Trading Volume, Intraday and Overnight Volatility of Stock Returns in the Nigerian Stock Exchange

Abstract

We have investigated in this paper the information arrival process in the Nigerian Stock Exchange (NSE) by considering some highly priced and highly capitalized 28 stocks (companies) registered in the market. By using the GARCH modelling approach with additional market information such as volume traded, intra-daily volatility, and overnight indicator, introduced as exogenous variables, we obtain similar results by previous authors, though trading volume does not predict the overall stock index of the market since it increased the overall volatility persistence. Our results therefore show the applicability of the Mixture of distribution Hypothesis (MDH) in the NSE market.

Key word:
JEL Classification: C22, G12, G17

1. Introduction

Quite a number of theoretical models have critically explained the information arrival process in the financial market with the use of Mixture of Distributions Hypotheses (MDH) and the sequential information arrival hypothesis. In the MDH framework, there is a positive relationship between returns and trading volume as they jointly depend on a common factor, information innovation. This further extends to the relationship between returns and overnight indicator (ONI) and intraday volatility (IDV) measured by open, close, high, and low prices. Thus, MDH extends the applicability of various daily prices of assets that are available far beyond the usual close price used in empirical volatility modelling. The dissemination of information is contemporaneous in MDH (see Clark, 1973; Epps and Epps, 1976; Tauchen and Pitts, 1983; Harris, 1986). On the other hand, the sequential arrival of information hypothesis proposed the stepwise dissemination of information such that a series of intermediate equilibria exists (Copeland, 1976; Tauchen and Pitts, 1983). Grammatikos and Saunders (1986) explained sequential information arrival models as the possibility of observing lead relations of daily contract price variability to volume, overnight, and intraday effects. The sequential arrival information model argues that each trader observes the information sequentially. Also, McMillan and Speight (2002) argue that the sequential arrival hypothesis supports a dynamic relationship whereby the past change in volume, overnight indicator, and intraday effect provide information on current absolute returns. In other words, the dynamic relationship is very important as it gives useful information about market dynamics of returns and volatility. Recent empirical studies have investigated the dynamic relationship between trading volume and returns. Some theoretical papers suggest 'causality' between changes in volatility and volume.

However, both MDH and sequential arrival of information hypotheses support a positive and contemporaneous relationship between volume-absolute returns and assume a symmetric effect for price increases and price decreases for futures contracts (Karpoff, 1987). However, many researchers have paid attention to trading volume because its role is vital in the stock market. On the other hand, the stock exchange is a place where shares of various companies are bought and sold among different investors. An increased trading volume gives rise to heightened investor expectations regarding the stocks. In a seminal paper by Karpoff (1987), the importance of trading volume and its effect on the volatility of financial assets is presented. Firstly, this relationship is known to depend on the rate of information flow to the market, information dissemination, market size, and the existence of short-event sale constraints. Secondly, the relationship also has important implications for event studies that use a combination of price and volume data. Lastly, the relationship has important implications for the empirical distribution of speculative assets. Other MDH factors are the ONI and IDV. Due to that, Lamoureaux and Lastrapes (1990) considered market activity and its impact on volatility by suggesting alternative proxies that have more of an *ex-ante* motivation such as volume, overnight indicator, and intraday volatility. Gallo and Pacini (2000) suggested an overnight indicator (ONI) which represents the surprise intervening between the closing of one day and the opening of the following day and is capable of a substantial reduction in the estimated persistence. Despite the importance, there is a dearth of studies on the volatility–volume relationship in the Nigerian Stock Market (NSM).

This paper estimates the volatilities of returns in the NSM and computes the persistence from each of the volatility speculations without volume, with contemporaneous volume, with lagged volume, Intra-Day Volatility (IDV), and Overnight Indicator (ONI). The volatility model applied is the Generalized Autoregressive conditional Heteroscedasticity (GARCH) model of Bollerslev (1986). The IDV and ONI are proxies for information arrival as proposed in Gallo and Pacini (2000).

This work has not been found in the literature in the context of the Nigerian market. The NSM's stock index, also known as the All-Share Index (ASI), serves as a comprehensive indicator of stock prices. The daily ASI has equivalent market capitalization and volume traded.

This paper is structured as follows: Section 2 presents the literature review. Section 3 presents the methodology employed. Section 4 comprises the data and empirical analysis while Section 5 gives the concluding comments.

