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Market Participation and Asset Price Volatility: Evidence from the Nigeria Stock Market

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Abstract

We investigate the effect of market participation on asset price volatility in the Nigerian stock exchange from February 1985 to March 2022. Stylized facts established include that the log relative return of the Nigerian stock exchange all share index is leptokurtic, negatively skewed and exhibits volatility clustering confirmed by the presence of ARCH Effect in the residual of the estimated mean equation (mean reversion). The EGARCH (1, 1) model with Student's t error distribution was the tool of analysis. Results indicate that internal shocks – the ARCH term significantly affect future volatility. Volatility persistence (long memory) emerged from the results of this study as a feature of the Nigerian stock exchange. However, despite showing the right negative sign, this study failed to conclude on the leverage effect component as the asymmetric coefficient was not significant. Market participation was found to have no significant effect on asset price volatility though it had a positive coefficient. It is therefore suggested that investors and other stock market participants take advantage of the stylized facts revealed in this study as they make their investment decisions.

Keywords: Market Participation, Asset Price Volatility, Trading Volume, EGARCH

1.0 INTRODUCTION

What accounts for the volatility of asset prices? Central to the determination of asset price volatility could be investor behaviour. Based on arrival of new information on corporate performance, economic factors, interest rates, exchange rates, fiscal activities of government and political developments, investors adjust their decision to participate in the stock market (Najeb, 2013; Dewi & Suaryana, 2016; Romli, Wulandari & Pratiwi, 2017; Nasir, Diana & Mawardhi, 2018; Sutrisno, 2020). Thus, market participation seems to reflect investor sentiment. Therefore any factor that could influence market participation possibly will affect asset price volatility. Literature reveals that apart from information on corporate performance, economic factors, interest rates, exchange rates, fiscal activities of government and political developments, "Market Participation" is affected by a number of other factors including but not limited to: risk aversion, belief and attitude, self-

confidence, optimism, social interaction, group membership, family, peer group, internet, learning from others, word of mouth communication with others, distance index, uncertainty avoidance index, individualism vs collectivism and herding behaviour (Cao, Wang, & Zhang, 2005; Georgarakos, Haliassos & Pasini, 2014; Han & Hirshleifer, 2016; Hornuf & Schmitt, 2016; Kong & Fan, 2017; He, 2018; Thomas & Luca, 2018, Rahimi, Khosro & Zabihi, 2020). Also, expanding financial literacy, increased transparency of financial markets, government protection of shareholders and income occur in the literature as other factors that affect market participation (Asgharian, Liu & Lundtofte, 2014; Thomas and Luca, 2018; YiLi, 2020).

Given the plethora of factors that affect Market participation, many of which rely on opinion data and some, though may be measurable, seem cumbersome to gather data on them, a summary of investor decisions could be proxy by the trading volume or value of shares traded on the floor of the exchange market. According to Chan and Fong (2000), trading volume reflects the information received by market participants. Sutrisno (2020) argue that small trading volume indicates that investors are not interested in investing while large trading volume shows that many investors are interested in making transactions to buy and sell shares. For Dewi and Suaryana (2016), investors refrain from trading stocks for lack of information on those stocks thereby decreasing trading volume. On the other hand, "if investors receive a lot of information about a stock, then investors will trade their shares a lot, this will result in increased trading volume of shares" (Dewi & Suaryana, 2016; Nasir, Diana & Mawardhi, 2018). "As technicians say, volume goes with the trend and shows how much conviction investors have in a trend" (Fedorov (2019).

The question is, does market participation (trading volume) affect asset price volatility? First, asset price volatility is the constant increase and decrease in the prices of financial assets While Volatility is "simply a measure of risk (uncertainty) or variability of price of a financial instrument over time" (Ihejirika and Anyanwu, 2013). The concept of "volatility" is used in two senses: 1. historical volatility - how much the company stock actually fluctuated in the past and 2. implied volatility - how much the market expects the stock will fluctuate in the future (see Islam, 2014; Paulo, David, Tiago & George, 2011). This variability according to Ihejirika (2019) presents both opportunities to increase one's wealth when financial assets increase in value as well as risks that could wipe out an investors accumulated wealth. Thus, asset price volatility has become a phenomenon that investors and stock market participants must deal with to protect the values of their assets while hoping to maximize their wealth.

