An Application of Asymmetric GARCH Models on Volatility of Banks Equity in Nigeria's Stock Market

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This paper examines the volatility of banks equity weekly returns for six banks (coded B1 to B6) using GARCH models. Results reveal the presence of ARCH effect in B2 and B3 equity returns. In addition, the estimated models could not find evidence of leverage effect. On evaluating the estimated models using standard criteria, EGARCH (1, 1) and CGARCH (1, 1) model in Student's t-distribution are adjudged the best volatility models for B2 and B3 respectively. The study recommends that in modelling stock market volatility, variants of GARCH models and alternative error distribution should be considered for robustness of results. We also recommend for adequate regulatory effort by the CBN over commercial banks operations that will enhance efficiency of their stocks performance and reduce volatility aimed at boosting investors' confidence in the banking sector.

Keywords: Equity, Volatility, Stock Market Returns

JEL Classification: C22, C52, C58, G12, G21

1.0 Introduction

The financial sector plays an important role in providing and channelling finance for investment. Beyond providing short-term finance for day-to-day operations of businesses and other temporary cash requirements, financial institutions, capital markets and institutional investors are also sources of long-term finance. Traditionally, banks play a vital role in the financial system since they help to finance private sector investments (OECD, 2013). Stock market volatility is a measure of the variance of the price of a financial asset over time. Market volatility is critical to investors since it provides information on the uncertainty of an asset (Hongyu and Zhichao, 2006). The volatility of an asset guides investors in their decision making process because investors are interested in returns and their uncertainty (Arestis et al, 2000: Mala and Reddy, 2007).

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The specification of appropriate volatility model for capturing variations in stock returns is important as it helps investors in their risk management decision and portfolio adjustment (Atoi 2014). Engle (1982) proposed the Autoregressive Conditional Heteroscedastic (ARCH) model to capture volatility of stock returns. Bollerslev (1986) and Taylor (1986) proposed the Generalized Autoregressive Conditional Heteroscedastic (GARCH) model. Several other GARCH models have been proposed to capture asymmetric properties of volatility such as the EGARCH, TGARCH, and PARCH, etc. These models have been used in literature to model conditional variance (volatility), see for example, Hamilton (2010), Shamiri and Isa (2009). Different specifications of these models have been applied in empirical literature to model the conditional variance of financial time series. For example, in Nigeria, symmetric and asymmetric GARCH models have been employed to model volatility of stock market returns (see Ogum et al. (2005), Olowe (2009), Ade and Dallah (2010), Kalu (2010) and Mishra (2010)). Emenike and Ani (2014) applied the GARCH model to the volatility of the banking sector indices in Nigeria.

Banks use models of volatility to measure the riskiness of their assets for the purposes of risk weighting and to value assets. It is very important to develop policies with respect to suitable bank models in order to foster an environment for better dynamics for SMEs lending and a lower cost of capital, which is critical for long-term investment decisions[2]. Therefore, this paper investigates volatility of six commercial banks listed in the Nigerian stock exchange while considering different error assumptions. Since the results of the analysis will be sensitive to monetary institutions in Nigeria, we therefore coded the banks as B1, B2, B3, B4, B5, and B6. Specifically, the paper considers the contribution of error assumptions in volatility modelling of the bank equities for robustness of results. The banks selected are among the top 25 banks in Africa and also featured in the top 1000 banks in the world with the exception of B5[3.] In order to eliminate the effect of 2008/2009 global financial crisis from distorting

[2] www.oecd.org/finance/lti

[3] http://www.vanguardngr.com

the results of the analyses, the data used spanned from January 4, 2010 to June 30, 2016.

An exploration of some empirical literature in Nigeria reveals that modelling volatility of Nigeria's bank equities remains a lacuna to be filled as it has not received much attention from most empirical studies on volatility despite the fact that it is one of the most actively traded sectors in NSE and also contribute immensely to market capitalization. Hence, one of the contributions of this paper is to fill this gap by providing empirical evidence on modelling conditional volatility of bank equities. In addition, some empirical literature in Nigeria do not give credence to other error distribution apart from normal distribution. However, studies have shown that financial time series are characterized with fat-tail. Therefore, this study is an attempt to fill these gaps in the empirical literature by using variants of error distributions. The rest of the paper is structured as follows: Section 2 reviews related theoretical and empirical literature, section 3 presents r the methodologies and their statistical properties, section 4 deals with data and presentation of results of the analysis, while section 5 concludes the study with Policy implications of findings.

2.0 Literature Review

Several researches have shown evidence that stock returns display volatility clustering, leptokurtosis and asymmetry. Volatility may disrupt the smooth working of the financial system and greatly affect economic performance (Rajni and Mahendra, 2007; Mollah, 2009). Engle (1982) was the first to show that conditional heteroscedasticity can be modelled using an autoregressive conditional heteroscedasticity model (ARCH) model. Engle (1982) noted that in estimating the parameters of ARCH model, the maximum likelihood is more efficient. Practitioners are often confronted with over-parameterization problem in empirical applications of the ARCH (q) model. Bollerslev (1986) introduced the generalized ARCH (p, q) model, the GARCH (p, q) is used to solve the problem of over-parameterization usually associated with ARCH (q) model. Bollerslev (1986) argued that a simple GARCH model provide a better fit than an ARCH model with a relatively long lag. Bollerslev and Taylor

(1986) proposed an extension of ARCH model with an Autoregressive Moving Average (ARMA). It has been observed that most of the empirical application of ARCH/GARCH models have been in the study of financial time series (see, Bollerslev and Woodridge (1992), Hamilton (2010)). The GARCH (1,1) model captures symmetry in volatility, but empirical evidence suggests that time-dependent asymmetry is a major component of volatility dynamics (Hsieh 1991). In an efficient market, the ARCH parameter is seen as news coefficient, while the GARCH parameter is viewed as the persistence coefficient.

Modifications to the original GARCH model were proposed to overcome the perceived problems with standard GARCH (p, q) models. Firstly, the non-negativity constraint may be violated in practical applications. Secondly, GARCH models cannot account for asymmetric effect of volatility. To overcome these shortcomings, some extensions of the original GARCH model have been introduced. The asymmetric GARCH family models such as: Threshold GARCH (TGARCH) proposed by Zakoian (1994), Exponential (EGARCH) proposed by Nelson (1991) and Power GARCH (PARCH) proposed by Ding et al. (1993).

For equities, it is often observed that downward spirals in the market are preceded by greater volatility than upward spirals of the same size. Hence, to model this effect, Zakoian (1994) introduced the threshold GARCH (TGARCH) model to account for leverage effect. To account for asymmetry in volatility (leverage effect), the TGARCH model allows the conditional variance to depend on the sign of lagged innovation. The exponential GARCH (EGARCH) model by Nelson (1991) permits asymmetric effects between positive and negative assets returns. EGARCH model specifies volatility in the form of logarithmic transformation. Hence, there are no restrictions on the parameters to ensure the non-negativity of the variance and also on the sign of the model parameters (Ma Jose, 2010; Atoi, 2014). Taylor (1986) and Schwert (1989) proposed the standard deviation GARCH model. Ding et al. (1993) further generalized the standard deviation GARCH model and called it Power GARCH (PGARCH). In this model, the conditional standard deviation raised to a power (positive exponent) is a function of the lagged conditional standard deviations and the lagged absolute innovations raised to the same power.