2. Review of Literature

In the last two decades, researchers have been very much interested in the relationship between trading volume, return, and volatility in financial markets. Quite a number of studies have investigated stock market return correlation with trading volume. The trading volume on a daily basis represents the total number of shares bought and sold in the stock market by investors and this volume has the predictive power for stock returns volatility regardless of the measure of volatility used (Leon, 2007). Volume is the evidence that the buying and selling of stock is on or not. The trading volume has been considered as an important technical indicator to measure the strength of the market since it contains useful information about stock behaviour (Hsieh, 2014). Some of the earlier works and propositions include; Clarks (1973), Lamoureux and Lastrapes (1990), and Anderson (1996), amongst others. Clark (1973) studied price movement with trading volume using the Mixture of Distribution Hypothesis (MDH). The MDH explores the role of trading volume as a proxy for a stochastic process of information arrival. Lamoureux and Lastrapes (1990) applied the daily returns and volumes of actively traded stocks in the US markets from 1980 to 1984 to test the relation between conditional volatility and trading volume and found that volatility persistence disappears when the daily trading volume enters the conditional variance model. Anderson

(1996) proposed the Modified MDH model which has led to an increasing number of studies on volatility-trading volume relationships.

Brailsford (1996) investigated the effect of trading volume as a proxy for information arrival on the persistence of volatility in the Australian Stock Market using the GARCH process and found trading volume to reduce the volatility persistence in Australian stocks. Kamath and Chusanachot (2000) concluded that GARCH effect does not completely disappear when the volume is included in the conditional variance model. Gallo and Pacini (2000) used the data of 10 actively traded US stocks from 1985 to 1995 and found the estimated persistence to decrease when trading volume was introduced in the conditional variance model. Wang, Wang, and Liu (2005) investigated the dynamic relationship between stock return volatility and trading volume of individual stocks on the Chinese stock market as well as market portfolios of these stocks. Their results indicated that trading volume positively influenced stock return volatility, and the inclusion of this in each individual stock reduced the persistence of the conditional volatility. Mpofu (2012) considered the case of the Johannesburg Stock Exchange in South Africa from 1988 to 2012 and found that stock returns positively related to the contemporary change in trading volume of stocks.

In a similar study, Choi, et al. (2012), for the Korean stock market, investigated the relationship between return volatility and trading volume as a proxy for the arrival of information to the market by measuring the relationship between return volatility and trading volume using the GJR-GARCH and exponential GARCH (EGARCH) models. They found a positive relationship between trading volume and volatility, implying that trading volume impacts the flow of information to the market. Their findings also support the validity of the mixture of distributions hypothesis.

For the Tehran stock exchange data, Meshkin, et al. (2014) applied GARCH family model and Granger causality on monthly data of trading volume to examine contemporaneous relationships between trading volume, volatility and stock return based on Mixtures of Distributions Hypothesis (MDH) and in the format. Their finding proved that MDH exist in the Tehran stock exchange. Their results also show that exponential GARCH model is a proper model for stock volatility and that trading volume and stock volatility have a one-way relationship. However, for the Pakistani data, trading volume and stock volatility were found to have causal relationship. Moreover, their variance equation of the GARCH Model shows the interaction between the trading volume and stock return in the Pakistani banking sector (Hussain, et al. 2014). With some of the studies reviewed above, we observed that the interaction between trading volume, intraday and volatility of stock returns for some countries has been studied extensively in literature. We seek to contribute to literature by also examining the nature of these factors in the Nigerian stock market.

Overnight indication and intra-daily volatility effects have been investigated in Gallo and Pacini (2000). The authors considered 10 actively traded US stocks using symmetric and asymmetric GARCH models, and found decreases in persistence of volatility by including volume traded variables. By using alternative proxies for trading activities such as ONI and IDV, the authors found importance of other daily captured prices such as opening, closing, high and low since these accounted for significant persistence in the GARCH system.

3 Methodology

The price-volume relationship of share price and stock index is investigated by using the volatility modelling approach as outlined in Bollerslev (1986). This modelling framework is the generalized Autoregressive Conditional Heteroscedasticity (GARCH) model. We first obtain daily returns, $r_{i,t}$ from the log-difference of daily prices, P_t , that is,

$$r_{i,t} = \log(P_{i,t} / P_{i,t-1}) \qquad (1)$$

Where $P_{i,t}$ is the closing price of stock, *i* on day *t*, and $P_{i,t-1}$ is the previous price of the stock. The essence of log-difference of price here is to obtain stationary time series equation from the non-stationary price series. The volume traded at time t is denoted by, $VT_{i,t}$, where previously traded volume is denoted as $VT_{i,t-1}$ on stock *i* is computed as

$$V_{i,t} = \log(VT_{i,t} / VT_{i,t-1}) \tag{2}$$

Empirical studies recognized daily trading volume as a measure of the amount of information flows in the market. Also with the fact that trading volume is a mixing variable which is often used as a weak exogenous variable, then we consider sufficient model specification as where $V_{i,t}$ is incorporated in the mean and variance models, as follows:

