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# Asymmetric Volatility of Daily Stock Market Returns: Further Evidence from Nigeria

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***Abstract:***
*In this study, we considered the asymmetric return-volatility relationship in the Nigerian stock market using 3179 daily market returns data for the period from 14th January 2003 to 31st December 2015. Two asymmetric GARCH models are employed; namely the TGARCH of Zakoian (1994) and the Power GARCH model of Ding, Granger and Engle (1993). We also assume that errors follow student-t distribution. BFGS optimization method with Marquardt procedure is employed to maximize the loglikelihood function. The risk-return relationship is also examined using the GARCH-in-mean framework suggested by Engle, Lilien and Robins (1987). Consistent with the recent findings of Ezirim, Nnaji and Ezirim (2017), the results of both TGARCH and PGARCH models show that there is no significant asymmetric volatility in the Nigerian stock market. Thus, returns and volatility are symmetrically related. The results also show that despite the high volatile nature of the Nigerian stock market, investors are not sufficiently rewarded. We therefore, conclude that both TGARCH and PGARCH models are not significantly different from the standard GARCH models in describing the time-varying properties of daily market returns in Nigeria.*

***Keywords:*** *Asymmetric volatility, TGARCH, PGARCH, student -t distribution*

## 1. Introduction

One of the empirical regularities of stock returns is that volatility exhibits asymmetric effects. Asymmetric volatility is the tendency for good news to increase returns volatility than bad news of the same magnitude (Black, 1976; Christie, 1982; Nelson, 1991).This asymmetric volatility was first reported by Black (1976) and Christie (1982) who attributed it to changes in the debt to equity ratio of firms. According to this position, a sudden fall in a firm's stock price would force the firm to immediately adjust its financial leverage position, thus, making its stock riskier and consequently increasing the volatility of its stock returns.

The asymmetric volatility is first modelled under the GARCH framework by Nelson (1991) in his well celebrated EGARCH (Exponential GARCH) model. Unlike the standard GARCH model which ignores this important property of asset returns, the EGARCH model incorporate the asymmetric parameter in the conditional variance process to capture the asymmetric effect on the return-volatility relationship. Since then, other several GARCH variant models have been introduced to capture the asymmetric effect in the volatility process. Among these models are the Threshold GARCH model of Zakoian (1994) and Power GARCH model of Ding, Granger and Engle (1993).

Using different GARCH variants models, several empirical studies have focused on the asymmetric effect on returns-volatility relationship at both firm level and market level in developed and developing countries. However, there are inconclusive results. While some studies find evidence that good news increases volatility than bad news (Aliyu, 2010; Emenike& Alake, 2012), others find evidence that bad news increases volatility than good news (Abdalla & Winker, 2012; Emenike, 2010; Jegajeevan, 2010; Okpara &Nwezeaku, 2009; Olowe, 2009). Yet, there are other studies that report evidence of no asymmetric volatility. This paper contributes to the on-going debate in the literature by considering the asymmetric return-volatility relationship in the Nigerian stock market using daily market returns data. The study employs two asymmetric GARCH models; namely, the TGARCH and the PGARCH models, assuming that errors follow the student t distribution. Most of the previous Asymmetric studies in Nigeria are based on normal distribution of errors.

The remainder of this study is structured as follows: The next section provides the theoretical and empirical literature review. Section 3 describes the data, models and distributional assumptions, section 4 provides empirical analysis and results and the study is concluded in section 5.

## 2. Literature Review

According to Nelson (1991), stock returns exhibit asymmetric volatility effects which is the tendency for negative shocks to increase volatility than positive shocks of the same magnitude. This asymmetric volatility effectoriginated from the works of Black (1976) and Christie (1982) who attributed it to changes in firm's financial leverage. According to these authors, a large fall in a firm's stock price would increase its financial leverage, which would in turn increase the volatility of its returns. Earlier influential studies that modelled this stylized fact within the GARCH framework include Schwert (1989), Nelson (1991), Glosten, Jagannathan and Runkle (1993), Ding, Granger and Engle (1993), Zakoian (1994),Engle and Ng (2003), and Bollerslev, Litvinova and Tauchen (2006). They all find evidence of asymmetric effect instock market volatility shocks.

