non-negativity constraint on market variance, and allows for conditional variance to respond asymmetrically to return innovations of different signs. Equations 3 and 4 were jointly estimated. The appeal of the models is that they capture both volatility clustering and unconditional return distributions with heavy tails (Mala and Reddy, 2007). To capture the most current priced activities and returns over time, the researcher resorted to using monthly data index running from January to December of each year from 1984 to 2009.

The monthly stock prices of the entire listed companies were used to obtain monthly stock returns over the period. The researcher therefore used the logarithm of relative prices multiplied by 100 to calculate continuously compounding monthly stock returns. According to Leon (2008) the use of logarithmic price changes prevents nonstationarity of the level of stock prices from affecting stock returns volatility. The computation is done as follows.

$$R_t = 100\ (\text{In}P_t / P_{t-1}) \qquad (10)$$

Where R_t = stock market returns
P_t = the stock market price index for the period t
P_{t-1} = the price index for the period t-1
Ln = the logarithm operator
This method is too common and has been used by so many authors (Rashid and Ahmad 2008, Leon 2008, Koulakiotis, Papasyriopoulos and Molyneux (2006), Kula, Amoo, Joseph-Raji (2007)

4. **Empirical Findings and Discussion**

The estimated risk returns variable results are presented in table 1 below.

Model	b_0	b_1	b_2	ω	β	α	γ
1	0.092558	-0.013269	0.593301	-	-	-	-
2	-0.029361	-0.019458	-	-1.485329	0.208616	1.507281	-0.275096

The model is the AR (1) – EGRACH (1, 1) – M with normally distributed error terms: z – statistics are in parentheses at the 5% level of significance.

The model is the AR(1) – EGRACH(1,1) – M with normally distributed error terms: z – statistics are in parentheses at the 5% level of significance.

The coefficient of the conditional variance is positive (0.593301) and insignificant (0.1111) for a risk averse investor implying that the forecast of this variance cannot be used to predict expected returns. This therefore suggests that investors are not rewarded for their exposure to risk. Thus, the Nigerian stock market returns are not affected by volatility trends and therefore have no predictive power for stock returns. This finding corroborates some past studies and at the same time contradicts others. In the first instance, it is in line with the findings of Nelson (1991), Glosten et al (2006), Leon (2008), Koulakiotis, Papasyriopoulos, Molyneux (2006) to mention a few. While it contradicts the finance theory which asserts that conditional expected returns should be positively and statistically significant in relation to conditional variance (Campbell an Hentschell, 1992). It also contradicts the findings of French (1987) Chou (1988), Baillie and De Gennero (1990) Harvey (1991), Turner et al (1989), Scrugges (1988) Bansal and Lundblad (2002) and the host of others. The persistent parameter β (0.208616) and/or (0.59300 - 0.007760= 0.58524) suggests that the degree of persistence is low and significant; meaning that increase in volatility is not likely to remain high over several periods. The absolute value of the standardized residual is larger and statistically significant thereby confirming the presence of volatility clustering. Conditional volatility tends to fall when the absolute value of the standardized residuals is larger. The leverage effect term (γ) in the output is negative and significant indicating the existence of leverage asymmetric effect in the Nigerian stock market during the period of study. That is an unexpected drop in price (bad news) increases predictable volatility more than unexpected increase in price (good news) of similar magnitude (Black, 1976, Christie, 1982).

Diagonostc test

	Raw series	Model
Mean deviation	-0.010845	0.149231
Standard deviation	0.380975	1.142824
Skewness	-10.57693	-8.959481
Kurtosis	139.9199	111.0661
Q_1	0.6157 (0.433)	0.6157 (0.433)
Q_{36}	10.340 (1.000)	10.340 (1.000)
Q^2_1	0.0071 (0.933)	0.0071 (0.933)
Q^2_{36}	0.4584 (1.000)	0.4584 (1.000)
J.B	247929.5 (0.000000)	154991.3 (0.000000)

The diagonastic check above is meant to verify whether the EGARCH (model) parameterization is mispecified as to be inappropriate for forecasting purposes. The Skewness and Kurtosis of the standardized residuals for the model are reduced though they still lead to a high valued Jarque – Bera statistics which indicate an improvement from that of raw series. Both skewness statistics show that the distribution is negatively skewed relative to the normal distribution (of 0 value). This in effect indicates a non symmetric series. The kurtosis is larger than 3, he Kurtosis for a normal distribution thereby suggesting that large market surprises of either sign are more likely to be observed at least unconditionally. Thus, all returns have fat tail or are Leptokurtic. The high value of kurtosis indicates that the normality (mesokurtic) hypothesis is rejected due to excess kurtosis. The Ljung – Box Q-statistics test for the absence of autocorrelation in the mean return series. The P – values of the Q^2 – statistics for the absence of hetroscedastcity range from 0.7 percent to 46 percent which is still insignificant. Thus, our diagnostic checks suggest that the models are fairly specified and can therefore be used for forecasting.