The first scenario uses first order autoregression with GARCH(1,1) as follows:

$$r_{i,t} = \alpha_0 + \alpha_1 r_{i,t-1} + \varepsilon_{i,t} \tag{3}$$

$$h_{i,t} = \beta_0 + \beta_1 \varepsilon_{i,t-1}^2 + \beta_2 h_{i,t-1} \tag{4}$$

where $\varepsilon_t \sim N(0,1)$ and α_0 and α_1 are respectively the constant and AR(1) parameters in the mean equation (3), and $\beta_0 > 0$ and β_1 and β_2 are non-negative parameters of GARCH model. Thus, $\beta_1 + \beta_2$ determines the volatility persistence of stocks in the stock market, i, and the greater this sum, the higher is the volatility persistence. By incorporating the trading volume $V_{i,t}$ in the variance equation, we have,

$$r_{i,t} = \alpha_0 + \alpha_1 r_{i,t-1} + \varepsilon_{i,t} \tag{3}$$

$$h_{i,t} = \beta_0 + \beta_1 \varepsilon_{i,t-1}^2 + \beta_2 h_{i,t-1} + \beta_3 V_{i,t} \tag{4}$$

Thus, β_3 determines if there is significant relationship between market conditional volatility h_t and change in volume traded $V_{i,t}$.

Other proxies information arriving at time *t* is the Intra-Day Volatility (IDV) and Overnight Indicator (ONI). An Intra-Day Volatility (IDV) measure is suggested in Gallo and Pacini (2000). The IDV is calculated as the difference between the highest and lowest price divided by the closing price. The IDV is calculated as follows:

$$IDV_t = \frac{P_{i,t}^{H} - P_{i,t}^{L}}{P_{i,t}^{c}} \tag{5}$$

where P_t^H, P_t^L and P_t^c are the highest, lowest and closing price on day *t* respectively. The IDV is then entered into the conditional variance model as,

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \gamma_1 IDV_{t-1} \tag{6}$$

Another indicator suggested in Gallo and Pacini (2000) is the Overnight Indicator (ONI). They argued that instead of computing the returns as the difference between closing prices, the difference between the opening price of any given day and the closing price of the previous day could represent an indicator of the trading activity during the day. The ONI is given as,

$$ONI_t = \left| \log \frac{P_{i,t}^{o}}{P_{i,t-1}^{c}} \right| \tag{7}$$

This enters the conditional variance equation as,

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \lambda_1 ONI_{t-1} \tag{8}$$

We assumed standard normal deviation throughout in the estimation. Therefore, it is easier to apply likelihood estimation approach in the estimation of GARCH models. It is expected, as noted in Wang, Wang and Liu (2005) that the inclusion of volume series, particularly in the variances' equation will absorb volatility persistence in GARCH(1,1) model specification. Thus β_3 is expected to be non-negative, and β_1 and β_2 are expected to be smaller in magnitude.

4. Data and Empirical analysis

The data used in this work is the 28 daily share prices of actively traded stocks of companies listed on the platform of the Nigerian Stock Exchange. These stocks are those of Access Bank, AIICO Insurance, Airline Service and Logistics, Berger Paints, Cadbury Nigerian Plc, Conoil, Dangote Cement, Dangote Flour, Diamond Bank, Dunlop Nigeria plc, FCMB, Fidson Health Care, First Bank Holdings, Flour Mills, Glaxo Smithkline, GTB, Guinness, Julius Berger, Mobil, Nestle, Oando, Total, Transcorp, Unilever, Vita Foam, WAPCO, Wema Bank and Zenith Bank. Daily closing price and volume traded in each of these shares are retrieved for the website of Capital Assets Nigeria,a subsidiary of the Nigerian Stick Exchange.[1] In order to overcome bias due to survivorship, the list of available and updated stocks that are available in the online database of Capital Assets Nigeria (www.capitalassets.com.ng) is included.

Table 1 presents data ranges and sample size, N of each of the time series. We also consider the All-Share Index (ASI) of the NSE with the daily volume traded between July 1, 2009, and August 13, 2018. For the individual stocks, the sample sizes are large enough for

[1]Capital Assets Limited is a dealing member of the Nigeria Stock Exchange (NSE) and is fully registered with the Securities & Exchange Commission (SEC) as an issuing house, fund manager and broker/dealer. The agency published daily dataset of stocks of the NSE. The Company is also authorized to deal in Treasury Bills by the Central Bank of Nigeria. This agency has the full permission to publish daily share prices as well as stock index of the NSE.

volatility modelling, and these have been selected after the global crisis of 2008/09 in order to remove influence of this period in the volatility of the markets.