The traditional assumption of normality in modelling financial time series could weaken the robustness of parameter estimates. Nelson (1991) noted that a student's t could mean infinite unconditional variance for the errors. Hence, an error distribution with a more fat-tailed than normal will help to increase the kurtosis at the same time reduce the serial correlation of the squared observations. Malmsten and Terasvirta (2004) argue that first order EGARCH model in normal error is not sufficiently flexible enough for capturing kurtosis and autocorrelation in stock returns. MaJose (2010) noted that the stationarity of TGARCH depends on the distribution of the disturbance term, which is usually assumed to follow Gaussian or Student's t.

Ogum et al. (2005) examined the volatility of Nigeria's stock market returns series. They fitted EGARCH model to the series, and the results showed the presence of asymmetric volatility in the Nigerian stock market. Olowe (2009) researched the relationship between stock market returns and volatility using an EGARCH-M model based on insurance and banking reforms, stock market collapse and the global financial crisis. The results revealed some evidence of relationship between volatility and stock returns, the impact of banking reforms and market crash was found to be negative, and insurance reforms and financial crisis had no effect on stock returns. Emenike (2010) examined the leverage effects, volatility persistence and asymmetries of returns by fitting GARCH (1, 1) and GJR-GARCH (1, 1) models to the monthly NSE All-share-index. The findings of the study showed that returns process is characterized by fat-tail, leverage effects and volatility persistence. Suleiman (2011) employed daily market capitalization index of the Nigerian stock market to assess the robustness of stock market returns volatility and its effect on capital market performance. The study utilized the ARCH/GARCH models to estimate the conditional variance of returns series. The findings from the study showed the presence of volatility in the conditional variance as well as long-term volatility persistence in the stock market.

Ade and Dallah (2010) examined the conditional variance of daily stock returns of the Nigeria's insurance stocks utilizing twenty six insurance companies' daily data for the estimation. EGARCH (1, 1) was found to be more efficient in modelling stock returns as it outperforms ARCH (1), GARCH (1, 1) TARCH (1, 1) in terms of model evaluation criteria and out-of-sample volatility forecasting. Bala and Asemota (2013) examined exchange-rate volatility with GARCH models using monthly exchange-rate returns series. They compared variants of GARCH models with and without volatility breaks and recommended the inclusion of important events in the estimation of GARCH models. Babatunde (2013) examines the contributions of Nigeria's stock market volatility on economic growth using EGARCH model. The study reveals that the volatility shock is quite persistent and this might distort economic growth of Nigeria.

Kosapattarapim et al. (2012) evaluated the volatility forecasting performance of best fitting GARCH models in emerging Asian stock markets using the daily closing price data from Thailand (SET), Malaysia (KLCI) and Singapore (STI) stock exchanges by simulating six studies in GARCH(p, q) with six different error distributions. Findings from the simulations shows that the volatility forecast estimates of the best fitted model can be used for volatility forecasting confidently. Kalyanaraman (2014) examined the conditional volatility of Saudi stock market by employing AR (1)-GARCH (1, 1) model to the daily stock returns data. The findings of the study showed that returns process is characterized by time varying volatility, volatility clustering, persistence, and are predictable and also follows a non-normal distribution. AL-Najjar (2016) utilized ARCH, GARCH, and EGARCH models to investigate the behaviour of Amman Stock Exchange (ASE) return volatility. The findings suggest that the symmetric ARCH /GARCH models are able to capture characteristics of ASE and also provide evidence of volatility clustering and leptokurtosis. Uyaebo et al. (2015) estimated asymmetric GARCH models with endogenous break dummy on two innovation assumptions using daily all share index of Nigeria, Kenya, United States, Germany, South Africa and China spanning from February 14, 2000 to

February 14, 2013. The results revealed that volatility of Nigeria and Kenya stock returns react to market shock faster than other countries do, and also suggest the absence of leverage effect in Nigeria and Kenya stock returns, but confirm its existence in others.

2.1 A Brief Report of the Performance of Bank Equities in the Nigerian Stock Market: Some Stylized Facts

The profit growth of a bank is very important not only to the financial institutions or government but also to private, public and foreign investors. Investors are attracted to banks that are less risky and have high profitability in terms of nature of the returns. Thus, it is very important to examine volatile returns of the banking equities as it could affect the growth of the banking sector. Empirical evidence has also shown that exchange rate fluctuation could affect the performance of banks in Nigeria. Emenike and Ani (2014) utilized the GARCH models to examined volatility of stock returns in Nigeria's banking sector, and their results revealed that stock returns volatility of the Nigerian banking sector exhibit clustering behaviour, high volatility persistence, leptokurtosis and sign of innovations have no effect on the volatility of stock returns of the banks.

Market capitalization in the Nigerian capital market has been on the increase overtime. However, the market capitalization decreased from ₦17.00 trillion in Q4 2015 to ₦15.88 trillion in Q1 2016 and increased to ₦17.28 trillion in Q2 2016 (NSE Fact Sheet 2016). The stock traded turnover ratio was 10.1 in 2010 but it declined to 9.9 in 2011 and further to 8.2 in 2014 and 8.2 in 2015. The highest value over the past 8 years was 384.8 in 2008, while its lowest value was 8.2 in 2014 and 2015 (World Bank, 2016). The banking index which stood at 268.49 at the end of Q4 2015 appreciated to 274.32 at the end of Q4 2016, representing 2.17% increase over the periods. The banking index for the 52-week period

ending December 30, 2016 was 2.17%, compared to -23.59% for the previous year. In the 2016 financial year, the banking index is one of the two sectoral indices that ended in the green zone as all the other ten NSE indices that track market and sector performance ended in the red zone.

Figure 1: Plots of Weekly Banking Index and Market Capitalization for 2016

3.0 Methodology

The study utilizes the ARCH and GARCH models to capture the volatility clustering and unconditional variance with heavy tails distribution that is present in financial time series. The assumption of homoscedasticity permits the use of the estimated regression equation to make forecast of the dependent variable. However, practically, all financial time series tend to exhibit varying variance; which vitiates the homoscedasticity assumption. Therefore, it becomes appropriate to consider frameworks that allow the variance to depend on its history.

3.1 The Autoregressive Conditional Heteroscedastic (ARCH) Models

The conditional mean equation and variance equation for an ARCH (q) model is given as:

$$y_t = \boldsymbol{\beta_1} + \boldsymbol{\beta_2 x_{2t}} + \boldsymbol{\beta_3 x_{3t}} + \boldsymbol{\beta_4 x_{4t}} + \mu_t \qquad \mu_t \sim N(0,\sigma_t^2) \qquad (1)$$

$$\sigma_t^2 = \beta_0 + \sum_{i=1}^{q} \beta_i \mu_{t-i}^2$$

(1b)where $\beta_0 > 0$; $\beta_i \geq 0$; $\forall\, i = 1,\ldots,q$

Where μ_t is the error generated from the mean equation at time *t*. and σ_t^2 is the conditional variance equation.