Using daily market data for two European indices; FTSE 100 and DAX 30, Peters (2001) considered the forecasting performance of four GARCH models; GARCH (1, 1), EGARCH (1, 1), GJR GARCH (1, 1) and PGARCH (1, δ, 1), based on three different distributions; normal, student-t and skewed student-t. The study covered a period of fifteen years from 02/01/1986 to 29/12/2000 and the results show that asymmetric models provide a better fit for the two markets, and that GJR GARCH and APARCH models both outperform the EGARCH model.

Abdalla and Winker (2012) investigated the stock returns-volatility relationship in two African stock markets, namely, the Sudanese and Egyptian markets under the GARCH framework using different univariate GARCH models; the standard GARCH, GARCH-M, EGARCH, TGARCH and PGARCH models. The sample consists of daily indices for the two countries covering from January 22, 2006 to November 30, 2010. The results show amongst others that leverage effect is presence in both the Sudanese and Egyptian markets. However, the PGARCH model failed to provide evidence of leverage effect in the Egyptian market.

Using both daily and monthly returns data, Jegajeevan (2010) examined the nature of returns-volatility relationship in the Colombo stock market between January 1998 and June 2009,with the focus being on persistence in volatility shocks, risk-return relationship and asymmetry in volatility shocks. The results from three basic GARCH models (the standard GARCH, EGARCH GARCH-M) show that although, daily returns exhibit both volatility persistence and asymmetry in volatility shocks there was no evidence of a significant risk-return relationship in the Colombo stock market.

In Nigeria, Okpara and Nwezeaku (2009) considered the firm-level risk-return relationship for 41 randomly selected companies in Nigeria using EGARCH (1, 3) model. The results show amongst others that asymmetric leverage effect is present in the Nigerian stock market. Similarly, Okpara (2011) considered the relationship between market returns and volatility in the Nigerian market using EGARCH-M model, using monthly data from 1984 to 2009. The results show that although volatility shocks are asymmetric in nature, returns are not significantly related to risk in the Nigerian stock market.

Olowe (2009) studied the returns-volatility relationship in Nigeria in the light of banking reform, insurance reform, stock market crash and global financial crisis using daily data ranging from January 2, 2004 to January 16, 2009. The results based on using EGARCH-M model suggest amongst others that leverage effect is present in the Nigerian market, and that there is a positive but in significant risk-return relationship in Nigeria.

Emenike (2010) fit both the standard GARCH and GJR GARCH models to monthly returns in Nigeria between January 1985 and December 2008. The results show amongst others that leverage effects is present in the Nigerian stock stock market.

Onwukwe, Bassey and Isaac (2011) examined the behaviour of daily stock returns for four quoted companies in Nigeria; namely, UBA, Unilever, Guinness and Mobil, between January 2, 2002 and December 31, 2006 using three GARCH models which include the basic GARCH, EGARCH and GJR GARCH models. The results provide amongst others evidence leverage effects and volatility persistence in the Nigerian Stock market.

Emenike and Alake (2012) considered the response of volatility to positive and negative news using GARCH (1, 1) model, EGARCH (1, 1) model and GJR GARCH (1, 1) model. They used daily stock return series of the Nigeria stock exchange (NSE ASI) for the period 2nd January 1996 through 30th December 2011. The results show that positive shocks have higher effects on predictable volatility than negative shocks of the same magnitude. This implies that contrary to asymmetric leverage effect that negative shocks have more impact on stock return volatility than positive shocks of the same magnitude; their results provided no evidence of such leverage effect. This result is consistent with earlier results of Aliyu (2010). He considered the impact of inflation on stock market returns and volatility using GARCH (1, 1) model and QGARCH (1, 1) model. They used monthly return series of the Nigeria stock exchange (NSE ASI) and Ghanaian stock exchange (GSE) from 1998 to 2010. The results show weak support for leverage effects in Nigeria. In the case of Ghana, the results provide evidence that positive shocks have higher impact on volatility than negative shocks of the same magnitude.