Table 1: Data description and sample

Company	Series start	Series end	N
Access Bank	23/02/2011	19/11/2018	1898
AIICO Insurance	23/02/2011	21/11/2018	1899
Airline Service and Logistics	23/02/2011	19/11/2018	1732
Berger Paints	23/02/2011	21/11/2018	1828
Cadbury Nigeria Plc	23/02/2011	21/11/2018	1868
Conoil	04/01/2010	16/11/2018	2181
Dangote Cement	04/01/2011	19/11/2018	1931
Dangote Flour	04/01/2011	19/11/2018	1757
Diamond Bank	23/02/2011	21/11/2018	1899
Dunlop Nigeria plc	23/02/2011	04/10/2018	1030
FCMB	04/01/2011	19/11/2018	1932
Fidson Health Care	23/02/2011	19/11/2018	1865
First Bank Holdings	04/03/2011	19/11/2018	1887
Flour Mills	23/02/2011	21/11/2018	1899
Glaxo Smithkline	23/02/2011	23/11/2018	1893
GTB	04/01/2010	16/11/2018	1547
Guinness	23/02/2011	19/11/2018	1899
Julius Berger	23/02/2011	21/11/2018	1860
Mobil	01/05/2010	16/11/2018	1972
Nestle	01/06/2010	16/11/2018	1978
Oando	04/01/2010	16/11/2018	2199
Total	01/06/2010	19/11/2018	2077
Transcorp	23/02/2011	19/11/2018	1898
Unilever	04/01/2010	19/11/2018	2178
Vita Foam	23/02/2011	19/11/2018	1891
WAPCO	04/01/2010	19/11/2018	2180
Wema Bank	04/01/2011	19/11/2018	1917
Zenith Bank	04/01/2010	19/11/2018	1934

For each stock, we obtained market returns by expressing logged difference of prices as percentage. Similarly, we obtained change in daily volume. Table 2 presents the statistical properties of the market returns for individual stocks. It shows that the average daily return over the sample period is around 0.013%. The return series are very volatile, with the average maximum daily return being 63.799% and minimum -77.388%.

As far as the distribution of returns over time is concerned, the skewness for company 1 and 12 are almost zero while the reaming skewness statistics are significant, with 18 out of 28 cases being titled to the right, indicating that the data are not symmetric. Moreover, all returns are characterized by statistically significant kurtosis, suggesting that the underlying data are leptorkurtic, that is, all series have a thicker tail and a higher peak than a normal distribution. So it is not surprising that the Jarque-Bera test suggests that all returns distributions are non-normal. The last column in Table 2 reports the Ljung-Box Q-statistics for the square of return series up to the 12^{th} lag length. It shows that the Q-statistics are generally large and statistically significant, confirming the persistence of variance. For the All Share Index (ASI), average returns are 0.012%, with standard deviation of 1.205%, minimum returns are -17.6% where maximum returns for non-normal and possess serial correlation which informed the choice if GARCH modelling.

Table 2: Preliminary analysis of daily returns (%)

Co.	Mean	Std.	Min	Max	skewness	kurtosis	Jarque-Bera	$Q^2(12)$
Panel A: Individual companies								
1	-0.014	2.478	-11.778	9.606	0.008	4.902	286.056**	250.49**
2	-0.025	3.075	-12.386	9.531	4.147	-0.028	104.302**	1037.4**
3	0.069	2.943	-11.778	18.550	0.128	6.9026	1103.199**	190.94
4	-0.027	2.162	-11.955	9.709	-0.404	9.533	3298.511**	63.633**
5	-0.058	3.033	-17.109	44.335	1.581	29.584	55753.12**	3.4555
6	-0.009	2.412	-10.536	9.751	0.118	11.199	6110.695**	396.80**
7	-0.122	3.268	-10.546	9.932	0.127	4.099	100.687**	495.13**
8	0.027	1.959	-10.255	8.201	0.234	8.201	2193**	210.46**
9	-0.059	3.423	-10.286	85.567	8.999	225.400	3642656.0**	0.9154
10	0.081	347.593	-1686.761	1249.980	-0.091	3.778	27.299**	142.67
11	-0.084	2.9199	-14.003	9.594	0.163	4.567	206.026**	520.86**
12	0.039	3.278	-11.507	16.015	0.009	4.239	119.194**	395.88**
13	-0.039	2.656	15.781	14.310	0.204	5.765	613.956**	304.21**
14	-0.078	2.914	-44.288	37.268	-1.033	46.791	151993.9**	5.442
15	-0.037	2.454	-31.728	14.794	-1.687	28.158	50805.72**	37.69**
16	0.055	2.222	-25.606	9.127	-2.317	28.691	43899.53**	4.584
17	0.043	1.671	-9.135	8.969	0.215	9.138	945.082**	9.773
18	-0.047	2.080	-12.289	9.750	-0.147	11.640	5817.259**	121.10**
19	-0.003	2.061	-21.7323	9.7568	-0.3552	14.419	10750.90**	66.186**
20	0.077	2.061	-14.564	36.059	2.934	57.924	238620.1**	1.583
21	-0.133	3.589	-40.551	12.167	-0.614	12.272	8011.609**	76.075**
22	-0.009	1.997	-10.060	9.757	0.157	9.678	3864.672**	239.10**
23	0.045	3.928	-27.161	30.910	0.444	7.556	1702.869**	217.05**
24	0.034	2.467	-26.172	28.469	0.173	19.087	23486.77**	379.91**