3.1.1 Generalized Autoregressive Conditional Heteroscedasticity (GARCH) Model

The conditional variance for GARCH (p, q) model is expressed as:

$$\sigma_t^2 = \beta_0 + \sum_{i=1}^{q} \beta_i \mu_{t-i}^2 + \sum_{j=1}^{p} \alpha_j \sigma_{t-i}^2 \qquad (2)$$

Where i = 1… q; j = 1,…p. σ_t^2 is the conditional variance, q is the order of the ARCH terms μ^2, p is the order of the GARCH terms σ^2, and β_0 is the constant term. The ARCH term is the lag of the squared residual which tells if volatility from previous period affects volatility in current period, while the GARCH parameter is the forecasted variance from the previous period. The sum of the ARCH and GARCH term will inform us if volatility shocks are persistent. In the GARCH (1,1) model, the AR (P) representation is replaced with an ARMA (p, q) representation:

$$y_t = \mu + y_{t-1}^{\prime}\gamma + \mu_t \qquad \mu_t \sim N(0, \sigma_t^2) \tag{3}$$

$$\sigma_t^2 = \beta_0 + \beta_1 \mu_{t-1}^2 + \alpha\sigma_{t-1}^2 \tag{3b}$$

In equation (3b), the mean (β_0) is the weighted average of the long run term, the three parameters (β_0, β_1 and α) are non-negative and covariance stationarity requires that $\beta_1 + \alpha < 1$ .The unconditional variance is given by:

$$\text{Var}(\mu_t) = \frac{\beta_0}{1-\beta_1-\alpha} \quad \text{, where } \beta_1 + \alpha < 1. \tag{4}$$

For $\beta_1 + \alpha > 1$, the unconditional variance of μ_t is undefined, and this would be termed 'non-stationarity in variance', while $\beta_1 + \alpha = 1$ is known as a 'unit root in variance'.

3.1.2 The Threshold GARCH (TGARCH) Model

The threshold GARCH model is also called the GJR-GARCH model. The GJR model is an extension of GARCH model with an additional term added to account for possible asymmetries. The TGARCH (p, q) is specified as:

$$\sigma_t^2 = \beta_0 + \sum_{i=1}^{q} \beta_i \mu_{t-i}^2 + \sum_{i=1}^{q} \gamma_i \mu_{t-i}^2 d_{t-i} + \sum_{j=1}^{p} \alpha_j \sigma_{t-j}^2 \tag{5}$$

Where $d_{t-i} = 1$ if $\mu_t < 0$ and 0 if $\mu_t \geq 0$, and the condition for non-negativity is $\beta_0 > 0$, $\beta_i > 0$, $\alpha_j \geqslant 0$, and $\beta_i + \gamma \geqslant 0$. In this model, good news implies that $\mu_{t-i}^2 > 0$ and has an impact of β_i and bad news implies that $\mu_{t-i}^2 < 0$ with an impact of $\beta_i + \gamma_i$. Bad news increases volatility when $\gamma_i > 0$, which implies the existence of leverage effect in the *i*-th order, and when $\gamma_i \neq 0$ the news impact is asymmetric. These two shocks of equal size have different effects on the conditional variance.

3.1.3 The Exponential GARCH (EGARCH) Model

The conditional variance of EGARCH (p, q) model is specified as:

$$\log(\sigma_t^2) = \beta_0 + \sum_{i=1}^{q} \beta_i \left|\frac{\mu_{t-i}}{\sigma_{t-i}}\right| + \sum_{i=1}^{q} \gamma_i \frac{\mu_{t-i}}{\sigma_{t-i}} + \sum_{j=1}^{p} \alpha_j \log(\sigma_{t-j}^2) \qquad (6)$$

In this model, good news implies that μ_{t-i} is positive with total effects $(1+\gamma_i)|\mu_{t-i}|$ and bad news implies μ_{t-i} is negative with total effect$(1-\gamma_i)|\mu_{t-i}|$. When $\gamma_i < 0$, bad news would have higher impact on volatility than good news (leverage effect is present). The news impact is asymmetric if $\gamma_i \neq 0$. The EGARCH model is covariance stationary when $\sum_{j=1}^{p} \alpha_j < 1$.

3.1.4 Power GARCH (PARCH) Model

The conditional variance of PGARCH (p, d, q) is given as:

$$\sigma_t^d = \beta_0 + \sum_{i=1}^{p} \beta_i \left(|\mu_{t-i}| + \gamma_i \mu_{t-i}\right)^d + \sum_{j=1}^{q} \alpha_j (\sigma_{t-j}^d) \qquad (7)$$

Where d > 0, $|\gamma_i| \leq 1$ establishes the presence of leverage effects. The symmetric model sets $\gamma_i = 0$ for all *i*. The first order PGARCH (1, d, 1) is expressed as:

$$\sigma_t^d = \beta_0 + \alpha_1 \left(|\mu_{t-1}| + \gamma_1 \mu_{t-1}\right)^d + \beta_1 (\sigma_{t-1}^d) \qquad (8)$$

If the null hypothesis that $\gamma_1 = 0$ is rejected, then leverage effect is present.

3.1.5 The Integrated GARCH (IGARCH) model

Assuming parameters of GARCH models are confined to sum to unity, and the constant term is left out, it results in the integrated GARCH (IGARCH) model given by:

$$\sigma_t^2 = \sum_{i=1}^{p} \beta_i \mu_{t-i}^2 + \sum_{j=1}^{q} \alpha_j \sigma_{t-j}^2 \qquad (9)$$

The conditional variance of a typical IGARCH (1, 1) model is stated as: $\sigma_t^2 = \beta_0 + \beta_1(\mu_{t-1}^2 - \beta_0) + \alpha_1(\sigma_{t-1}^2 - \beta_0)$. It shows mean reversion, and is a constant for all time.

3.1.6 The Component GARCH (CGARCH) Model

Unlike integrated GARCH model, the component GARCH model permits mean reversion to a varying level q_t, such that:

$$\sigma_t^2 = q_t + \beta_1 (\mu_{t-1}^2 - q_{t-1}) + \alpha_1(\sigma_{t-1}^2 - q_{t-1}) \quad (10)$$

$$q_t = \beta_0 + \rho(q_{t-1} - \beta_0) + \emptyset(\mu_{t-1}^2 - \sigma_{t-1}^2)$$

Combining the transitory and permanent equation above, we have

$$\sigma_t^2 = (1 - \beta_i - \alpha_j)(1 - \rho)\beta_0 + (\beta_i + \emptyset)\mu_{t-1}^2 - (\beta_i \rho + (\beta_i + \alpha_j)\emptyset)(\alpha_j\emptyset + (\alpha_j + \emptyset)\mu_{t-1}^2 - (\alpha_j\rho - (\beta_i + \alpha_j)\emptyset)\sigma_{t-2}^2 \quad (11)$$

The asymmetric component model joins the component with asymmetric TARCH model. The equation brings asymmetric effects into the transitory equation and estimates model of the form:

$$q_t = \beta_0 + \rho(q_{t-1} - \beta_0) + \emptyset(\mu_{t-1}^2 - \sigma_{t-1}^2) + \psi_2 z_{1t} \quad (12)$$

$$\sigma_t^2 = q_t + \beta_i(\mu_{t-1}^2 - q_{t-1}) + \gamma(\mu_{t-1}^2 - q_{t-1})d_{t-1} + \alpha_j\left(\sigma_{t-j}^2 - q_{t-1}\right) + \psi_2 z_{2t} \quad (15)$$

Where z is the exogenous variable and d is the dummy variable indicating negative shocks. $\gamma > 0$ indicates presence of transitory leverage effects in the conditional variance.