Recently, Ezirim, Nnaji and Ezirim (2017) considered the asymmetric return-volatility relationship in the Nigerian stock market within the GARCH framework using both daily and weekly data ranging from 14/01/2000 to 31/01/2013. The study was based on three asymmetric GARCH models; EGARCH, TGARCH and PGARCH models, with the assumption that errors follow a generalized error distribution. The main issue addressed in the study is whether volatility feedback is the cause of the observed asymmetry in volatility shocks in the Nigerian stock market. The study found that there is a positive relationship between market returns and its volatility, and that asymmetric volatility is present in the Nigeria stock market only when weekly returns are considered.

## 3. Methodology

### *3.1. Data*

The data used consist of 3179 daily market data from 14th January, 2003 through 31st December 2015 collected from Cash craft via www.cashcraft.com. All analyses are done in EViews 9. The price data were converted into compounded returns by taking logarithms:

$$R_t = \log\left(\frac{P_t}{P_{t-1}}\right) \quad (1)$$

where $R_t$ is the current market returns, $P_t$ is the current market index price, $P_{t-1}$ is the previous market index price, and log is the logarithm. Figures 1 and 2 show graphical plots of daily market prices and returns over the period under study.

As we can observe from figure 1, the movement of market index was not smooth. Initially, the index fluctuated around its mean, but later it showed a steady increase, and finally it showed a steady decrease. This suggests that a considerable volatility was recorded over the sample period. To make the picture clearer, figure 2 shows that volatility is high in some periods and low in other periods. In order words, volatility clustering is present in the Nigerian stock market.