Conclusion

This study investigated the relationship between the stock market returns and volatility in Nigerian stock market using end of the month data over a span of twenty two years. The risk – return tradeoff was tested within an EGARCH – in – mean framework. The result reveals that the Nigerian stock market is volatile and that the forecast of variance cannot be used to predict expected returns Thus, investors in this market are not rewarded for their exposure to risk. The study also reveals that there exists a leverage asymmetric effect in the Nigerian stock market during the period of study. That is an unexpected drop in price (bad news) increases predictable volatility more than unexpected increase in price (good news) of similar magnitude.

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APPENDIX 1
DATA AND GRAPH PRESENTATION
Source: NSE Fact book (Various Issues)
Table 1: Month-End All-Share Index in Naira Values (1984-2009)

MONTH	1984	1985	1986	1987	1989	1988	1990
JANUARY	106.9	106.9	143.6	166.9	190.8	240	343
FEBRUARY	106.1	111.2	139.7	166.2	191.4	251	249.3
MARCH	107.2	113.4	140.8	161.7	195.5	259.9	356
APRIL	106.8	115.6	145.9	157.5	201	257.5	362
MAY	104.5	116.9	144.2	154.2	199.2	257.1	382.3
JUNE	104.3	116.3	147.4	196.1	206	259.2	417.4
JULY	105	117.2	150.9	193.4	211.5	269.2	445.4
AUGUST	107	116.9	151	193	217.6	281	463.6
SEPEMBER	104	119.1	155	194.9	223.8	279.9	468.2
OCTOBER	102	124.6	160.9	194.8	228.5	298.4	480.3
NOVEMBER	103.4	127.3	163.6	193.6	231.4	311.2	502.6
DECEMBER	105.5	128.4	163.8	190.6	233.6	325.3	513.8

MONTH	1992	1993	1994	1995	1996	1997	1998
JANUARY	794	1113.4	1666.3	2285.33	5135.07	7668.28	6435.62
FEBRUARY	810.7	1119.9	1715.3	2319.77	5180.36	7699.28	6426.17
MARCH	839.1	1131.1	1792.8	2551.13	5266.2	8661.38	6298.5
APRIL	844	1147.3	1845.8	2785.49	5412.35	8729.79	6113.9
MAY	860.5	1186.7	1875.5	3100.79	5704.12	8592.32	6033.9
JUNE	870.8	1187.5	1919.1	3596.17	5798.72	8459.29	5892.08
JULY	893.3	1188.8	1926.3	4314.27	5919.43	8148.8	5817.03
AUGUST	969.3	1195.5	1914.1	4664.61	6140.95	7681.99	5795.71
SEPEMBER	1022	1217.3	1956	4858.06	6501.88	7130.79	5697.67
OCTOBER	1076.5	1310.9	2023.4	5066.01	6634.78	6554.77	5671
NOVEMBER	1098	1414.5	2119.3	5095.16	6775.61	6395.76	5688.19
DECEMBER	1107.6	1548.8	2205	5092.15	6992.1	6440.51	5672.76

MONTH	2000	2001	2002	2003	2004	2005	2006
JANUARY	5752.9	8794.22	11031.95	13210.11	22712.88	23073.79	23679.44
FEBRUARY	5955.73	9180.53	10644.75	13623.36	25169.29	21953.5	23842.99
MARCH	5966.24	9159.83	11557.15	13762.5	22965.97	20682.37	23336.6
APRIL	5892.79	9591.58	11669.13	13390.09	26205.2	21961.7	23301.22
MAY	6095.35	10153.79	11657.11	14002.21	27505.64	21482.08	24745.66
JUNE	6466.72	10937.26	12618.82	14537.8	29098.89	21564.78	26161.15
JULY	6900.73	10576.43	12737.88	13992.86	27062.13	21911	27880.5
AUGUST	7394.05	10328.95	13005.05	15813.07	25076.12	22935.36	33096.37
SEPEMBER	7298.88	10274.16	12451.83	16252.67	22739.68	24635.91	32554.6
OCTOBER	7415.34	10091.44	12007.92	18874.21	23526.13	25873.81	32643.68
NOVEMBER	7141.43	11169.57	11628.19	20268.15	24155.43	24355.85	31632.54
DECEMBER	8111.01	10963.11	12137.72	19942.84	23844.45	24085.76	33189.3