Returning to the question of how market participation (trading volume) affect asset price volatility, Sadullah and Ayben (2021) indicate that the stock indices (price) is not affected by any shock related to volume but reaction of volume to the shocks applied to the index (price) are positive. Jakree and Ilhyock (2021) found that the relationship is unilateral running from volatility to market participation measured by trading volume and average transaction size. Gaudio, Ivan and Santoro (2021) show that shock to the capital share of income display a modest capacity to explain macroeconomic fluctuations. Sutrisno's (2020) study "reveals that the stock trading volume significantly affects stock price volatility". So far there is no consensus as to the nature

of relationship between these variables. In this study, we conceptualize market participation as trading volume and investigate its relationship with asset price volatility in Nigeria. Given the above introduction, next is review of related literature followed by the methodology - data and the analytical tools employed. Analysis of data and results occupy section four. The paper concludes in section five.

2. LITERATURE REVIEW

2.1 Theoretical Review

2.1.1 The Mixture of Distribution Hypothesis (MDH) - Clark (1973)

Clark (1973) proposed the mixture of distribution hypothesis (MDH) to explain price-volume relationship. The theory states that the correlation between variances of return and volume are positively contemporaneous. This suggests that volume and return series respond simultaneously to new information with no "inter-temporal causality". Epps and Epps (1976), Tauchen and Pitts (1983), and Harris (1986) further extend the MDH. Carroll, & Kearney, (2015) tested the mixture of distributions hypothesis on target stocks. They found "strong evidence for MDH-consistent positive volume–volatility relationships before and after takeover announcements that are supportive of the applicability of the MDH in the market for corporate control". Earlier, Luu and Martens' (2002) tested the MDH using realized Volatility. They used intraday returns volatility rather than daily return volatility and conclude that "the mixed evidence on MDH in the existing literature can in part be attributed to the use of poor realized volatility measures". Other researchers investigating the MDH include: Malay and Wang (2010), Chandrapala (2011), Sangram (2016); Zhou, (2020) among others.

2.1.2 Sequential Information Arrival Hypothesis (SIAH) - Copeland (1976)

> "Suppose an asset market exists where individuals receive information sequentially and in random order. Start with an initial equilibrium where they all possess an identical set of information. Then allow a single piece of news to be generated. As each individual receives it, he reacts by shifting his demand curve. Finally, when all individuals have received the news, they once again possess an identical set of information and a new equilibrium is established".

Copeland (1976) used the above quoted statement to introduce his much referenced work "a model of asset trading under the assumption of sequential information arrival". Several researchers have and are still researching on the hypothesis (Jennings, Starks & Fellingham 1981, Batta 2014, Sangram 2016, Pengfei, Zhang, Xiao & Shen 2019). Most results lend support to the conclusions reached by Copeland (1976) that "in a world with sequential information arrival, the expected number of trades is related to the absolute value of price changes". Copeland (1976) in a foot note categorically stated that "Sequential information arrival offers an explanation of

positive correlation between the absolute values of price changes and volume".

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Empirical Review

Recently, Jakree and Ilhyock (2021) investigated the effect of asset price volatility on market participation using the data from Thai foreign exchange market. The findings of the study showed that the volatility of the US dollar/Thai baht exchange rate effect is positive on market participation measured by trading volume and average transaction size. The effect of the volatility of FX on trading volume according to the study is positive for foreign end-customers and interbank players, but negative for local end-customers. This variability is described by different purposes of FX transactions: financial returns for the former and real demand for the later. Finally, we show that the effect of volatility on trading volume is negative at high levels of volatility and during a period of high regulatory unpredictability.