3.2 Distributional Assumptions

In modelling the conditional variance of the six banks equities, three conditional distributions for the standardized residuals of returns innovations would be considered: the Gaussian, Student's t, and the generalized error distribution (GED).

3.2.1 The Normal (Gaussian) Distribution

The Normal distribution log-likelihood contributions are assumed to be of the form:

$$\text{LogL}(\theta_t) = \sum_{t=1}^{T} L(\theta_t) = -\frac{1}{2}\text{Log}[2\pi] - \frac{1}{2}\sum_{t=1}^{T}\text{Log}(\sigma_t^2) - \frac{1}{2}\sum_{t=1}^{T}\frac{\mu_t^2}{\sigma_t^2} \quad (13)$$

where $\mu_t^2 = [y_t - \gamma y_{t-1}]^2$.

3.2.2 The Student's *t* Distribution

The student's *t* distribution likelihood contributions are assumed to be of the form:

$$L(\theta)_t = -\frac{1}{2}\log\left[\frac{\pi[v-2]\Gamma\left[\frac{v}{2}\right]^2}{\Gamma\left[\frac{v+1}{2}\right]^2}\right] - \frac{1}{2}log\sigma_t^2 - \frac{[v+1]}{2}\log\left[1 + \frac{\left[y_t - x_t^{'}\gamma\right]^2}{\sigma_t^2[v-2]}\right] \quad (14)$$

Where σ_t^2 is the variance at time t, and the degree of freedom $v > 2$ controls the tail behavior.

3.2.3 The Generalized Error Distribution (GED)

The GED likelihood function is specified as:

$$L(\theta)_t = -\frac{1}{2}\log\left[\frac{\Gamma[1/r]^3}{\Gamma\left[\frac{3}{r}\right]\left[\frac{r}{2}\right]^2}\right] - \frac{1}{2}\log\sigma_t^2 - \left[\frac{\Gamma\left[\frac{3}{r}\right]\left[y_t - x_t^{'}\gamma\right]^2}{\sigma_t^2\Gamma\left[\frac{1}{r}\right]}\right]^{r/2} \quad (15)$$

r > 0 is the shape parameter which account for the skewness of the returns. The higher the value of r, the greater the weight of tail. The GED is a normal distribution if r = 0 and fat-tailed if r < 2.

3.3 Test for ARCH Effect and Lagrange Multiplier (LM) Test

A precondition for the application of GARCH model is that, the null hypothesis of no ARCH effect (serial correlation) in the return series should be rejected. The LM test for ARCH in the residuals μ_t of estimated mean equation is used to test the null hypothesis that there is no ARCH effect in the estimated mean equation with an appropriate significant level using the equation below:

$$\boldsymbol{\xi_0^2 = \psi_0 + \sum_{l=1}^{q}\pi_l\xi_{t-l}^2 + \mu_t} \quad (16)$$

The volatility models above are estimated by allowing ε_t in each of the variance equation to follow normal, student's t and generalized error distributions. The best model for each return is selected based on the Akaike Information Criterion (AIC) and Schwarz information criterion (SIC). The diagnostic test for standardized residuals (Ljung-Box) of the stock returns in each of the best fitted models are conducted. The serial correlation in the residuals using Q-Statistics (correlogram of Residuals) are conducted to ascertain the robustness of the estimated models. The presence of leverage effect among the asymmetric models is examined by testing the null hypothesis that $\gamma = 0$ at a significance level. Rejection of the null hypothesis implies the presence of leverage effect.

4.0 Data Presentation

The data consist of daily equities of six commercial Banks in Nigeria, listed as Bank B1 to Bank B6. The data spans from January 2010 to June 30, 2016. These period are selected to mitigate the effect of 2008/2009 global financial crises. The daily equities are converted to weekly equities by taking the average of each week, thereby removing holiday effects. The data are obtained from www.cashcraft.com as provided by the NSE. Weekly returns defined as $y(x_t) = \log(x_t) - \log(x_{t-1})$, where $y(x_t)$ is the equity return for a particular bank at time t, x_t is the equity of that bank at time t, and x_{t-1} is the equity of the bank at time t-1.