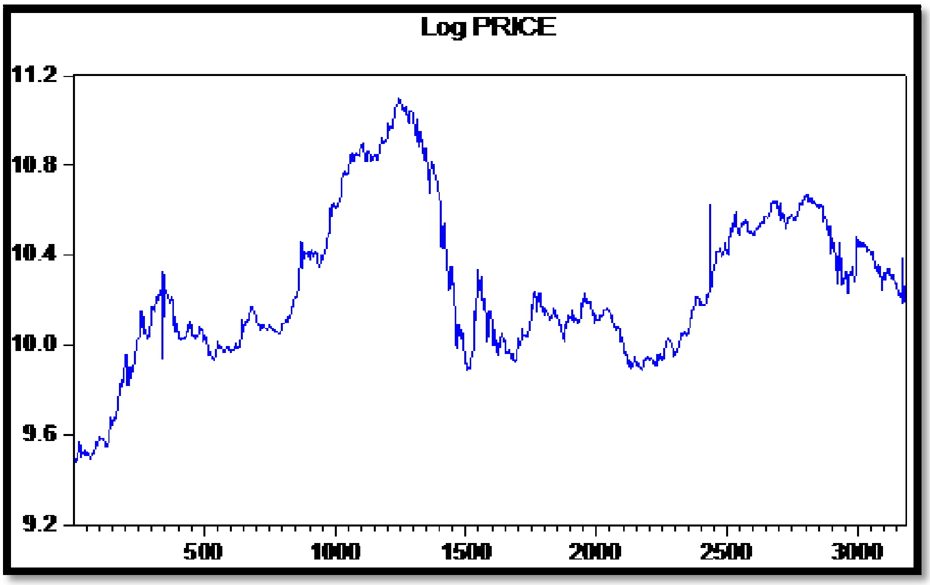


*Figure 1: Daily Log Prices of NSE ASI*

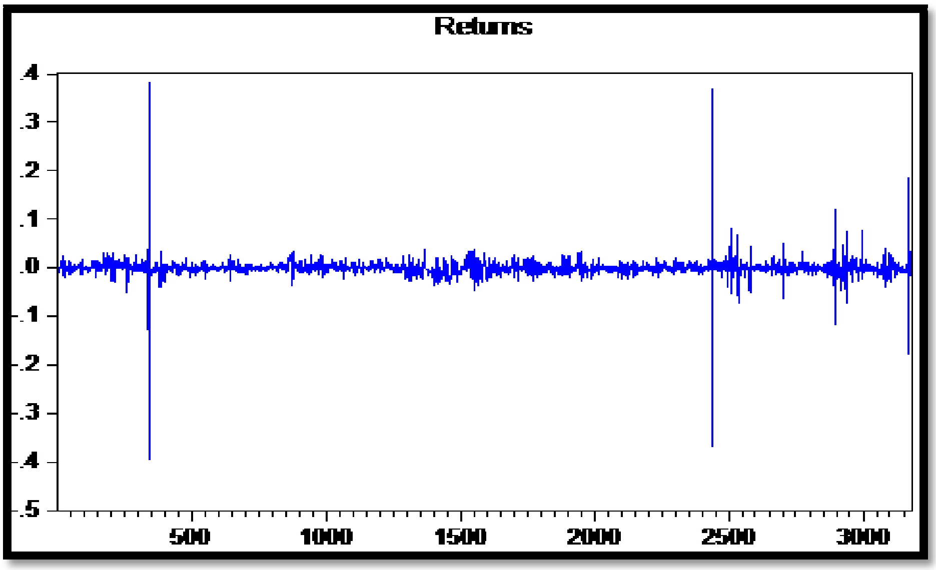


*Figure 2: Market Returns*

*3.2. Models*

To examine the asymmetric volatility of the Nigerian stock market return series, we employ the Threshold GARCH model suggested independently by Zakoian (1994), and the Power GARCH model suggested by Ding, Granger and Engle (1993). The success of each of these models in capturing the asymmetry in the return-volatility relations is well documented in the literature. The mean equation is specified as:

$$R_t = \theta + \gamma\sigma_t^2 + \epsilon_t \qquad (1)$$

where $\epsilon_t$ is error term. Consistent with the GARCH-M model of Engle, Lilien and Robins (1987), we include the conditional variance in the mean equation so that the coefficient $\gamma$ captures the return-volatility relationship in the Nigerian stock market.

The standard TGARCH specification is given by:

$$\sigma_t^2 = \psi + \alpha\epsilon^2_{t-1} + \lambda.d_{t-1}\epsilon^2_{t-1} + \beta\sigma^2_{t-1} \qquad (2)$$

where $d_{t-1} = 1$ if $\epsilon_{t-1} < 0$ and 0 otherwise.

In the specification at (2), positive shocks and negative shocks have different impacts on conditional variance $\sigma_t^2$. There is positive shock if $\epsilon_{t-1} > 0$ and negative shock if $\epsilon_{t-1} < 0$. The effect of positive shock is $\alpha$ while the effect of bad news is $\alpha + \gamma$. Thus, asymmetric effect is present if $\lambda \neq 0$, and leverage effect is present if $\lambda > 0$. However, if $\lambda = 0$, then the TGARCH model is a standard GARCH model of Bollerslev (1986) and Taylor (1986).

The standard PGARCH specification is given by:

$$\sigma_t^{\delta} = \psi + \alpha(|\epsilon_{t-1}| - \lambda\epsilon_{t-1})^{\delta} + \beta\sigma^{\delta}_{t-1} \qquad (3)$$

where $\delta > 0$ and $\lambda$ is the coefficient of asymmetric coefficient. The PGARCH model at (3) is very flexible and attractive because the power parameter $\delta$ can be estimated rather than imposed. According to Ding, Granger and Engle (1993), the PGARCH model includes several other ARCH/GARCH variants as its special cases. For example, the model is a TGARCH specification if $\delta = 2$ and the standard GARCH specification of Bollerslev (1986) if $\delta = 2$ and $\lambda = 0$. Asymmetric effect is present if $\lambda \neq 0$.