Sadullah and Ayben (2021) examined empirically the correlation between stock prices and volumes for the selected Middle Eastern and North African countries (Bahrain, Dubai, Egypt, Israel, Jordan, Kuwait, Lebanon, Oman, Qatar, and Saudi Arabia). The study employed Markov Regime Switching Vector Autoregressive Model (MSVAR) to analyze the relation in bearish and bullish position. They used daily data and different periods for each stock market depending on the accessibility of data for the period 01/01/2016 to 21/11/2019. The results from Markov switching models indicate that the stock indices (price) is not affected by any shock related to volume in any of the country in any regime of recession, moderate growth, or expansion. The reaction of volume to the shocks applied to the index (price) are positive for all regimes for 4 countries, but the reaction differ according to the regime for the others in terms of the nature of the direction as positive or negative.

Prem (2020) sought to ascertain the central role played by trading volume in the pricing of financial assets in the Nepalese stock market. A sample of 49 stocks' data from mid- July 2011 to mid-July 2018 was analyzed using Granger Causality in a bivariate VAR model framework. Prem (2020) show that there was no causal relationship between trading volume and stock returns considering the market as a whole. However, the results indicated that sector-wise, commercial banks' trading volume granger causes stock returns. Similarly, the study found unilateral causal relationships running from trading volume of finance companies, hydropower companies, and insurance companies to stock returns.

Pengfei, Zhang, Xiao & Shen (2019) in their study "Trading volume and return volatility of Bitcoin market: evidence for the sequential information arrival hypothesis" using both linear and nonlinear correlation and causality tests suggest that there exist a "significant lead–lag relationships between trading volume and return volatility". Pengfei, Zhang, Xiao & Shen (2019) in the same study also find that "trading volume and return volatility are negatively correlated.

Balcilar , David, Gupta and Elie (2017) investigated whether trading volume Granger causes Bitcoin returns and volatility. Their approach consisted of a "non-parametric causality-in-quantiles test" applied to a data set starting from 19th December 2011 to 25th April 2016. The outcome of their analysis shows that "volume can predict returns" but "cannot

help predict the volatility of Bitcoin returns".

Hazem and Mohamed (2015) used different method of analysis to study the relationship between trading volume and stock return volatility for industrial firms listed on Muscat securities market. These tests includes vector autoregressive model (VAR), Brailsford model, and the pairwise Granger causality test. The empirical and econometric results of the findings showed prove of a positive significant effect of return volatility on trading volume. Likewise, the VAR model showed proof of a positive significant effect of trading volume on stock returns. The pairwise Granger causality test posits that trading volume Granger-cause stock return.

Sushil and Vibha (2014) used Daily data of adjusted closing stock prices, trading volume of 39 securities and S&P CNX Nifty from January 1, 1998 to May 31, 2013 to study the relationship between the stock prices and trading volume. The Toda and Yamamoto (1995) procedure was used for analyzing the data. The Lag length selected by **Akaike information criterion (**AIC) and final prediction error (FPE) criterion was confirmed by running Lagrange Multiplier (LM) test and the level of causality determined by Toda and Yamamoto test was confirmed by using VAR methodology. Although, Toda and Yamamoto and VAR test did not produce similar results, however, the empirical analysis provided enough grounds to say that there is presence of interaction between stock prices and trading volume.

Emenike and Opara (2014) made use of the daily All-Share Index and closing trading volume of the Nigerian Stock Exchange for the period of 2000-2011 to investigate the relationship between stock returns volatility and trading volume in Nigeria. The results of the GARCH-X (1,1) and GARCH (1,1) models showed that the relationship between trading volume and stock returns volatility is statistically significant and positive.

Izz Eddien, Qasim & Ahmed (2013) in order to find the empirical relationship between return volatility and trading volume used data from the Amman Stock Exchange (ASE) for 27 individual stocks, using daily data for the period 2002-2012. The results showed that trading volume significantly contributes to the return volatility of stocks in Amman stock Exchange, as shown in many studies. Contrarily, the results also showed that the Trading volume has no significant effect on the reduction of the volatility persistence for majority of stocks in the sample.

