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Stock Price Volatility Modelling with Regimes in Conditional Mean and Variance

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Authors' contributions

This work was carried out in collaboration between both authors. Author AS wrote the introduction, literature review and discussion of findings. Author JTO wrote the methodology and conducted the statistical analysis. Both authors read and approved the final manuscript.

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ABSTRACT

This study examined the presence and nature of volatility in the Nigerian Stock market. Through a graphical presentation of the Nigerian stock prices, it was observed that there exist two regimes of volatility clustering between the periods of 1985M6 to 1999M12 and 2000M1 to 2018M6. Employing a regime covariate autoregressive (AR-X) with an exponential GARCH model, that allows for a shift in intercept, it was found that the second regime, 2000 M1 to 2018 M6, is more volatile, and that modelling of Nigerian stock market requires a technique that considers more than one regime of volatility clustering. Consequently, the study recommends that local and foreign investors take into consideration the high volatility of the recent Nigerian stock prices in making their investment decision and that policymakers take cognizance of the volatility in designing macroeconomic policies.

Keywords: All share index; volatility; clustering; exponential GARCH; stock market.

JEL Classification: C22, C52, E44.

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1. INTRODUCTION

The debate on changes in the volatility of stock prices has received considerable attention in recent years. This is because volatility is used as a measure of risk by market participants as an input in portfolio management, and an indispensable tool in the pricing of options. The stock market allows investors to use various instruments to satisfy their liquidity and risk preferences, thus encouraging savings and providing non-financial corporations with equity finance possibilities. A well-functioning stock market performs the roles of mobilisation of savings, fund term matching with the efficient allocation of investment resources and acceleration of economic growth. However, the stock market is characterised by large volatility which cast doubt on the efficiency and accuracy of the valuation of investment opportunities [1]. Stock prices volatility has a great influence not only on the financial sector but on the general economy. Given its imperativeness in financial and general economic development, stock prices volatility has been under scrutiny over the years and is still being studied vigorously.

To explain the causes of volatility, two different schools of thoughts have emerged. The first school of thoughts argue that stock price volatility is due to changes in fundamental factors. They argued that market movements are explained entirely by the information that is provided to the market. Using an efficient market hypothesis, it is argued that the information changes affect the stock prices, and as such future prices can be predicted. As new information flows into the market, market volatility keeps changing [2, 3]. The second school of thoughts argued that stock price volatility cannot be fully explained by only fundamental factors. Changes in the market are warranted by the investor's reaction, his psychological or social beliefs, which bring about greater variation in stock prices. According to LeRoy and Porter [4, 5], financial markets exhibit dramatic movements, and stock prices may appear too volatile to be justified by only changes in fundamental factors, several non-fundamental factors like learning effects and incomplete information [6, 7], which also play significant roles in influencing stock price volatility. However, the proponents of efficient market hypotheses argued that violation of market hypothesis is a result of small sample bias [2] and non-stationarity of stock prices [8]. Given the non-stationarity of most stock prices, they grow explosively and cause bubbles or instability in the stock market. In other to find a good estimation tool for stock price volatility, researchers like French, Schwert and Stambaugh [9], Schwert and Sequin [10] have emphasised the need to take cognisance of heteroscedasticity problem in modelling stock prices volatility.

Given the foregoing, several studies have been conducted to investigate the nature and causes of stock price volatility, to provide an appropriate recommendation for policymakers and research tool for academics. Given the difference in the size and frequency of dataset, and econometric techniques being used by various researchers, inconsistent results have been derived about the nature and sources of the volatility of stock prices. The present study contributes to the debate about the nature and causes of stock price volatility by using an estimation method that takes care of the presence of different episodes of volatility clustering in the Nigerian stock market.