25	-0.024	2.643	-20.290	9.717	-0.272	6.538	1008.456**	84.290**
26	-0.029	2.836	-54.633	49.651	-0.888	110.651	1052444**	501.48**
27	-0.047	3.295	-10.536	9.531	0.183	3.942	81.576**	2146.5**
28	0.023	2.388	-15.006	15.374	-0.103	7.501	1634.098**	387.06**
Mean	-0.013	14.993	-77.388	63.799	0.425	24.719	189558.521	296.095
Median	-0.019	2.650	-13.195	11.050	0.123	9.336	2745.756	200.700
Panel B: All Share Index								
	0.012	1.205	-17.628	12.149	-0.304	35.978	100723.6**	330.12**

In Table 3, we present the results of serial correlation of volume traded in individual stocks. The presence of serial correlation in volume traded is important in the implementation of MDH with GARCH specification since the presence of serial volume in volume is expected to cause the conditional heteroscedasticity of stock returns. The results indicated significant serial correlations up to lag 12 of the Ljung-Box Q statistics. Thus, the rate of information arrival is serially correlated. Using ASI returns instead, we obtained slowly decreasing significant serial correlations.

Table 3: Autocorrelations up to the lag 12 for the volume series

Co.	1	2	3	4	5	6	7	8	9	10	11	12
Panel A: Individual companies												
1	0.149**	0.057**	0.055**	0.054**	0.026**	0.021**	0.054**	0.032**	0.092**	0.065**	0.089**	0.021**
2	0.046**	0.088**	0.021**	0.192**	0.024**	0.034**	0.066**	0.005**	0.086**	0.013**	0.027**	0.077**
3	0.184**	0.018**	0.013**	0.005**	0.008**	0.017**	0.012**	0.033**	0.016**	0.028**	0.011**	0.015**
4	0.105**	0.089**	0.034**	0.079**	0.017**	0.053**	-0.004**	0.060**	0.025**	-0.016**	0.016**	0.024**
5	0.246**	0.131**	0.066**	0.066**	0.090**	0.061**	0.045**	0.048**	0.051**	0.069**	0.086**	0.066**
6	0.336**	0.203**	0.261**	0.123**	0.083**	0.068**	0.058**	0.042**	0.051**	0.038**	0.051**	0.071**
7	0.248**	0.187**	0.153**	0.140**	0.135**	0.096**	0.081**	0.073**	0.042**	0.069**	0.055**	0.053**
8	-0.001	0.001	-0.000	0.090**	-0.000**	0.001**	-0.000**	-0.000**	0.000	-0.001	-0.002	0.000
9	0.001	-0.000	0.001	0.000	0.002	0.002	0.001	-0.001	0.001	-0.000	0.000	0.000
10	0.0006	0.015	-0.004	-0.006	-0.007	-0.006	0.006	-0.007	0.000	-0.008	0.064	-0.009
11	0.194**	0.207**	0.121**	0.092**	0.109**	0.117**	0.098**	0.06288	0.063**	0.082**	0.070**	0.078**
12	0.119**	0.074**	0.054**	0.095**	0.074**	0.073**	0.047**	0.032**	0.054**	0.019**	0.035**	0.029**
13	0.195**	0.136**	0.130**	0.125**	0.086**	0.076**	0.089**	0.085**	0.053**	0.071**	0.072**	0.046**
14	0.305**	0.134**	0.162**	0.142**	0.109**	0.058**	0.041**	0.079**	0.054**	0.040**	0.161**	0.181**
15	0.132**	0.240**	0.037**	0.047**	0.009**	0.020**	0.111**	0.059**	0.001**	-0.001**	0.011**	0.049**
16	0.216**	0.160**	0.131**	0.066**	0.135**	0.106**	0.127**	0.130**	0.080**	0.104**	0.103**	0.092
17	0.211***	0.096**	0.083**	0.155**	0.058**	0.048**	0.053**	0.061**	-0.032**	-0.010	0.021**	0.034**
18	-0.002	0.170**	-0.001**	-0.003**	-0.001**	-0.003**	-0.003**	-0.002**	-0.003**	-0.002**	-0.003**	-0.003**
19	0.005	0.003	-0.000	-0.004	0.004	0.066	-0.001	-0.001	-0.004	0.019	-0.003	0.006
20	0.140**	0.046**	0.017**	-0.016**	0.002**	0.017**	0.018**	-0.005**	0.024**	0.003**	0.017**	0.035**
21	0.325**	0.250**	0.248**	0.238**	0.216**	0.185**	0.170**	0.126**	0.131**	0.126**	0.074**	0.082**
22	0.263**	0.022**	0.013**	0.030**	0.016**	0.015**	0.016**	0.011**	0.013**	0.015**	0.008**	0.019**
23	0.016	0.011	0.012	0.011	0.011	0.009	0.013	0.008	0.008	0.004	0.008	0.031
24	0.271**	0.137**	0.138**	0.043**	0.008**	-0.002**	0.036**	0.008**	0.064**	0.075**	0.000**	0.025**
25	0.323**	0.258**	0.207**	0.161**	0.131**	0.127**	0.166**	0.137**	0.172**	0.135**	0.190**	0.126**
26	0.18588	0.117**	0.089**	0.050**	0.035**	0.032**	0.060**	0.063**	0.061**	0.078**	0.063**	0.023**
27	0.371**	0.032**	0.026**	0.007**	0.053**	0.032**	0.002**	-0.002**	0.002**	-0.001**	-0.002**	-0.002**
28	0.205**	0.198**	0.135**	0.163**	0.120**	0.097**	0.064**	0.071**	0.069**	0.075**	0.009**	0.023**
Panel B: All Share Index												
ASI	0.994**	0.988**	0.982**	0.977**	0.972**	0.966**	0.961**	0.956**	0.954**	0.952**	0.949**	0.946**