Sabri (2008) studied the price–volume movements in the Arab stock markets, in order to ascertain the effect of changes in trade volume on the volatility of stock prices as expressed by the unified AMF stock price index. 8 out of the 15 Arab stock markets listed in the Arab Monetary Fund database were used and monthly data from 1994 to 2006 was used for the analysis. The result of the analysis showed that there is an increase in both trading volume and stock price volatility, which may be considered a recent phenomenon in the majority of the Arab stock markets. The study also found that the volume–stock price movements are significantly related for all selected markets, while the highest (to lowest) correlation coefficient between volume and stock price movement was found in the Amman stock market, Muscat stock market, Kuwait stock market and Saudi stock market (in that order). It is also seen that the correlation between volume and price movement is higher in the stock markets of the oil Arab states compared to the non-oil Arab states.

3.0 METHODOLOGY

3.1 Data

Asset prices in this study was proxy by the Nigerian exchange group (NGX) all share index (ASI) while trading volume represent market participation. Monthly time series data on the two variables were collected from the Central Bank of Nigeria statistical data base from January 1985 to March 2022. The data collected were transformed to log relative returns using equations 1 and 2 below (see Black & Scholes, 1973; Chen, Firth & Rui, 2001; Chandrapala, 2011; Ihejirika & Anyanwu, 2013; Sangram, 2016; Ihejirika, 2019; ZHOU, 2020)

$$ASILRR_t = \text{In}(\text{ASI}_t) - In(ASI_{t-1}) = In\left(\frac{ASI_t}{ASI_{t-1}}\right) \dots\dots\dots\dots\dots\dots 1$$

$$\text{TVLRR}_t = \text{In}(\text{TV}_t) - In(TV_{t-1}) = In\left(\frac{TV_t}{TV_{t-1}}\right) \dots\dots\dots\dots\dots\dots 2$$

Where

$ASILRR_t$ = NGX ASI $log\ relative\ returns\ at\ t$

ASI_t = NGX ASI at time t

$In(ASI_t) = natural\ logarithm\ of\ NGX\ ASI\ at\ time\ t$

ASI_{t-1} = NGX ASI at time $t-1$

ln(ASI_{t-1} = natural logarithm of NGX ASI $t-1$

$TVLRR_t = trading\ volume\ log\ relative\ returns\ at\ time\ t$

TV_t = trading volume at time t

$In(TV_t) = natural\ logarithm\ of\ \ trading\ volume\ at\ time\ t$

TV_{t-1} = trading volume at time $t-1$

$In(TV_{t-1}) = natural\ logarithm\ of\ \ trading\ volume$ at time $t-1$

Method of Data Analysis

Volatility studies utilize the ARCH (Engle (1982), GARCH (Bollerslev, 1986), EGARCH (Nelson, 1991), among other ARCH- GARCH family models to capture the properties of time-varying volatility in financial time series. Necessary conditions are that there should be presence of volatility clustering and ARCH effect. To establish volatility clustering in asset prices and trading volume, we estimate the mean equation (see equation 3) and check the residual for volatility clustering as well as use the residual diagnostics to test the ARCH effect.

$$ASILRR_t = C_1 + \in \cdots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots 3$$

The conditional variance equation is shown below in equations 4.

$$H_t = C_2 + C_3 H_{t-1} + C_4 e^2{}_{t-1} + C_5 TVLRR \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots 4$$

Equation 4 examines the effect of trading volume on asset price volatility

Where,

$H_t = current\ \ month\ ASILRR\ volatility$

$H_{t-1} = previous\ month\ ASILRR\ volatility\ - GARCH\ TERM$

$e^2{}_{t-1} = previous\ month\ \ information\ about\ ASILRR\ volatility -\ \ ARCH\ TERM$