Dependent Variable: RETURNS

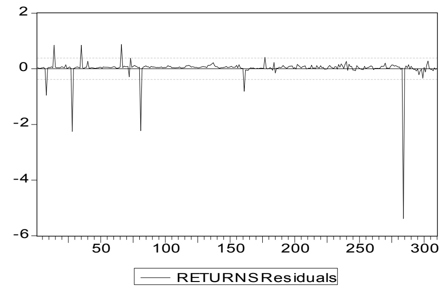
Dependent Variable: RETURNS
Method: ML - ARCH
Date: 06/27/11 Time: 14:02
Sample: 1 310
Included observations: 310
Convergence achieved after 26 iterations

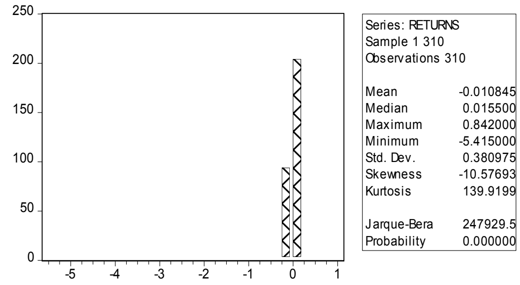
	Coefficient	Std. Error	z-Statistic	Prob.
RETURNSLAG	-0.013269	1.000542	-0.013262	0.9894
	Variance Equation			
C				0.092558
ARCH(1)	-0.007760	0.008717	-0.890285	0.3733
GARCH(1)	0.593301	0.372413	1.593126	0.1111
R-squared	-0.000852	Mean dependent var		-0.010845
Adjusted R-squared	-0.010664	S.D. dependent var		
S.E. of regression	0.383001	Akaike info criterion		
Sum squared resid	44.88707	Schwarz criterion		
Log likelihood	-147.4699	Durbin-Watson stat		

Dependent Variable: RETURNS

Dependent Variable: RETURNS
Method: ML – ARCH
Date: 06/27/11 Time: 07:48
Sample: 1 310
Included observations: 310
Convergence achieved after 52 iterations

	Coefficient	Std. Error	z-Statistic	Prob.
RETURNSLAG	-0.019458	6.93E-06	-2805.799	0.0000
C	-0.029361	4.70E-05	-624.3911	0.0000
	Variance Equation			
C	-1.485329	0.046854	-31.70132	0.0000
|RES|/SQR[GARCH](1)	-1.507281	0.043701	-34.49078	0.0000
RES/SQR[GARCH](1)	-0.275096	0.032447	-8.478255	0.0000
EGARCH(1)	0.208616	0.022953	9.088885	0.0000
R-squared	-0.002462	Mean dependent var		-0.010845
Adjusted R-squared	-0.018950	S.D. dependent var		0.380975
S.E. of regression	0.384568	Akaike info criterion		0.480518
Sum squared resid	44.95928	Schwarz criterion		0.552839
Log likelihood	-68.48031	Durbin-Watson stat		1.968286





Corrollologram of Standard Residual for the Model
Date: 06/27/11 Time: 11:12
Sample: 1 310
Included observations: 310