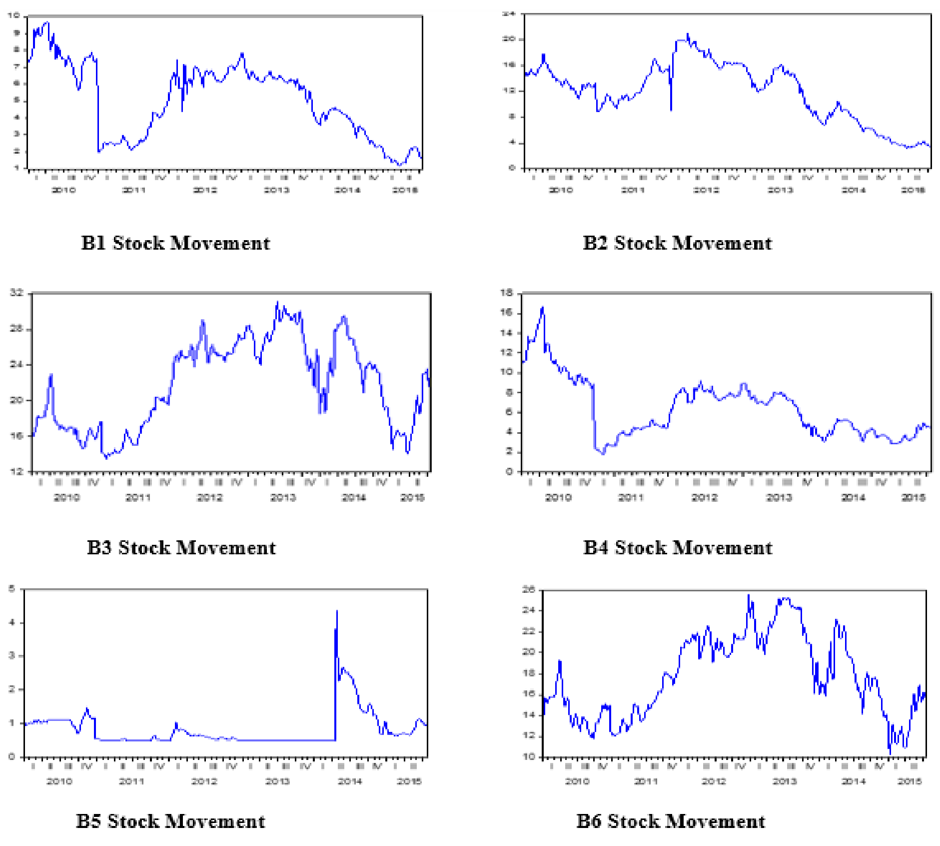


Figure 2: Time Series Plot of the Banks Stock Market Movement

Visual inspection of figure 2 reveals that at the beginning of the sample period, B1, B2, and B4 displayed relatively high equities up to second half of 2010. Similar trend was observed in B3 and B6. In the fourth quarter of 2010, B1 and B4 experienced a significant drop in equity. From 2012, all the banks started trending high, with the exception of B5. B5 stock movement seems to be the most relatively calm. In addition, visual inspection of the plots in figure 3 indicates that return series oscillates around the mean value for all the series, hence, they are mean reverting. B1, 2B and B5 return series are relatively calm, i.e. the amplitude is small for most of the observations. From the graph in figure 3, two periods stand out as times of pronounced fluctuations in B2: fourth quarter of 2010 and 2011. The pronounced period of fluctuations for B1 and B4 are observed in the fourth quarter of 2010. Period of pronounced fluctuations was observed in the second quarter of 2014 for B5. This could be as a result of losses recorded after succumbing to adverse money market condition and adverse risk management in 2013. However, in 2014, it reported a gross earnings of ₦77 billion up from N63 billion in 2013.

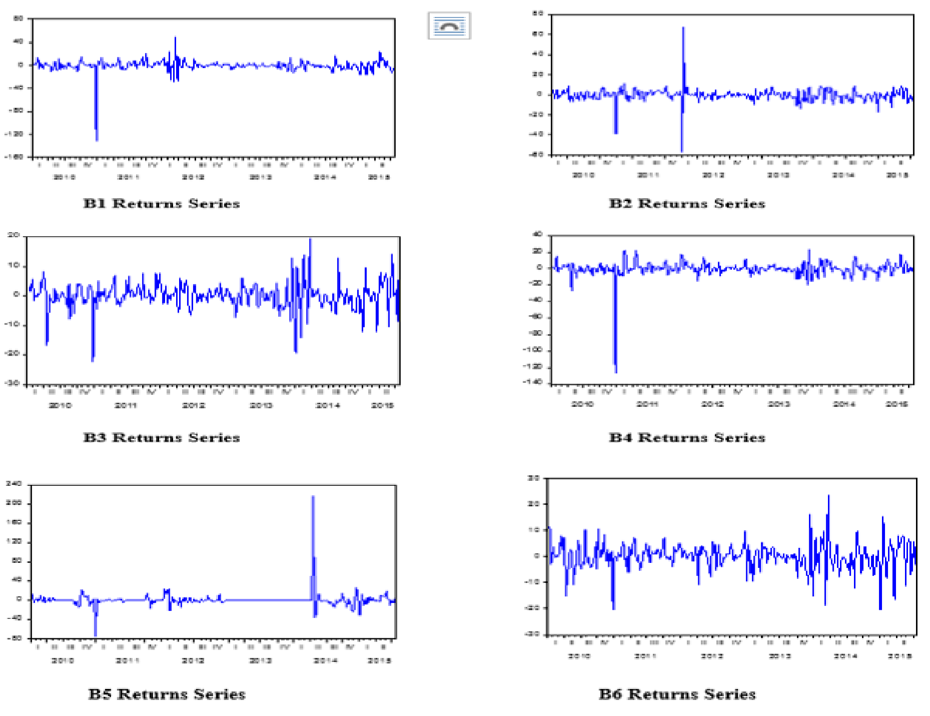


Figure 3: Time Series Plots of the Banks Stock Return Series

Howbeit, it is difficult to tell from visual inspection if any of these series exhibit clustering behavior, but, with the application of conditional volatility model, this can be accounted for.

Table 1: Descriptive Statistics of the Six banks' Equity Returns Series

Variables	Mean	Median	Maximum	Minimum	Standard Deviation	Skewness	Kurtosis	Jargue-Bera	p-value
B1	-0.5228	-0.2071	49.4484	-131.9878	10.5802	-6.333	85.7179	84323.99	0.0000
B2	-0.4894	-0.3281	67.744	-56.7959	7.1881	0.7336	44.8472	21113.22	0.0000
B3	0.1254	0.2194	19.3167	-22.1578	4.6573	-0.5549	7.3627	244.0345	0.0000
B4	-0.3093	-0.1565	23.4698	-126.6061	9.9474	-6.9889	91.5954	96869.59	0.0000
B5	0.03	0	216.9054	-75.8816	15.2552	9.4773	144.906	246813.3	0.0000
B6	0.05494	0.291	23.6943	-20.6424	5.2582	-0.3634	6.3921	144.9215	0.0000

Table 1 reports negative mean returns of -0.5228 for B1, -0.4894 for B2, and -0.3093 for B4. This implies that on the average, B1, B2, and B4 investors recorded losses more than gains. Within the sample period, B3 had the highest mean return than the other banks. The standard deviation shows that B5 is the most volatile while B3 is the least volatile bank equities. The skewness indicates that the returns distribution is negatively skewed for B1, B3, B4, and B6. B2 and B5 have a positive skewness, which implies that their returns rises more than it drops, reflecting the renewed confidence in these banks. All the banks equity return series shows evidence of fat tails since their kurtosis exceed 3. The high Jarque-Bera statistic and their corresponding p-values for all the banks' returns show that the return series are not normally distributed.

4.1 Unit Root Test Results

The unit root tests of Augmented Dickey-Fuller (ADF) and Philips-Peron (PP) Test are employed to determine the order of integration of the six banks equity return series.

Table 2: Unit Root Tests for the Equity Return Series (ADF) and Unit Root Test Results for Equity Return Series (PP)

Banks		t-Stat	Lag	Prob
B1	Level	-17.4824	0	0.0000
B2	Level	-21.5183	0	0.0000
B3	Level	-7.0895	5	0.0000
B4	Level	-15.672	0	0.0000
B5	Level	-13.6645	1	0.0000
B6	Level	-7.1883	4	0.0000

Note: the AIC is used for selecting the lag length

Banks		t-Stat	Lag	Prob
B1	Level	-17.4999	2	0.0000
B2	Level	-21.4921	6	0.0000
B3	Level	-14.8225	6	0.0000
B4	Level	-15.7289	6	0.0000
B5	Level	-18.0843	2	0.0000
B6	Level	-15.4785	4	0.0000

Note: Bartlett Kernel (Newey-West correction) for Autocorrelation

The results displayed in Table 2 indicate that the null hypothesis of unit root is rejected for all the six banks. Hence, the return series are stationary at level.

4.2 Autocorrelation and Partial Autocorrelation of Return Series

Based on the behaviour of AC, PAC plots (see Appendix 1 and 2) and the AIC, the mean equations were estimated (see Appendix 3). Hence, different AR, MA, and ARMA models are fitted to the return series by varying the order combinations using Akaike information criterion (AIC) to obtain the optimal order.