$C_1 - C_5\ = coefficients$

For the exponential GARCH (EGARCH) model we adopt the E-views version to explore not only the Generalized Error Distribution (GED) but also the normal as well as the Student's t-distributions (see equation 7 below).

$$log(\sigma_t^2) = \omega + \sum_{j=1}^{q} \beta_j \log\left(\sigma_{t-j}^2\right) + \sum_{i=1}^{p} \alpha_i \left|\frac{\epsilon_{t-i}}{\sigma_{t-i}}\right| + \sum_{k=1}^{r} \gamma_k \frac{\epsilon_{t-k}}{\sigma_{t-k}} \ldots\ldots\ldots 7$$

Where:

$log(\sigma_t^2)$ = the logarithm of conditional variance

ω = a constant term

ϵ_{t-1}^2= news about volatility from the previous period, measured as the lag of the squared residual from the mean equation: (the ARCH term).

σ_{t-1}^2 last period's forecast variance: (the GARCH term)

We test leverage effects using the hypothesis that $\gamma_i < 0$. If $\gamma_i \neq 0$, asymmetric condition is established. If $\left(\frac{\epsilon_{t-i}}{\sigma_{t-i}} > 0\right)$ implies "good news" while if $\left(\frac{\epsilon_{t-i}}{\sigma_{t-i}} < 0\right)$ ="bad news". To produce a leverage effect, α_i, must be negative. For volatility shocks to be persistent, the ARCH and GARCH coefficients ($\alpha + \beta$) should be very close to one (mostly for high frequency financial data).

4.0 RESULTS AND ANALYSIS

4.1 Unit root test

We subjected the log relative returns series to unit root test which indicate that they are I(0) stationary which satisfies the assumption of stationary variables for ARCH- GARCH estimation (Ndwiga & Muriu, 2016).

4.2 Descriptive Statistics

Table 4.1: Descriptive Statistics of ASILRR and TVLRR

Series	Mean	Median	Maximum	Minimum	Std. Dev.	kewness	Kurtosis	Obs
ASILRR	0.005884	0.006418	0.140501	-0.1589	0.026849	-0.45108	9.119813	446
TVLRR	0.008419	0.006263	0.184098	-0.2595	0.033505	-1.80315	24.53886	446

From table 4.1 above, we observe that both ASILRR and TVLRR exhibit fat tails with kurtosis in excess 3. ASILRR and TVLRR are both negatively skewed

4.3 Test for volatility clustering

Figures 4.1 below show the graph of the residuals from the estimated mean equation 3 above on ASILRR.