Table 4 presents the results of GARCH(1,1) model without trading volume being included as exogenous variable in the model specification. Panel A shows the results for the individual stocks, while Panel B shows the results for ASI returns. Note that we have allowed for first order autocorrelation (AR) in the mean equation and the intercept and AR(1) parameters in this case are not reported. We focused now on the estimated parameters for the variance equation with parameters $\hat{\beta}_0$ as the constant and $\hat{\beta}_1$ and $\hat{\beta}_2$, respectively as the ARCH and GARCH parameters, both measuring volatility persistence of the conditional variance series. The ARCH term, ε_{t-1}^2 is the squares of the shocks, that is previous shocks and this is related with the current conditional volatility series, σ_t^2 by the $\hat{\beta}_1$, while σ_{t-1}^2 is the GARCH term, and the effect of previous conditional volatility, σ_{t-1}^2 on current conditional volatility σ_t^2 is accessed by $\hat{\beta}_2$. Taking Co. 1 for example, the coefficient for the previous shock is 0.1581 and for its GARCH term for variance is 0.7228, both are highly significant above the 5% level. The sum of these two coefficients is 0.8809, which implies that the persistence in volatility is high. We have cases where persistence of volatility is above and this we found in Co. 2, 9, 14 and 27. The case of very low volatility persistence for Co. 10, 16 and 25. As seen in the results, in most of the companies, volatility persistence of stocks are very high. The result is consistent with the findings of Wang et al. (2004) who found high persistence of volatility in Chinese stock markets. The average mean volatility shock is 0.1806 while the median is 0.1620, which compare fairly with those obtained in individual stocks, and also the GARCH parameter. Both average and median values of persistence are, respectively 0.8539 and 0.8850 which compare with what obtains in the individual stocks.

By looking at the estimates of GARCH model obtained for ASI returns, volatility persistence of shocks 0.2212 while that of variance is 0.6313 and the overall persistence of volatility is 0.8525 which is very close to the mean and median estimates of volatility for individual stocks. Therefore, this paper effectively includes representative stocks for ASI, considering their pricing and market capitalization.

Table 4: GARCH(1,1) model estimation (without volume traded)