2. LITERATURE REVIEW

During the survey of the literature, it was found that several cross- country and country-level studies have been conducted using different econometrical methods. The most related ones to the present study are reviewed below:

Baig, Aslam and Bilal [11] investigated the volatility of stock markets between three South Asian Stock Markets (Pakistan, India and Sri Lanka), and stock markets of Group of Eight Countries (France, Germany, Canada, Italy, Russia, Japan, USA and United Kingdom) from the period of January 1st 2005 to August 31st 2015, using ARCH and GARCH models. They found that South Asian Stock Markets are less volatile while Stock Markets of the Group of Eight Countries are highly volatile. Boţoc [12] also investigated whether the volatility of stock markets of Central European (Hungary, Poland, the Czech Republic, Slovakia, Slovenia and Croatia) exhibits a symmetric or an asymmetric response to past shocks, particularly the relevance of structural breaks. He also investigated whether CEE emerging markets are correlated with other emerging ones, and with the developed markets, for optimizing investment portfolios. Using a family of GARCH models (EGARCH, Threshold-GARCH, APARCH, and Threshold-CGARCH on daily data from 2002 to 2015, he found that markets react differently to similar negative and positive returns, except for the rapid growth period when the greed sentiment dominates the markets. Furthermore, the structural break dates affect volatility, the highest asymmetric coefficient being recorded for the pre-crisis period. For the bivariate approach, the results suggest that CEE stock markets are correlated with emerging stock markets rather than developed ones. For both pairs, the correlation is consistently higher for the break dates characterized by an increase in volatility. This confirms other studies that the co-movements increase when international factors dominate the national ones, and influence stock markets.

Similarly, Bala and Premaratne [13] used GARCH models and Vector Autoregression, investigate volatility co-movement between the Singapore stock market and the markets of US, UK, Hong Kong and Japan on the daily returns of 1992 to 2002. They found that there is a high degree of volatility co-movement between the Singapore stock market and that of Hong Kong, US, Japan and UK. Their results support small but significant volatility spillover from Singapore into Hong Kong, Japan and US markets despite the latter three being dominant markets. Their study equally reveals the possibility of volatility to spill over from the smaller market to the dominant market. Using daily all share index of Nigeria, Kenya, United States, Germany, South Africa and China spanning from February 14, 2000, to February 14, 2013, Uyaebo, Atoi and Usman [14] estimated asymmetric generalized autoregressive conditional heteroscedasticity models with endogenous break dummy on two innovation assumptions all share index of Nigeria, Kenya, South Africa, China, United States and Germany. They used the first order Asymmetric GARCH family models on Student's t and generalized error distribution (GED) to select the best stock market volatility models for these countries based on Akaike Information Criterion (AIC) to compare their market volatilities. The best-fitted models are compared in terms of conditional volatility reaction to market shocks and volatility persistence alongside the asymmetric properties. They found that the volatility of Nigeria and Kenya stock returns react to market shock faster than other countries do. The results also suggest the absence of leverage effect in Nigeria and Kenya stock returns but confirm its existence in others.

Aside from cross-country studies above, other inter-country and country-level studies are reviewed as follows. Andersen and Bollerslev [15] investigated relative explanatory power of intraday activity patterns, macroeconomic announcements and long-term volatility factors on the volatility and variability of both intraday and intraday of the United States and German stock prices. They found that the characteristics of most stock prices account for a substantial fraction of return variability at intraday and interday level. In similar but with a higher frequency study, Andersen, Bollerslev and Cai [16] used flexible Fourier form regression (FFFR), which can filter out the intraday market microstructure effects, and Fractionally Integrated Exponential GARCH, (FIEGARCH) to examine the nature of volatility in 5-min returns for the Nikkei 225 equity index spanning the 4 years from 1994 through 1997. They found that the Nikkei 225 index volatility is significantly higher at the opening of the morning and the close of the afternoon sessions than during the mid-morning and mid-afternoon sessions. These features, combined with an increase in volatility immediately before and after the lunch break, resulting in two distinct U-shapes; one in the morning and one in the afternoon.

Cai, Chen, Hong and Jiang [17] used Mincer-Zarnowitz regression model and GARCH model investigated whether economic variables contain forecasting information for the future Chinese stock market volatility. They found that the dividend-price ratio, dividend payout ratio, dividend yield, inflation, stock turnover, and changes in the M1 money supply positively and significantly forecast the Chinese stock market volatilities. Shocks to economic fundamentals (like increases in dividend payment, inflation, turnover, and money supply: M1) lead to a high future stock market volatility and hence high market risk. In a related study, Fabozzi, Tunaru and Wu [18] used a series of GARCH models to investigate to test volatility transmission between the two Chinese markets. They found that there is no volatility transmission between the two markets. In a similar study, Angabini and Wasiuzzaman [19], used symmetric and asymmetric GARCH models for the effect of the global financial crisis of 2007/2008 on the Malaysian stock market volatility. They the time frame into two categories: the first period from June 2000, after the recovery of the East Asian crises to the end of 2007, excluding the time of the crises, while the second includes the crises, from June 2000 to March 2010. Using AR (4) to model the conditional mean and GARCH (1,1), EGARCH (1,1), GJR-GARCH (1,1) for conditional variance, they found that Malaysians stock prices exhibit leptokursis, clustering effect, asymmetric and leverage effect. They also found that there was a significant increase in volatility and leverage effect, with a small drop due to the financial crisis.