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	0.044	0.044	0.6157	0.433
.|. |	.|. |	2	-0.039	-0.041	1.0931	0.579
.|. |	.|. |	3	-0.031	-0.028	1.4053	0.704
*|. |	*|. |	4	-0.067	-0.066	2.8235	0.588
.|. |	.|. |	5	-0.016	-0.013	2.9067	0.714
.|. |	.|. |	6	-0.044	-0.049	3.5117	0.742
.|. |	.|. |	7	-0.042	-0.044	4.0867	0.770
.|. |	.|. |	8	-0.038	-0.044	4.5488	0.805
.|. |	.|. |	9	0.055	0.051	5.5252	0.786
.|. |	.|. |	10	0.025	0.009	5.7336	0.837
.|. |	.|. |	11	0.017	0.011	5.8227	0.885
.|. |	.|. |	12	0.013	0.008	5.8752	0.922
.|. |	.|. |	13	-0.020	-0.017	6.0071	0.946
.|. |	.|. |	14	-0.056	-0.056	7.0330	0.933
.|. |	.|. |	15	0.004	0.012	7.0393	0.957
.|. |	.|. |	16	0.018	0.017	7.1415	0.970
.|. |	.|. |	17	0.048	0.050	7.9075	0.968
.|. |	.|. |	18	0.015	0.006	7.9816	0.979
.|. |	.|. |	19	-0.012	-0.010	8.0329	0.986
.|* |	.|* |	20	0.067	0.069	9.5479	0.976
.|. |	.|. |	21	0.021	0.016	9.6987	0.983
.|. |	.|. |	22	0.007	0.012	9.7133	0.989
.|. |	.|. |	23	0.008	0.025	9.7374	0.993
.|. |	.|. |	24	-0.009	0.009	9.7642	0.995
.|. |	.|. |	25	-0.004	0.006	9.7699	0.997
.|. |	.|. |	26	0.006	0.010	9.7809	0.998
.|. |	.|. |	27	-0.019	-0.016	9.9011	0.999
.|. |	.|. |	28	-0.007	0.000	9.9196	0.999
.|. |	.|. |	29	0.002	-0.002	9.9206	1.000
.|. |	.|. |	30	-0.001	0.000	9.9207	1.000
.|. |	.|. |	31	0.022	0.025	10.094	1.000
.|. |	.|. |	32	0.006	0.000	10.107	1.000
.|. |	.|. |	33	0.019	0.018	10.237	1.000
.|. |	.|. |	34	0.016	0.020	10.325	1.000
.|. |	.|. |	35	0.007	0.007	10.340	1.000
.|. |	.|. |	36	-0.001	0.003	10.340	1.000

Corrollologram of standard Residual Squared for the Model
Date: 06/27/11 Time: 11:15
Sample: 1 310
Included observations: 310

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	-0.005	-0.005	0.0071	0.933
.|. |	.|. |	2	0.009	0.009	0.0312	0.984
.|. |	.|. |	3	-0.003	-0.003	0.0350	0.998
.|. |	.|. |	4	0.000	0.000	0.0350	1.000
.|. |	.|. |	5	-0.006	-0.006	0.0482	1.000
.|. |	.|. |	6	-0.006	-0.006	0.0590	1.000
.|. |	.|. |	7	-0.002	-0.002	0.0606	1.000
.|. |	.|. |	8	-0.003	-0.003	0.0628	1.000
.|. |	.|. |	9	-0.007	-0.007	0.0788	1.000
.|. |	.|. |	10	-0.009	-0.009	0.1027	1.000
.|. |	.|. |	11	-0.009	-0.009	0.1291	1.000
.|. |	.|. |	12	-0.007	-0.007	0.1444	1.000
.|. |	.|. |	13	-0.006	-0.006	0.1580	1.000
.|. |	.|. |	14	-0.001	-0.001	0.1585	1.000
.|. |	.|. |	15	0.002	0.001	0.1592	1.000
.|. |	.|. |	16	-0.008	-0.009	0.1827	1.000
.|. |	.|. |	17	-0.008	-0.009	0.2051	1.000
.|. |	.|. |	18	-0.008	-0.009	0.2286	1.000
.|. |	.|. |	19	-0.004	-0.004	0.2338	1.000
.|. |	.|. |	20	-0.005	-0.005	0.2415	1.000
.|. |	.|. |	21	-0.009	-0.009	0.2674	1.000
.|. |	.|. |	22	-0.010	-0.010	0.2986	1.000
.|. |	.|. |	23	-0.010	-0.010	0.3293	1.000
.|. |	.|. |	24	-0.009	-0.010	0.3589	1.000
.|. |	.|. |	25	-0.009	-0.010	0.3884	1.000
.|. |	.|. |	26	-0.009	-0.010	0.4190	1.000
.|. |	.|. |	27	-0.004	-0.004	0.4236	1.000
.|. |	.|. |	28	-0.003	-0.004	0.4276	1.000
.|. |	.|. |	29	-0.004	-0.005	0.4321	1.000
.|. |	.|. |	30	-0.003	-0.004	0.4357	1.000
.|. |	.|. |	31	-0.003	-0.004	0.4385	1.000
.|. |	.|. |	32	-0.003	-0.004	0.4425	1.000
.|. |	.|. |	33	-0.003	-0.005	0.4467	1.000
.|. |	.|. |	34	-0.004	-0.005	0.4513	1.000
.|. |	.|. |	35	-0.003	-0.005	0.4553	1.000
.|. |	.|. |	36	-0.003	-0.004	0.4584	1.000

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