4.3 ARCH Effect Test

We test for ARCH effects in the estimated mean equation to ascertain the presence of serial correlation in the residuals.

Table 4: Heteroscedasticity Test (ARCH Effect Test)

Lag	Return series	B1	B2	B3	B4	B5	B6
Lag 1	F-statistic	0.0031	87.3827	6.3883	0.0017	0.1474	1.8591
	Observed R-squared	0.0031	67.3469	6.2924	0.0017	0.1483	1.8600
	Probability F-statistics	0.9554	0.0000	0.0120	0.9664	0.7013	0.1738
	Probability Chi-square	0.9552	0.0000	0.0121	0.9663	0.7001	0.1726
Lag 5	F-statistic	0.0030	25.1042	3.9420	0.0066	0.0338	3.2307
	Observed R-squared	0.0154	88.2501	18.8027	0.0338	0.1727	15.5921
	Probability F-statistics	1.0000	0.0000	0.0018	1.0000	0.9994	0.0075
	Probability Chi-square	1.0000	0.0000	0.0021	1.0000	0.9994	0.0081
Lag 10	F-statistic	0.0091	12.1357	2.2506	0.0195	0.0211	1.6486
	Observed R-squared	0.0950	86.8720	21.6154	0.2034	0.2199	16.1659
	Probability F-statistics	1.0000	0.0000	0.0155	1.0000	1.0000	0.0931
	Probability Chi-square	1.0000	0.0000	0.0172	1.0000	1.0000	0.0950

Table 4 shows the result of the ARCH effect test in the squared residuals of the mean equation of return series for the six banks. Given the high values of the F and chi-squared statistics and their corresponding small p-values up to lag 10, there is evidence to conclude that there is presence of ARCH effect in the return series even at 1% significant level for B2 and B3. Thus, rejecting the null hypothesis of no ARCH effect in these two series. This result provide further justification for the application of conditional volatility models. However, the null hypothesis of no ARCH effect cannot be rejected for the other series. Hence, the conditional variance equation cannot be modelled for these four series.

4.4 ARCH/GARCH Estimation Results

The presence of ARCH effect with other estimated stylized facts of these series gave credence to the estimation of ARCH/GARCH family models for B2 and B3 using a student's t distribution. All coefficients of the ARCH models for the two return series are positive thereby satisfying the necessary and sufficient conditions for ARCH family model.

Table 5: Parameter estimates for ARCH/GARCH Models for B2

Table 5: Parameter Estimates for ARCH/GARCH Models for B2

Parameters	ARCH	GARCH (1,1)	EGARCH	TGARCH	PARCH	CGARCH	IGARCH
Constant	-0.4494	-0.4229	-0.4759	-0.4591	-0.4742	-0.4409	-0.4894
C	(0.2596)	(0.2613)	(0.2502)	(0.2637)	(25.9345)	(0.2612)	
Intercept	20.1401	20.2284	3.1539	18.8304	49.4868	33.6879	
β_0	(4.3853)	(5.9634)	(0.8631)	(3.3472)	(154.5502)	(13.2199)	
ARCH term	0.4729	0.4539	0.6236	0.3926	-0.286	0.0519	51.4908
β_1)	(0.2123)	(0.2039)	(0.1868)	(0.2499)	(1.4334)	(0.2851)	
GARCH term		-0.0019	-0.0904	-0.0133	0.5756	-0.0021	-50.4908
α_1		(0.1710)	(0.2447)	(0.0167)	(1.3202)	(1.0242)	
γ			0.0214	0.0481	0.0526		
			(0.1247)	(0.3188)	(4.7331)		
d					1.0000		
$\emptyset$						0.396	
						(0.3513)	
ρ						0.4791	
						(0.2336)	
$\beta_1 + \alpha_1$		0.452	0.5332	0.3793	0.2896	0.0498	1
μ		6.0756					
Log L	-859.112	-858.9093	-855.867	-859.1081	-1621.314	-858.2152	
AIC	5.9800	5.9855	5.9713	5.9938	11.6860	5.9945	
SC	6.0434	6.0616	6.0602	6.0826	11.3574	6.096	
Observed	289	289	289	289	289	289	289

Note: Numbers in parenthesis indicates standard errors

The intercept of the ARCH model and the ARCH term are positive and significant at 5% level. The value of the ARCH coefficient implies that the square lagged error terms has positive and significant impact on the current period volatility of B2 returns. Also, the speed of reaction of stock volatility to market event is high. The estimated GARCH (1, 1) model shows that all the parameter estimates of variance equation are positively significant at 5% level, except the coefficient of the GARCH term which is insignificant and negative, implying that previous period volatility does not have significant effect on the conditional volatility at the current period. The ARCH coefficient also revealed that the previous error terms has positive and significant effect on current period volatility and the degree to which volatility react to market event is high. The sum for all the estimated models are very low, thus, shocks to returns of this Bank dies out very quickly with the exception of EGARCH and IGARCH models. However, the persistence of volatility is highest with the IGARCH (1, 1) model since the value is 1, implying that it account for volatility persistence more, and the persistence will die out very slowly. The unconditional variance of returns (μ) which is the long run average variance is 6.0756.

In the EGARCH model, the intercept and the ARCH term are positive and highly significant, but the GARCH parameter is not significant. The ARCH term suggest that the tendency of volatility of B2 to react to market shocks is significant, and the extent to which it react to this shock is high. Also, previous period volatility does not have effect on current period volatility and is covariance stationarity since α_1 is less than 1. The leverage effect term, γ is not significant at 5% level, suggesting the absence of leverage effect. In the TGARCH model, the ARCH term is not significant, but the intercept is significant. That is, the squared lagged error does not have a significant impact on the current period volatility and the speed of reaction of volatility to market shock is high. Also, the GARCH coefficient suggests that previous period variance has no impact on the conditional volatility and it also shows that volatility persistence is high. The long run average is ($1-\beta_1 - \alpha_1 - \gamma/2 = 0.5967$), The leverage effect is positive and not significant at 5% level, implying that negative shock does not drives volatility more than equal magnitude of positive shock. Power ARCH (PARCH) model revealed that all the coefficients are positive and not significant at 5% level when d = 1. The speed of reaction of volatility to market shock is moderate and volatility persistence is low. Parameter estimates from the CGARCH model reveals that the intercept and ρ are positive and significant, while the other coefficients are positive but not significant. The speed of reaction of volatility to market events is low. Comparing all the estimated models based on the information criteria, and the log likelihood statistics, EGARCH is the best fitting model for B2.

The GARCH Models of B3 are presented in Table 6. The intercept of the ARCH model is positive and significant while the ARCH term is positive but not significant at conventional levels. The conditional volatility reaction to market shock is high. The intercept and the ARCH term of the GARCH (1, 1) model are not significant at 5% level, while the coefficient of the GARCH term is positive and significant. The significant value of the GARCH term implies that previous period volatility does have significant effect on the conditional volatility at the current period, and also, volatility persistence is low. The GARCH (1, 1) model satisfy the covariance stationarity condition. Volatility persistence are greater than 0.5 and they are close to unity, with the exception of PARCH model. Thus, shocks to returns of the Bank dies out very slowly. However, the persistence of volatility is highest with the IGARCH (1, 1) model since the value is 1. The unconditional standard deviation of returns (μ) is 6.5570.