Using EGARCH estimation techniques, Babajide, Lawal and Somoye [20] examined the impact of the systematic risk emanating from the macroeconomy on stock market volatility based on monthly data sourced from 1985 to 2013 on the Nigerian economy. They investigated whether the volatilities of the selected macroeconomic variables, (inflation, interest rate and exchange rate) exerts influence on the volatility of stock market price (All share index). They found that all the macroeconomic variables tested exert influence on stock market pricing and that the stock market pricing is most influenced by exchange rate volatility. They recommended that policymakers should pay close attention to the innovations in the macroeconomic variables when formulating macroeconomic or financial stability policy. Market practitioners are also encouraged to consider the volatility of macroeconomic variables in their portfolio decision-making process. Similarly, Osahon [21] used the Autoregressive Conditional Heteroscedasticity (ARCH) model and Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model to investigate the presence of volatility clustering in the Nigerian stock market, using time series data of share prices for the period 1995 to 2009. They found that the market exhibits volatility clustering, with the response function decaying on monthly basis, depicting volatility at the value of 1.1783. Based on model selection criteria using Akaike Information Criterion (AIC), Schwarz Bayesian Criterion (SBC) and Hannan and Quin Criterion, the GARCH (1 1) are better than the ARCH (1) model. It is suggested that aggressive trading on a wide range of securities be encouraged as this will increase market depth and hence reduce volatility.

Atoi [22] estimated first-order symmetric and asymmetric volatility models each in normal, student's-t and generalized error distributions to select the best forecasting volatility model with the most appropriate error, using All Share Index from January 2, 2008, to February 11, 2013. She found the presence of leverage effect meaning that volatility responds more to bad news than it does to the equal magnitude of good news. She further stated that the last twenty-eight days out-of-sample forecast adjudged Power-GARCH (1, 1, 1) in student's t error distribution as the best predictive model based on Root Mean Square Error and Theil Inequality Coefficient. She, therefore, recommended that empirical works should consider alternative error distributions to achieve a robust volatility forecasting model that could guarantee some sound policy decisions. Nkoro and Uko [23] investigated the relationship between exchange rate and inflation volatility and stock prices volatility in Nigeria, on quarterly data from 1986Q1-2012Q4. They used GARCH (1,1)-S models of extended GARCH-X models. They found that there is a negative relationship between stock market prices volatility and exchange rate and inflation volatility.

The literature review shows that different variants of ARCH, GARCH, EGARCH and TGARCH have been adopted to understand the behaviours of the stock markets of the different countries, Nigeria inclusive. Different findings were derived about the nature of the volatility clustering of the stock market indices, given the difference in the period and methodology adopted. A survey of the literature shows that no study has considered the differences in the two regimes when modelling Nigerian stock market volatility. In this light, this study employs a regime covariate autoregressive (AR-X) with an exponential GARCH model, which allows for a shift in intercept, to capture these complexities.

3. RESEARCH METHODOLOGY

Monthly Average All Share Index data, sourced from the Central Bank of Nigeria, is used in this study. The data sourced spanned 1985M01 to 2018M06. Unlike the previous studies on the volatility of stock market volatility, a seasonal unit root test developed by Hylleberg, Engle, Granger and Yoo [24] was used to confirm the zero frequency syndromes in the Nigerian stock market data. The graphical illustration of the all share index returns (Fig. 1) revealed that there is a change in its data generating process from the first month of the year 2000. From the year 1985 to 1999, there is no much clustering in the stock market returns but the clustering becomes visible from 2000 to 2018. This suggests that the stock market volatility from 1985 to 1999 will be lesser than the subsequent periods and that the two regimes need to be taken into consideration when modelling Nigerian stock market volatility. This study uses a regime covariate autoregressive (AR-X) with an exponential GARCH model, that allows for a shift in the intercept. The regime covariate autoregressive (AR-X) is used to model the conditional mean. The X's are the possible seasonal dummies that significantly affect the stock market returns.