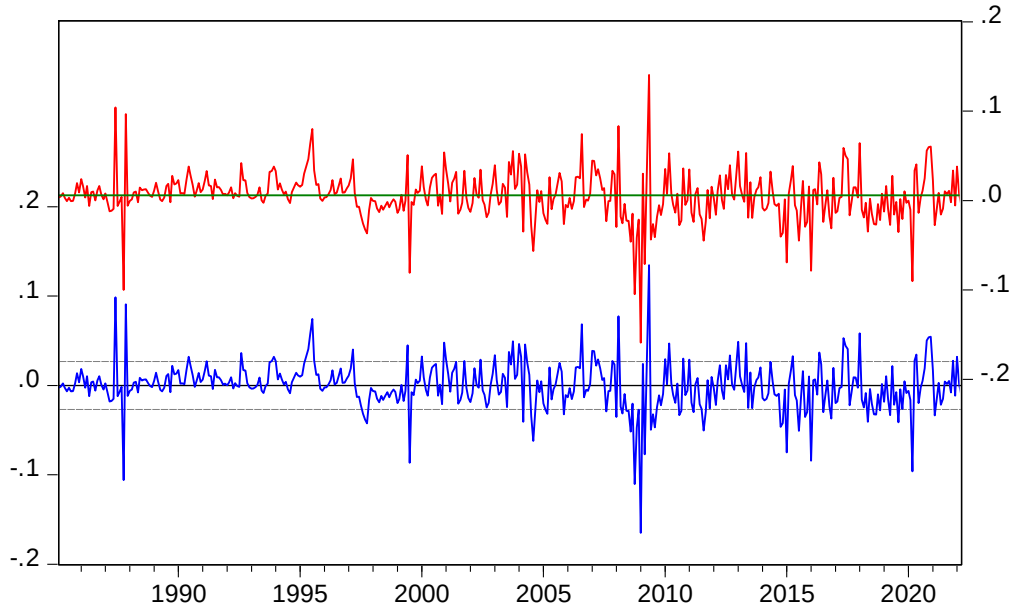


Figure 4.1: Graph of ASILRR residuals 1985M02 - 2022M03

Figures 4.1 above seem to suggest that ASILRR exhibit volatility clustering. Table 4.2 below confirms the presence of heteroscedasticity i.e. there is ARCH effect in the residuals of ASILRR.

Table 4.2 ASILRR

Heteroskedasticity Test: ARCH

F-statistic	4.233776	Prob. F(1,443)	0.0402
Obs*R-squared	4.212630	Prob. Chi-Square(1)	0.0401

4.4 GARCH(1,1) and EGARCH(1,1) Choice of Model and Error Distributions

We stated earlier that to estimate the GARCH and EGARCH models we adopt the E-views version to explore not only the Generalized Error Distribution (GED) but also the normal as well as the Student's t-distributions. The Nelson (1991) model used only Generalized Error Distribution (GED). Below in tables 4.3a and 4.3b are shown the choice of Model and error distributions based on the least values of Akaike info criterion and Schwarz criterion.

From tables 4.3a and 4.3b below, based on the Akaike info criterion and Schwarz criterion, the EGARCH Model performs better than the GARCH model irrespective of which error distribution was used. Consequently the study adopts the EGARCH model.

Table 4.3a: GARCH(1,1) choice of Model and error distributions ASILRR model

Criteria	GED	NORMAL	STUDENT'S t	Choice
Akaike info criterion	-4.730185	-4.665605	-4.738892	STUDENT'S t
Schwarz criterion	-4.675023	-4.619637	-4.683731	STUDENT'S t
Decision	The study adopts the STUDENT'S t distribution for GARCH (1,1) model			

Table 4.3b: EGARCH(1,1) choice of Model and error distributions ASILRR model

Criteria	GED	NORMAL	STUDENT'S t	Choice
Akaike info criterion	-4.753273	-4.695758	-4.762501	STUDENT'S t
Schwarz criterion	-4.688918	-4.640597	-4.698147	STUDENT'S t
Decision	The study adopts the STUDENT'S t distribution for EGARCH (1,1) model			

Similarly, from tables 4.3a and 4.3b above, STUDENT'S t distribution emerged as the choice of error distribution and thus was adopted in the estimation of EGARCH model that follows.

4.5. Results of the estimated conditional variance equation EGARCH (1,1) model

In table 4.4 below is presented both the mean and variance equations results. The volatility of asset prices as captured by ASILRR is the dependent variable represented in the equation as LOG(GARCH). Below the variance equation in table 4.4, C3 corresponds to News about ASILRR volatility from the previous period - the Arch term. The results indicate that News about ASILRR volatility from the previous period significantly affect its future volatility. Further results show that the asymmetric coefficient C4 though has the right negative sign is insignificant. Thus, the study could not conclude that there is a leverage effect. On the other hand, there is

evidence of long memory seen from the GARCH term (i.e. C5 - Last period's forecast variance) leading to the conclusion that there is volatility persistence in the Nigerian stock exchange index return. C6 is the coefficient of market participation (trading volume in this study). Although there is a positive relationship between market participation and asset prices, market participation does not significantly affect future volatility of asset prices.