Co.	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_1 + \hat{\beta}_2$
Panel A: Individual companies			
1	0.1581**	0.7228**	0.8809
2	0.1581**	0.8511**	1.0092
3	0.0435**	0.9371**	0.9806
4	0.0782**	0.8489**	0.9271
5	0.1658**	0.5124**	0.6782
6	0.1454**	0.6001**	0.7455
7	0.1838**	0.7623**	0.9461
8	0.1878**	0.6427**	0.8305
9	0.4161**	0.6367**	1.0528
10	0.1507**	0.2529**	0.4036
11	0.2597**	0.6288**	0.8885
12	0.2100**	0.5926**	0.8026
13	0.2603**	0.5550**	0.8153
14	0.2061**	0.8259**	1.0320
15	0.1067**	0.8413**	0.9480
16	0.3944**	0.1222**	0.5166
17	0.0135**	0.9299**	0.9434
18	0.1072**	0.7743**	0.8815
19	0.0907**	0.8686**	0.9593
20	0.1057**	0.7114**	0.8171
21	0.4395**	0.4757**	0.9152
22	0.1342**	0.7240**	0.8582
23	0.1552**	0.6793**	0.8345
24	0.1662**	0.7589**	0.9251
25	0.1867**	0.2779**	0.4646
26	0.1023**	0.8878**	0.9901
27	0.1952**	0.8272**	1.0224
28	0.2366**	0.6033**	0.8399
Mean	**0.1806**	**0.6733**	**0.8539**
Median	**0.1620**	**0.7171**	**0.8850**
Panel B: All Share Index			
ASI	0.2212**	0.6313**	0.8525

By including volume traded in the variance equation, as results obtained in Table 5, it is interesting to observe that in 3 out of 28 cases (Co.10, 16 and 25), volatility persistence marginally increased while introducing volume, and in the remaining 25 cases, there is obvious reduction in volatility persistence. The coefficients of volume in the GARCH framework are large in magnitude and are significant in most of the cases, except for Co. 5, 10 and 14 where these coefficients are not significant, even some of the standard GARCH model parameters here are not significant as well. By looking at the estimates of mean and median for ARCH and GARCH parameters, we found drastic reduction in values compared to those obtained in Table 4. For the ASI returns, it is alarming to note that volatility persistence increased to 0.9367 when volume indicator is included, as opposed to 0.8525 when volume is not included. Thus, coefficient of volume indicator is -5.19 and this is highly significant.

Table 5: GARCH(1,1) model estimation (with volume traded in variance equation)

Co.	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_3$	$\hat{\beta}_1 + \hat{\beta}_2$
Panel A: Individual companies				
1	0.0183	0.5594**	0.9012**	0.5777
2	0.0393**	0.5744**	1.2335**	0.6137
3	0.0264**	0.5355**	0.9729**	0.5619
4	0.0208	0.5880**	1.5279**	0.6088
5	0.0086	0.5914	0.0647	0.6000
6	0.0197	0.5929**	1.6272**	0.6126
7	0.1612**	0.7722**	0.8498**	0.9334
8	0.0501**	0.5687**	0.4957**	0.6188
9	0.0662**	0.5437**	1.4373**	0.6099
10	0.1507**	0.2548	355.0368	0.4055
11	0.2547**	0.6235**	0.4511**	0.8782
12	0.0284**	0.5789**	1.2540**	0.6073
13	0.0128**	0.5743**	1.5880**	0.5871
14	0.0175**	0.5812	1.5264	0.5987
15	0.0389**	0.5624**	1.6243**	0.6013
16	0.3757**	0.1694**	-0.3999**	0.5451
17	0.0213**	0.5611**	0.8225**	0.5824
18	0.1475**	0.5798**	1.1078**	0.7273
19	0.1047**	0.4916**	0.6895**	0.5963
20	0.0027	0.5868**	1.4424**	0.5895
21	0.2598**	0.5646**	0.7339**	0.8244
22	0.0649**	0.4933**	0.6762**	0.5582

23	0.1476**	0.6791**	1.1897**	0.8267
24	0.0222**	0.5687**	1.0800**	0.5909
25	0.0157**	0.5848**	0.9004**	0.6005
26	0.0967**	0.8836**	-0.1312**	0.9803
27	0.1252**	0.5686**	1.4136**	0.6938
28	0.2429**	0.5905**	-0.1858**	0.8334
Mean	**0.0907**	**0.5651**		**0.6558**
Median	**0.0447**	**0.5744**		**0.6043**
Panel B: All Share Index				
ASI	0.2072**	0.7295**	-5.1940**	0.9367

By incorporating indicator for intraday volatility (IDV) as results, reported in Table 6, we found significant IDV in 22 of the 28 cases considered. In these 22 cases, we have in only the case of Co. 20 where past IDV is negatively related to current conditional volatility. It is also noticeable that by including IDV, volatility persistence of conditional volatility reduced for each of the stocks.