*3.3. Methods and Distributional Assumptions*

The specification of GARCH and its variant models require an assumption about the conditional distribution of the errors. Here, we assume that errors follow a studentt distribution. Thus, the log likelihood function to maximise this assumption is given by:

$$L_t = -\frac{1}{2}\log\left(\frac{\pi(v-2)\Gamma(v/2)^2}{\Gamma(v+1)/2)^2}\right) - \frac{1}{2}\log\sigma_t^{2} - \left(\frac{v+1}{2}\right)\log\left(1 + \frac{\epsilon_t^{2}}{\sigma_t^{2}(v-2)}\right) \qquad (4)$$

where; $L_t$ is the loglikelihood function, $\sigma_t^2$ is the conditional variance and $\varepsilon_t^2$ is the square of error term. The degree of freedom $v > 2$controls the tail behaviour. The t-distribution approaches the normal as $v \infty 2$ (EViews, 2015).The BFGS method of optimization is employed to maximize the loglikelihood function using the Marquardt procedure.

## 4. Data Analysis and Results

*4.1. Summary Statistics*

Some summary statistics which describe the distributional features of the returns data are presented in table 1. As this table shows, the mean market returns for the period under study were 0.02%, with a standard deviation of 1.8%, suggesting that the market was highly volatile over the sample period. The huge difference between the maximum and minimum further shows evidence of high variability of market returns. The negative skewness (= -0.27) and the large excess kurtosis (= 236.58) are features of the data that are clearly observed. Thus, the market index decreases more often than it increases, and there are more data extremes. The large Jarque-Bera value of 16835048 with a zero p-value confirms the non-normality of the distribution of market returns.

| Statistic | Value |
|---|---|
| Mean | 0.000247 |
| Maximum | 0.381842 |
| Minimum | -0.395684 |
| Std. Dev. | 0.018381 |
| Skewness | -0.273828 |
| Kurtosis | 236.5807 |
| Jarque-Bera | 7226961. |
| Probability | 0.000000 |

*Table 1: Descriptive Statistics*

*4.2. Testing for ARCH Effects*

Examining the data for possible presence of heteroskedasticity or ARCH effects is usually the first step in estimating GARCH type models. The result of the Engle (1982) ARCH LM test on market returns is presented in table 2. As expected, the value of the test statistic is considerably high with zero probability, suggesting clear evidence of ARCH effects in the market returns data. This implies that GARCH models can be fitted to our data.

| ARCH LM Test | Value |
|---|---|
| F-statistic | 244.490 (0.0000) |
| $TR^2$ | 1382.836 (0.0000) |

*Table 2: Test for ARCH Effects*

*4.3. The Estimation Results for TGARCH Model*

The estimation results for the standard TGARCH model are shown in table 3. As we can see, the degree of freedom parameter estimate for the student t distribution is greater than 2 and is highly significant ($v = 3.50$, p-value = 0.0000), suggesting that the distribution of the conditional errors is indeed non-normal. For the mean equation, the risk-premium coefficient ($\gamma$= 0.024, p-value = 0.6485) which captures the return-volatility relationship is positive but insignificant, suggesting that investors are not adequately rewarded for taking additional risks in the Nigerian stock market. The AR term is positive and highly significant, evidence that daily market returns data are generated by an autoregressive process. For the variance equation, both ARCH ($\alpha = 0.537$, p-value = 0.0000) and GARCH ($\beta$= 0.388, p-value = 0.0000) terms are positive and highly significant, suggesting that conditional variance is generated by an ARCH/GARCH process. However, the asymmetric term($\lambda$ =-0.0018, p-value = 0.9840) is negative but not significant, suggesting that although, there is tendency for bad news to increase volatility than good news of equal magnitude, the TGARCH model is however, not significantly different from the standard GARCH model of Bollerslev (1986) and Taylor (1986). Both the ARCH LM and Q-statistic are associated with very high probabilities, suggesting evidence that both ARCH effects and autocorrelation are no longer present in the estimated TGARCH model. Thus, the model has no specification problem.