Table 4.4: estimated conditional variance results

Dependent Variable: ASILRR
Method: ML ARCH - Student's t distribution (BFGS / Marquardt steps)
LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)
*RESID(-1)/@SQRT(GARCH(-1)) + C(5)*LOG(GARCH(-1)) + C(6)
*TVLRR

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.007815	0.000840	9.306682	0.0000
	Variance Equation			
C(2)	-1.257143	0.338262	-3.716476	0.0002
C(3)	0.527522	0.109613	4.812592	0.0000
C(4)	-0.073051	0.057647	-1.267229	0.2051
C(5)	0.883784	0.040682	21.72432	0.0000
C(6)	0.703181	1.565068	0.449297	0.6532
T-DIST. DOF	4.721074	1.198292	3.939837	0.0001

To establish the reliability and usefulness of the estimated model and results, the study examined the model for any remaining ARCH effects in the residuals and for serial correlation using the correlogram of standardized residuals squared. The results are shown below.

Table 4.5 test for remaining ARCH Effects in the residuals

Heteroskedasticity Test: ARCH

F-statistic	0.048196	Prob. F(1,443)	0.8263
Obs*R-squared	0.048409	Prob. Chi-Square(1)	0.8259

The Heteroskedasticity Test: ARCH result in table 4.5 above indicates that there are no remaining ARCH effects in the residual of the estimated EGARCH model.

Similarly, considering the Q-statistic result of the correlogram of standardized residuals squared shown in table 4.6 below, we find no serial correlation in the residuals of the estimated EGARCH model.

Table 4.6 test for serial correlation

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
.|. |	.|. |	1	-0.010	-0.010	0.0488	0.825
.|. |	.|. |	2	-0.053	-0.053	1.3303	0.514
.|. |	.|. |	3	-0.007	-0.008	1.3514	0.717
.|* |	.|* |	4	0.103	0.100	6.1032	0.192
.|. |	.|. |	5	-0.039	-0.038	6.7919	0.237
.|. |	.|. |	6	-0.006	0.003	6.8101	0.339
.|. |	.|. |	7	0.035	0.033	7.3662	0.392
.|. |	.|. |	8	-0.019	-0.030	7.5392	0.480
.|. |	.|. |	9	-0.048	-0.038	8.6056	0.474
*|. |	*|. |	10	-0.067	-0.072	10.669	0.384
.|. |	.|. |	11	-0.033	-0.047	11.178	0.429
.|. |	.|. |	12	-0.017	-0.019	11.315	0.502
*|. |	*|. |	13	-0.072	-0.073	13.719	0.394
.|. |	.|. |	14	-0.019	-0.014	13.879	0.459
.|. |	.|. |	15	-0.023	-0.027	14.116	0.517
.|. |	.|. |	16	-0.028	-0.031	14.491	0.562
.|. |	.|. |	17	0.042	0.055	15.299	0.574
.|. |	.|. |	18	-0.011	-0.019	15.352	0.638
.|. |	.|. |	19	-0.022	-0.021	15.569	0.686
.|. |	.|. |	20	-0.019	-0.020	15.732	0.733
.|. |	.|. |	21	-0.013	-0.040	15.812	0.780
.|. |	.|. |	22	0.003	-0.003	15.817	0.825
.|. |	*|. |	23	-0.054	-0.070	17.200	0.799
.|. |	.|. |	24	0.037	0.021	17.847	0.810
.|. |	.|. |	25	-0.035	-0.046	18.440	0.823
.|* |	.|. |	26	0.080	0.072	21.450	0.718
.|. |	.|. |	27	-0.025	-0.015	21.753	0.750
.|. |	.|. |	28	0.010	0.002	21.800	0.790
.|. |	.|. |	29	0.008	0.009	21.832	0.827
.|. |	.|. |	30	-0.040	-0.059	22.594	0.832
.|. |	.|. |	31	0.025	0.023	22.885	0.853
.|. |	.|. |	32	0.008	-0.007	22.916	0.881
.|. |	.|. |	33	0.021	0.004	23.120	0.900
.|. |	.|* |	34	0.070	0.079	25.508	0.853
.|. |	.|. |	35	-0.021	-0.032	25.723	0.874
.|. |	.|. |	36	0.030	0.042	26.149	0.886

*Probabilities may not be valid for this equation specification.