Taken into consideration the change in the stock market behaviour, the model for this study is presented below. Equation (1) describes the conditional mean for stock market returns while the last equation described the conditional variance for stock market returns. In equation (1),"w" is the regime dummy that captures the years 1985-1999. The term "sd's" in the conditional mean equation are the seasonal dummies. The autoregressive and the seasonal dummies will be selected based on a backward stepwise least square method.

$$smr_t = w\left(\alpha_0 + \sum_{i=1}^{N} \alpha_i smr_{t-i} + sd\right) + (1 - w)\left(\beta_0 + \sum_{i=1}^{M} \beta_i smr_{t-i} + sd\right) + v_t \quad (1)$$

$$w = \begin{cases} 1, & 1985M1 - 1999M12 \\ 0, & 2000M1 - 2018M6 \end{cases} \quad (2)$$

$$v_t \sim N(0, h_t) \quad (3)$$

$$logh_t = \gamma_0 + \gamma_1 \left|\frac{v_{t-1}}{\sqrt{h_{t-1}}}\right| + \gamma_2 \left(\frac{v_{t-1}}{\sqrt{h_{t-1}}}\right) + \gamma_3 logh_{t-1} + \gamma_4 w \quad (4)$$

Equation (1) and (4) will be estimated using the method of maximum likelihood. We assumed that error term in equation (1) follows a conditional normal distribution. We shall also present the result for the t-distribution due to its fat tail properties.

4. DATA DESCRIPTION AND RESULT DISCUSSION.

4.1 Graphical Representation of Nigerian Stock Prices

The first panel of Fig. 1 below shows the graphical representation of the All Share Index while the second part shows the change or return of the index.

Panels a and b of Fig. 1 above show a visible pattern of trend and seasonal variations in the All Share Index of Nigerian stock market. The two panels show that there is a tendency for the variables' means and variances not to be constant over time. It also shows the presence of two regimes, with a difference in the nature of the volatility clustering between the two regimes. The first part, ranges from 1985M1 to 1999M12, shows a low level of volatility clustering. The second part, ranging from 2000M1 to 2018M6, shows a high level of volatility clustering. The presence of the two regimes requires a modelling approach that takes care of the differences in the volatility clustering to statistically ascertain the extent and nature of volatility clustering in the two regimes. This study takes care of this by including seasonal dummies that take care of the difference between the two regimes.

4.2 Descriptive Statistics of Nigerian All Share Index

To further explain the nature of the data, a descriptive statistics table of the All Share index is presented in Table 1.

Table 1 shows the descriptive statistics of all share indexes for the subsamples and the full sample. The numbers of observations for the two subsamples are 180 and 222 while the full sample comprises of 402 observations. It can be shown that the subsamples and the full sample are positively skewed. Interestingly, the values of the kurtosis of the three categories of the variable show that the index is highly platykurtic as none of the values is close to three. The probability values of the Jarque-Bera show that the distribution property of all share index is not close to normal distribution.

4.3 Unit Root Test

Given that there is a presence of seasonal difference in the All Share Index data, HEGY unit root test method is adopted to ascertain the level of stationarity of the data. The result is presented:

The probability values for the unit root tests in Table 2 prompt us to accept the null hypothesis at first difference, hence we may conclude that all share index returns is zero integrated variables.

4.4 Regression Result

Table 3 below shows the estimates of the NLMACH model, its interpretation is presented at the bottom of the table.