| Parameter | Estimate | Standard Error | p-Value |
|---|---|---|---|
| Mean Equation | | | |
| $\gamma$ | 0.024759 | 0.054318 | 0.6485 |
| $\theta$ | -8.63E-05 | 0.000288 | 0.7644 |
| AR(1) | 0.384374 | 0.016885 | 0.0000 |
| Variance Equation | | | |
| $\psi$ | 2.55E-05 | 2.85E-06 | 0.0000 |
| $\alpha$ | 0.537370 | 0.076138 | 0.0000 |
| $\lambda$ | -0.001879 | 0.093528 | 0.9840 |
| $\beta$ | 0.388789 | 0.031303 | 0.0000 |
| t. Dist DoF (v) | 3.500300 | 0.195361 | 0.0000 |
| ARCH LM (1) | 0.0018 (0.9655) | Q(10) | 10.217 (0.333) |

*Table 3: Estimates of TGARCH Model*

### *4.4. The Estimation Results for PGARCH Model*

The estimation results for the standard PGARCH model are shown in table 4. As we can see, the results are largely comparable with those of the TGARCH in table 3, with the degree of freedom parameter estimate for the student t distribution being greater than 2 and highly significant (v = 3.50, p-value = 0.0000).This confirms that the conditional errors follow a student-t distribution. The conditional variance ($\gamma$ = 0.024, p-value = 0.6383c) in the mean equation also has positive insignificant coefficient, confirming that investors are not adequately rewarded for taking additional risks in the Nigerian stock market. The positive and highly significant of ARCH ($\alpha$ = 0.453, p-value = 0.0000) and GARCH ($\beta$= 0.472, p-value = 0.0000) terms in the variance equation confirms that conditional variance is generated by an ARCH/GARCH process. Also, like the case of the TGARCH model, the asymmetric term ($\lambda$ =-0.003, p-value = 0.9489) is negative but insignificant, suggesting that the PGARCH model is also not significantly different from the standard GARCH model of Bollerslev (1986) and Taylor (1986). The estimated PGARCH model is well behaved as both the ARCH LM statistic and Q-statistic are insignificant. Thus, both ARCH effect and autocorrelation are no more present in the estimated PGARCH model.

| Parameter | Estimate | Standard Error | p-value |
|---|---|---|---|
| Mean Equation | | | |
| $\gamma$ | 0.024822 | 0.052802 | 0.6383 |
| $\theta$ | -9.00E-05 | 0.000284 | 0.7511 |
| AR(1) | 0.381392 | 0.016720 | 0.0000 |
| Variance Equation | | | |
| $\psi$ | 0.000249 | 0.000202 | 0.2176 |
| $\alpha$ | 0.453079 | 0.047493 | 0.0000 |
| $\lambda$ | -0.003060 | 0.047748 | 0.9489 |
| $\beta$ | 0.472257 | 0.037154 | 0.0000 |
| $\delta$ | 1.487150 | 0.176960 | 0.0000 |
| t. Dist DoF (v) | 3.505384 | 0.195361 | 0.0000 |
| ARCH LM (1) | 0.0018 (0.8919) | Q(10) | 11.989 (0.214) |

*Table 4: Estimates of PGARCH Model*

## 5. Conclusions

In this study, we considered the asymmetric return-volatility relationship in the Nigerian stock market using 3179 daily market returns data for the period from 14th January 2003 to 31st December 2015. Consistent with the recent findings of Ezirim, Nnaji and Ezirim (2017), the results of both TGARCH and PGARCH models show that there is no significant asymmetric volatility in the Nigerian stock market. Thus, returns and volatility are symmetrically related. These findings however, contradict most of the previous studies both in developed and developing countries. The results also show that despite the high volatile nature of the Nigerian stock market, investors are not sufficiently rewarded. We therefore, conclude that both TGARCH and PGARCH models are not significantly different from the standard GARCH models in describing the time-varying properties of daily market returns in Nigeria.

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