Furthermore, to ascertain why the distribution of the residuals deviates from normality, we plot the quantiles using the standardized residuals. Presented below in figure 4.2 is the graph of the Quantile-Quantile (Theoretical) indicating what drives the departure from normality.

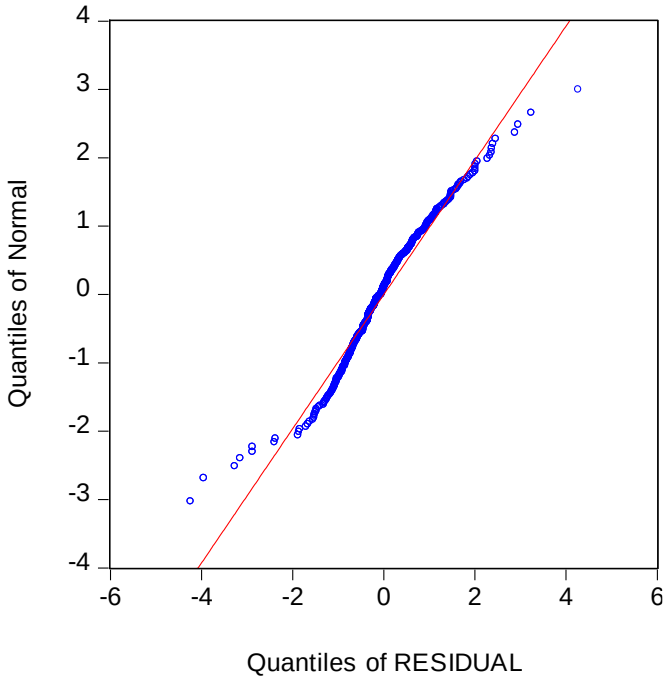


Figure 4.2 Quantiles of estimated ASILRR EGARCH Model residuals

There is evidence of large negative shocks that outweigh the positive shocks that is propelling the residuals away from normality (see figure 4.2 above).

Finally, the EGARCH model below summarizes the relationship between market participation and asset price volatility in the Nigerian stock market.

Estimation Equation:
==========
ASILRR = C(1)

LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(4)*RESID(-1)/@SQRT(GARCH(-1)) + C(5)*LOG(GARCH(-1)) + C(6)*TVLRR

Substituted Coefficients:
==========
ASILRR = 0.00781514411919

LOG(GARCH) = -1.2571425828 + 0.527522009582*ABS(RESID(-1)/@SQRT(GARCH(-1))) - 0.0730513435703*RESID(-1)/@SQRT(GARCH(-1)) + 0.883784417747*LOG(GARCH(-1)) + 0.703180551906*TVLRR

5. CONCLUSION

This study investigated the effect of market participation on asset price volatility in the Nigerian stock exchange from February 1985 to March 2022. Stylized facts established include that the log relative return of the Nigerian stock exchange all share index is leptokurtic, negatively skewed and exhibits volatility clustering confirmed by the presence of ARCH Effect in the residual of the estimated mean equation. The EGARCH (1, 1) model with Student's t error distribution was the tool of analysis. Results indicate that internal shocks – the ARCH term significantly affect future volatility. Volatility persistence (long memory) emerged from the results of this study as a feature of the Nigerian stock exchange. However, despite showing the right negative sign, this study failed to conclude on the leverage effect component as the asymmetric coefficient was not significant. Market participation was found to have no significant effect on asset price volatility though it had a positive coefficient. It is therefore suggested that investors and other stock market participants take advantage of the stylized facts revealed in this study as they make their investment decisions. Finally, this study relied on monthly data. Perhaps, a higher frequency data (daily) may reveal more on the relationship between market participation and asset price volatility.

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