Table 6: Parameter Estimates for ARCH/GARCH Models for B3

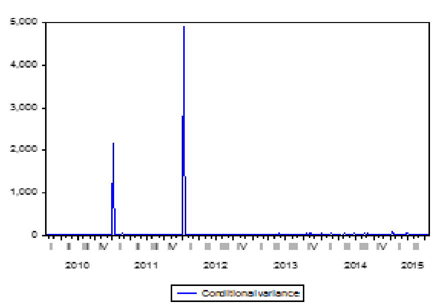
Parameters	ARCH	GARCH (1,1)	EGARCH	TGARCH	PARCH	CGARCH	IGARCH
Constant C	0.2482 (0.2215)	0.2008 (0.2230)	0.1973 (0.2261)	0.1739 (0.2282)	0.1712 (23.5540)	0.1134 (0.2139)	0.1254
Intercept β_0	17.1364 (6.7521)	4.5273 (2.3146)	0.32 (0.2806)	4.7496 (2.3721)	20.4468 (60.2034)	18.2255 (5.3587)	
ARCH term β_1	0.5931 (0.3336)	0.3796 (0.1962)	0.434 (0.1707)	0.2033 (0.1768)	0.5758 (0.3598)	0.3447 (0.1092)	21.6157
GARCH term α_1		0.5151 (0.1548)	0.7969 (0.1049)	0.5302 (0.1601)	-0.1316 (0.7476)	1.1042 (0.2740)	-20.6157
γ			-0.0492 (0.0920)	-0.2735 (0.2590)	0.0573 (5.6662)		
d					1.0000		
Ø						0.5717 (0.2887)	
ρ						0.7511 (0.0587)	
$\beta_1 + \alpha_1$		0.8947	1.2309	0.7335	0.4442	1.4489	1.0000
μ		6.557					
Log L	-807.666	-802.1127	-802.9696	-801.4456	-1367.749	-796.0335	
AIC	5.6239	5.5924	5.6053	5.5947	9.5138	5.5711	
SC	5.6874	5.6685	5.6941	5.6835	9.6026	5.6853	
Observed	289	289	289	289	289	289	289

***Note: Numbers in parenthesis indicates standard errors*.**

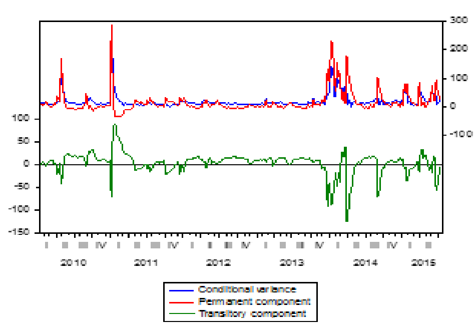
In the EGARCH model, both the ARCH term and the GARCH term are positive and significant. The EGARCH is covariance stationarity since α_1 is less than 1. The tendency of volatility of B3 to react to market shocks is significant, and the extent to which it react to this shock is high with a moderate volatility persistence. The leverage effect term γ is not significant at 5% level. In the TGARCH model, the ARCH term is not significant while the GARCH term and the intercept are significant. The long run average is $(1-\beta_1 - \alpha_1 - \gamma/2 = 0.1297)$ and the leverage effect is not significant at 5% level. Result from power ARCH (PARCH) model revealed that all the coefficients are positive and not significant at 5% level when d = 1. Parameter estimates from the CGARCH model reveals that all coefficients are positive and significant. Comparing all the estimated models based on the information criteria and the log likelihood statistics, CGARCH is the best fitting model for B3.

Figure 4 indicates that the volatility models selected captures the major trends as well as periods of high and low equity returns as depicted by the plots of the conditional volatilities of the fitted GARCH models.

Figure 4: Conditional volatilities from fitted EGARCH model for B2 and CGARCH model for B3 respectively



B2 Returns Volatility



B3 Returns Volatility

4.5 Diagnostics

Diagnostics tests results are presented in Table 7 and 8.

Table 7: Diagnostic Test for the Two Best Fitted GARCH Family Models

Heteroscedasticity Test: ARCH		Lag 1	Lag 5	Lag 10
EGARCH (1, 1)	F-statistics	0.0243	0.0845	0.0716
	Prob. F(1,286)	0.8760	0.9946	1.0000
	Obs*R-squared	0.0254	0.4310	0.7440
	Prob. Chi-square(1)	0.8755	0.9944	1.0000
CGARCG (1, 1)	F-statistics	0.6638	0.1574	0.1771
	Prob. F(1,286)	0.4159	0.9776	0.9977
	Obs*R-squared	0.6669	0.8020	1.8319
	Prob. Chi-square(1)	0.4141	0.9769	0.9975

The null hypothesis that there is no remaining ARCH effect in the models is not rejected at 5% significant level based on the Chi-squared statistic. The conformity of the residuals of the estimated model to homoscedasticity is an indication of goodness of fit. The probability value of the Q-statistics in Table 8 for all lags are higher than 0.05, confirming that there is no serial correlation in the standardized residuals of the estimated models at 5% significant level.

Table 8: Serial Correlation Test Results of the two Best Fitted Volatility Models

	EGARCH (1, 1)				CGARCH (1, 1)			
Lag	AC	PAC	Q-Stat	Probability	AC	PAC	Q-Stat	Probability
1	-0.0150	-0.0150	0.0619		0.0170	0.0170	0.0816	
2	-0.0370	-0.0370	0.4616	0.4970	-0.0390	-0.0390	0.5183	0.4720
3	0.0470	0.0460	1.1141	0.5730	-0.0630	-0.0610	1.6705	0.4340
4	-0.0380	-0.0380	1.5446	0.6720	-0.0180	-0.0180	1.7667	0.6220
5	0.0750	0.0780	3.2274	0.5210	0.0830	0.0790	3.7879	0.4350
6	-0.0160	-0.0190	3.2988	0.6540	-0.0800	-0.0880	5.6821	0.3380
7	-0.0750	-0.0660	4.9690	0.5480	-0.0190	-0.0120	5.7898	0.4470
8	0.0380	0.0270	5.3908	0.6120	0.0910	0.0970	8.2538	0.3110
9	0.0070	0.0100	5.4073	0.7130	0.0460	0.0350	8.8941	0.3510
10	0.0230	0.0260	5.5672	0.7820	0.0260	0.0190	9.0990	0.4280

5.0 Conclusion and Policy Implications

This study investigates equity returns volatility for six banks in the Nigeria's stock exchange. Results from the ARCH effect test revealed that B2 and B3 were the only banks that could reject the test of no ARCH effect. The preliminary analysis indicates that B3 was the least volatile and the most profitable bank during the sample period, and based on model selection criteria EGARCH and CGARCH were adjudged the best volatility models for B2 and B3 respectively. However, the EGARCH model rejected the existence of a leverage effect, implying that equity returns of B2 has equal response to same magnitude of positive and negative shocks. The findings of the study is quite important in assessing various financial decisions relating to asset allocation and risk management strategies of investors and bank managers in B3 and B2 as their decisions will have direct role and effect on asset pricing, risk and portfolio management, assessing leverage and investment decisions that will affect the bank performance especially in an emerging economy where vast number of investors are described as risk averters. The study recommends that, given the level of risk associated with portfolio investment, financial analysts, investors, and empirical work should consider variants of GARCH models with alternative error distributions for robustness of results. We also recommend for adequate regulatory effort by the CBN over commercial banks operations that will enhance efficiency of their stocks performance and reduce volatility aimed at boosting investors' confidence in the banking sector.