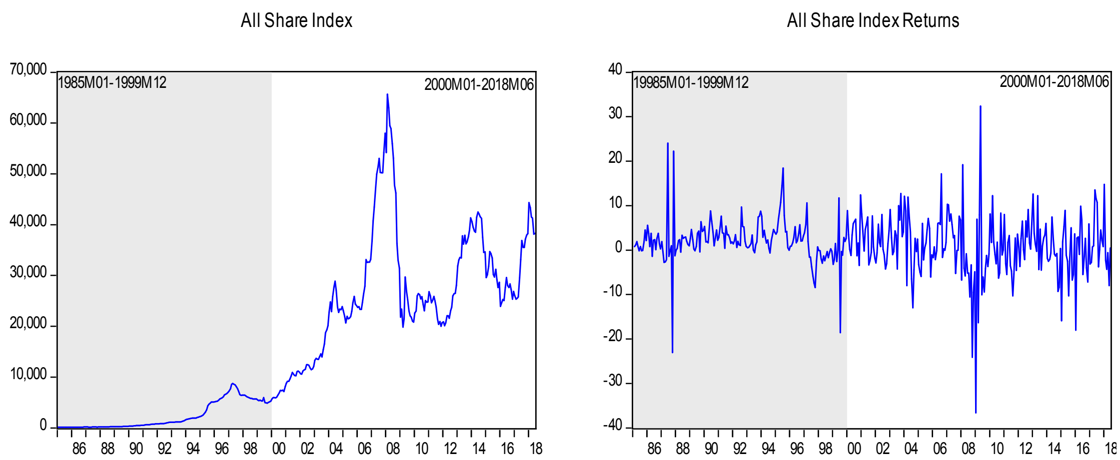

Fig. 1. Nigerian all share index

Table 1. Statistical properties of all share index

	LOG(ASI) 1985M1-1999M12	**LOG(ASI) 2000M1-2018M6**	**LOG(ASI) 1985M1-2018M6**
Mean	2315.477	27003.96	15949.42
Median	875.2500	25331.24	10615.95
Maximum	8729.800	65652.38	65652.38
Minimum	111.3000	5752.900	111.3000
Std. Dev.	2596.747	12316.32	15417.64
Skewness	0.902590	0.568046	0.778705
Kurtosis	2.287698	3.288167	2.757338
Jarque-Bera	28.24537	12.70712	41.61387
Probability	0.000001	0.001741	0.000000
Observation	180	222	402

Source: Author's computation

Table 2. Hegy seasonal unit root test result

	HEGY @ level	**HEGY @ 1Difference**
Constant + trigonometric terms + trend	LOG(ASI)	LOG(ASI)
	-1.17[0.88657]	-4.88[0.00014]***

Source: Author's computation (Note: We only report the zero frequency of the test)

The upper part of Table 3 shows the estimated model for the first sub-period while the middle part shows the estimated model for the second sub-period. The third part is the estimated form of the conditional variance equation with shift dummy "w". The model estimated is based on the parsimonious model selector. Due to this, all the parameters selected for the estimation are statistically significant.

$$smr_t = \begin{cases} 0.684 + 0.399smr_{t-1} + 0.123smr_{t-5} + 1.633sd6, & w = 1 \\ -0.674 + 0.274smr_{t-1} + 0.134smr_{t-3} + 0.162smr_{t-5} + 3.537sd5 + 5.917sd12, & w = 0 \end{cases}$$

$$logh_t = 3.351 + 0.570\left|\frac{v_{t-1}}{\sqrt{h_{t-1}}}\right| - 0.938w$$

Table 3. Regime-estimated parameters (dependent variable: smr)

Adjusted sample: 1985M07-2018M06 (396 observations)				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
constant1	0.683990	0.235240	2.907630	0.0036***
smr(-1)	0.398550	0.064620	6.167627	0.0000***
smr(-5)	0.123311	0.069835	1.765758	0.0774*
sd6	1.633066	0.936580	1.743647	0.0812*
constant2	-0.673926	0.406881	-1.656323	0.0977*
smr(-1)	0.273658	0.074475	3.674476	0.0002***
smr(-3)	0.134314	0.052520	2.557359	0.0105**
smr(-5)	0.162341	0.059709	2.718869	0.0066***
sd5	3.537184	1.564619	2.260732	0.0238**
sd12	5.917258	1.163226	5.086936	0.0000***
Conditional Variance Equation				
constant	3.350545	0.112024	29.90913	0.0000***
alpha1	0.570106	0.077296	7.375613	0.0000***
alpha2	-0.938207	0.125926	-7.450463	0.0000***
χ^2ARCH(1)	0.0479[0.8267]			
χ^2ARCH(2)	0.7715[0.6799]			
χ^2ARCH(3)	3.0916[0.3777]			

Source: Author's computation; (**) (***) denotes significance at 10%, 5% and 1% respectively*