Table 6: GARCH(1,1) model estimation (with IDV in variance equation)

Co.	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\gamma}_1$	$\hat{\beta}_1+\hat{\beta}_2$
Panel A: Individual companies				
1	0.1732**	0.4863**	43.1230***	0.6595
2	0.2479**	0.7210**	36.9739**	0.9689
3	0.0307**	0.9441**	15.5868**	0.9748
4	0.0890**	0.7777**	50.0321**	0.8667
5	0.1332**	0.5621**	35.7606**	0.6953
6	0.1439**	0.5817**	36.1532**	0.7256
7	0.1917*	0.6664**	31.7575**	0.8581
8	0.1592**	0.5226**	45.8581**	0.6818
9	0.4213**	0.6234**	7.1287**	1.0447
10	NA	NA	NA	NA
11	0.2259**	0.6458**	22.7058**	0.8717
12	0.2061**	0.4988**	31.8751**	0.7049
13	0.1747**	0.4759**	67.4045**	0.6506
14	0.1251**	0.8605**	22.7856**	0.9856
15	o.0987**	0.7978**	74.3274**	0.8965
16	0.0055	0.8262**	52.1092**	0.8317
17	0.0083**	0.9358**	2.7717	0.9441
18	0.0778**	0.7965**	47.5499**	0.8743
19	0.0743**	0.8791**	17.4219**	0.9534
20	0.1354**	0.6970**	-28.5399**	0.8324
21	0.3269**	0.3826**	123.5768**	0.7095
22	0.1194**	0.7226**	22.9097**	0.8420
23	0.1520**	0.6765**	5.3704	0.8285

24	0.1703**	0.7576**	-4.8753	0.9279
25	0.1876**	0.2766**	-0.7807	0.4642
26	0.0506**	0.9123**	26.5792**	0.9629
27	0.1521**	0.7712**	32.8043**	0.9233
28	0.1838**	0.4658**	54.2739**	0.6496
Mean	**0.1505**	**0.6764**		**0.8270**
Median	**0.1520**	**0.6970**		**0.8581**

Finally, we consider the case of overnight indicator (ONI). We first observed that there are more packed zeros in the computed overnight indicator and due to that GARCH models were not computed in 19 cases out of the 28 cases. In those remaining 9 companies, we observed significant ONI coefficients in 8 cases. Critical look indicates that these cases of overnight indication include banks and other companies. We also observed reduction in volatility persistence in 8 cases of 9 when ONI is included in the variance equation, while the once case with increase in volatility is Co. 17.

Table 7: GARCH(1,1) model estimation (with ONI in variance equation)

Co.	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\lambda}_1$	$\hat{\beta}_1 + \hat{\beta}_2$
Panel A: Individual companies				
1	0.1958**	0.4562**	59.8067**	0.6520
2	NA	NA	NA	NA
3	NA	NA	NA	NA
4	NA	NA	NA	NA
5	NA	NA	NA	NA
6	NA	NA	NA	NA
7	0.1838**	0.7626**	-0.1777	0.9464
8	NA	NA	NA	NA
9	NA	NA	NA	NA
10	NA	NA	NA	NA
11	0.2500**	0.6132**	24.5934**	0.8632
12	NA	NA	NA	NA
13	0.2827**	0.4565**	45.4137**	0.7392
14	NA	NA	NA	NA
15	NA	NA	NA	NA
16	0.4354**	-0.0076**	-39.6400**	0.4278
17	0.0242**	0.9396**	-8.4297**	0.9638
18	NA	NA	NA	NA
19	NA	NA	NA	NA
20	NA	NA	NA	NA
21	0.4219**	0.4407**	41.8224**	0.8626
22	NA	NA	NA	NA
23	0.1509**	0.6252**	25.9351**	0.7761
24	NA	NA	NA	NA

25	NA	NA	NA	NA
26	NA	NA	NA	NA
27	NA	NA	NA	NA
28	0.2041**	0.6227**	32.9109**	0.8268

5. Conclusion

In this paper, we have investigated information arrival process in Nigerian Stock Exchange (NSE) by considering some highly priced and highly capitalized 28 stocks (companies), registered in the market. This information arrival process uses Mixture of Distributions Hypotheses (MDH) and the sequential information arrival hypothesis, in which trading volume is expected to be positively related to the market volatility. We also considered intraday volatility and overnight indicators as other proxies of such information flow, other than volume traded in daily stocks. Our sample has excluded 2008/09 in order not to be influenced by the global crisis' effect. By using GARCH modelling approach with additional market information introduced as exogenous variable, we obtained results similar to other authors such as Gallo and Pacini (2000), Wang, Wang and Liu (2014), inter alia. Volume traded is found to influence conditional volatility, and thus reduced the volatility persistence of each stock.

Though, we were silenced about the performance of each company's stocks, but we found that this performance is not company specific. Trading volume and intraday volatility acted as indicators at the micro level of Nigerian stock market, and these are able to catch information arrivals in individual stocks. Trading volume is ineffective to predict the overall market performance of NSE since it increased the overall volatility persistence. Thus, trading volume does not account for all the sources of conditional heteroscedasticity as noted in Wang, Wang and Liu (2014). Our findings therefore confirm the applicability of MDH for individual stocks of NSE.

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