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APPENDIX

Appendix 1: Autocorrelation and Partial Autocorrelation for B1, B2, and B3

	B1				B2				B3			
Lag	AC	PAC	QS	Prob	AC	PAC	QS	Prob	AC	PAC	QS	Prob
1	-0.0330	-0.0330	0.3244	0.5690	-0.2350	-0.2350	16.1840	0.0000	0.1220	0.1220	4.3200	0.0380
2	-0.0660	-0.0670	1.5990	0.4500	-0.0080	-0.0670	16.2030	0.0000	-0.1260	-0.1430	8.9682	0.0110
3	0.0810	0.0770	3.5128	0.3190	0.0590	0.0440	17.2290	0.0010	-0.0850	-0.0520	11.1090	0.0110
4	-0.0850	-0.0850	5.6369	0.2280	-0.0160	0.0090	17.3080	0.0020	0.0480	0.0500	11.7800	0.0190
5	0.0300	0.0360	5.9052	0.3160	0.0600	0.0660	18.3850	0.0030	0.1370	0.1110	17.3570	0.0040
6	0.0020	-0.0140	5.9064	0.4340	-0.0020	0.0270	18.3860	0.0050	-0.0840	-0.1150	19.4620	0.0030
7	-0.0260	-0.0080	6.1016	0.5280	-0.0540	-0.0480	19.2450	0.0070	-0.0810	-0.0200	21.4080	0.0030
8	-0.0400	-0.0550	6.5774	0.5830	0.0240	-0.0080	19.4170	0.0130	0.0720	0.0840	22.9620	0.0030
9	0.0060	0.0090	6.5894	0.6800	-0.0070	-0.0080	19.4310	0.0220	0.0850	0.0320	25.1280	0.0030
10	0.0240	0.0180	6.7564	0.7480	0.0110	0.0120	19.4700	0.0350	0.0670	0.0550	26.4950	0.0030
11	-0.0360	-0.0290	7.1401	0.7880	0.0470	0.0550	20.1430	0.0430	-0.0690	-0.0370	27.9400	0.0030
12	-0.0370	-0.0440	7.5521	0.8190	-0.1120	-0.0860	23.9350	0.0210	-0.0850	-0.0550	30.1430	0.0030
13	-0.0620	-0.0700	8.7307	0.7930	0.0260	-0.0230	24.1330	0.0300	0.0510	0.0360	30.9210	0.0030
14	0.0000	-0.0010	8.7307	0.8480	0.0830	0.0760	26.2360	0.0240	-0.0480	-0.0920	31.6260	0.0050
15	0.0860	0.0770	11.0250	0.7510	-0.0140	0.0370	26.2940	0.0350	-0.0590	-0.0380	32.6860	0.0050

Appendix 2: Autocorrelation and Partial Autocorrelation for B4, B5 & B6

	B4				B5				B6			
Lag	AC	PAC	QS	Prob	AC	PAC	QS	Prob	AC	PAC	QS	Prob
1	0.0760	0.0760	1.6861	0.1940	-0.0630	-0.0630	1.1497	0.2840	0.0960	0.0960	2.6965	0.1010
2	-0.0350	-0.0410	2.0353	0.3610	-0.1020	-0.1060	4.1858	0.1230	-0.2070	-0.2190	15.2910	0.0000
3	0.0500	0.0560	2.7581	0.4300	-0.0030	-0.0170	4.1879	0.2420	-0.0980	-0.0560	18.1330	0.0000
4	0.0680	0.0590	4.1326	0.3880	0.0430	0.0320	4.7417	0.3150	-0.0160	-0.0470	18.2100	0.0010
5	0.0360	0.0310	4.5246	0.4770	0.0260	0.0290	4.9374	0.4240	0.1810	0.1650	27.9020	0.0000
6	0.0310	0.0280	4.8052	0.5690	-0.0220	-0.0110	5.0843	0.5330	0.0710	0.0190	29.4190	0.0000
7	-0.1660	-0.1770	13.0440	0.0710	-0.0340	-0.0310	5.4278	0.6080	-0.0690	-0.0130	30.8330	0.0000
8	-0.0750	-0.0560	14.7210	0.0650	-0.0270	-0.0370	5.6519	0.6860	-0.0630	-0.0190	32.0140	0.0000
9	0.0700	0.0620	16.1830	0.0630	-0.0100	-0.0240	5.6806	0.7710	-0.0530	-0.0490	32.8570	0.0000
10	0.0320	0.0330	16.4950	0.0860	-0.0240	-0.0330	5.8567	0.8270	0.0610	0.0310	33.9780	0.0000
11	0.0070	0.0370	16.5110	0.1230	-0.0040	-0.0080	5.8607	0.8820	0.0470	-0.0050	34.6360	0.0000
12	-0.0660	-0.0600	17.8280	0.1210	-0.0190	-0.0220	5.9686	0.9180	-0.0880	-0.0770	36.9890	0.0000
13	-0.0290	-0.0180	18.0750	0.1550	0.0030	0.0010	5.9721	0.9470	-0.0040	0.0390	36.9930	0.0000
14	0.0150	-0.0210	18.1460	0.2000	0.0090	0.0060	5.9968	0.9670	-0.0090	-0.0260	37.0200	0.0010
15	0.0170	-0.0090	18.2290	0.2510	0.0140	0.0150	6.0595	0.9790	0.0070	0.0020	37.0350	0.0010

Appendix 3: Estimation of the Mean Equations

The estimated mean equation for all the Banks are specified below:

$$y_{B1} = -0.5218 - 0.10236\mu_{t-4}$$

$$y_{B2} = -0.4925 - 0.2436\mu_{t-1}$$

$$y_{B3} = 0.1305 + 0.1601\mu_{t-1}$$

$$y_{B4} = -0.3143 + 0.0593\mu_{t-1} - 0.0201\mu_{t-2} + 0.0633\mu_{t-3} + 0.0988\mu_{t-4} + 0.0111\mu_{t-5} + 0.0374\mu_{t-6} + 0.1634\mu_{t-7}$$

$$y_{B5} = 0.0154 - 0.0946\mu_{t-2}$$

$$y_{B6} = 0.0330 + 0.1245y_{t-1} + 0.2202y_{t-2}$$