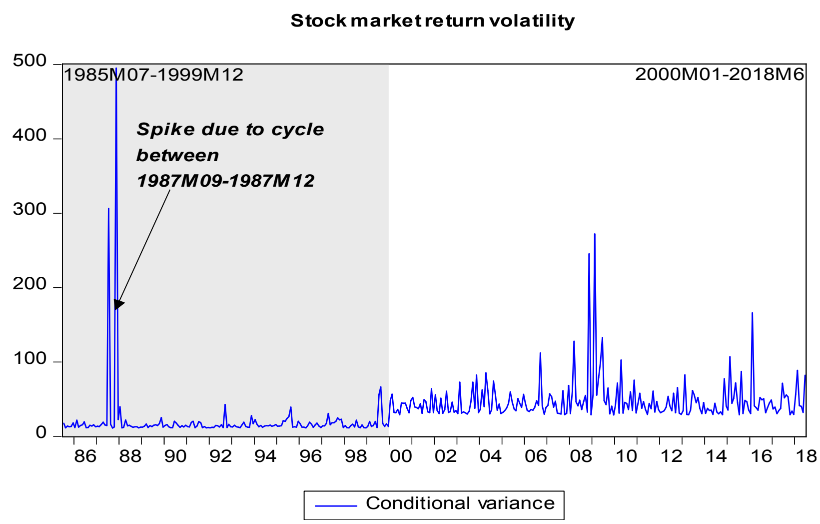

Fig. 2. Stock Market Return Volatility

For brevity and ease of interpretation, the estimated model in Table 3 above is presented in equation form above. We can see that the first sub-sample is driven by autoregressive or order one and five with a month six seasonal dummy. The second subsample is driven by a more complex autoregressive process. It is driven by autoregressive of order one, three and order five with fifth and twelfth-month seasonal dummies. The leverage or threshold effect γ_2 in volatility and the higher moment volatility γ_3 are not significant statistically, and were removed automatically. In essence, the conditional variance is driven by constant and the absolute standardized error term with the regime dummy.

5. DISCUSSION OF RESULTS

The goal of this paper was to investigate the presence and nature of volatility clustering in the Nigerian stock market prices from 1985M1 and 2018M6. Given that graphical representation of the All Share Index return shows the presence of two regimes in the Nigerian All share index, this study deems it fit to use an estimation model takes care of the presence of regimes in volatility clustering. Using a regime covariate autoregressive (AR-X) with an exponential GARCH model, that allows for a shift in intercept, it was found that the second regime, 2000M1 to 2018M6, is highly volatile than the first regime It was found that Nigerian All Share Index shows lower volatility in the period of 1985M1 to 1999M12, with the presence of orders one and five episodes of volatility, and six months' seasonal dummy. But between 1999M12 and 2018M6, the All Share index shows higher and more complex volatility clustering, indicated by the presence of orders one, three and five episodes of volatility, and five and twelve months of seasonal dummies.

The finding of this study is also corroborated by the Fig. 2. The figure shows that the conditional variance of the models wherein the first regime shows lower volatility while the second regime shows a higher and more complex volatility clustering. The findings of this study are similar to that of Babajide, Lawal and Somoye [20], Osahon [21], Atoi [22] where it was also found that Nigerian stock prices exhibit a high rate of volatility. The current study differs from the existing studies by identifying that the rate of volatility differs across two regimes. Unlike previous studies on the volatility of Nigerian stock market the current used an up-to-date data and equally demonstrated the need to use modelling technique that takes take of the presence of more than one regime in the Nigerian stock market.

6. CONCLUSIONS AND POLICY IMPLICATIONS

Going by the finding of this study, it can be concluded that the rate of volatility in the Nigerian stock prices differs across regimes. It is, therefore, necessary to use an estimation method that takes care of differences in regimes when modelling the Nigerian stock market. Taking this into consideration will reveal the hidden treasure underlying the stock market volatility processes between the periods. This study recommends that:

i. Policymakers put in place proactive measures that will address the high volatility inherent in the present-day Nigerian stock market.
ii. Local and foreign investors take cognizance of the high volatility of the recent time in deciding their investment decisions.
iii. Policymakers take into consideration the high volatility of Nigerian stock prices when designing macroeconomic policies.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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