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UNIVARIATE ANALYSIS OF VOLATILITY OF STOCK MARKET RETURNS USING GARCH MODELS.

BY

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Abstract

This study examines the univariate analysis of volatility of stock market returns using GARCH model and also determines a causal relationship between volatility and stock returns. The data is a real time data directly obtained from yahoo finance with seven thousand eight hundred and ninety-four observations. The preliminary examination of graphical results show that stationarity was achieved at second difference, so also unit roots test (Augmented Dickey Fuller test) and correlogram conducted show that the series was stationary at second difference. The correlation between the high (highest price at which a stock was traded during a period) and low (lowest price at which a stock was traded during a period) opening stock is high and heteroscedasticity between the opening and closing stock is high. Lastly, GARCH (1,1) model was chosen as it produced the least Akaike Information Criterion (AIC) value. So also, GARCH (1, 1) model applied gives parsimonious results which establishes a very significant ARCH (1) and GARCH (1) relationship and shows that the markets returns are significant since probability level is less than 0.01. Thereafter, we subjected the results obtained to forecasting evaluation indices where it was discovered that Theil-U produced a better fit, the bias and the variance proportion are very close to zero and covariance proportion is very close to one. All pointing to the fact that the model GARCH (1, 1) will have a very good forecasting ability in stock returns.

Keywords: ARCH, GARCH, volatility, stock returns, financial markets, performance measure indices.

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1.0 INTRODUCTION/ REVIEW OF LITERATURE

Volatility is an important topic in the literature on economic and financial time series. Stock price forecasting improves as a result of the science of modeling volatility. Similarly, early detection of stock return volatility trends leads to improved investment sustainability strategies. There is a literature on volatility forecasting using GARCH type and other financial models. Koy and Ekim (2016) used the GARCH, EGARCH, and TGARCH models to explain the volatility of four Borsa Istanbul sub-indices from 2011 to 2014. They concluded that there is no significant asymmetric effect of shocks on banking share volatility. Other sub-indices, on the other hand, do exhibit asymmetry. Molnár (2016) used daily data to examine the volatility of six stock indices, including the Nasdaq-100, using the Range-GARCH (1,1) model. He confirmed that Nasdaq volatility was violent when forecasted using the R-GARCH model, which outperformed the standard GARCH (1,1) model. Augustyniak et al. (2018) advanced the Factorial Hidden Markov Volatility model as a new avenue for simulating the volatility of the Nasdaq-100 index, among other series, in their study. At both short and long-run intervals, this new method outperformed other peer methods in modeling and forecasting Nasdaq-100 return series volatility. Okii (2015) investigates the characteristics of stock returns in Central and Eastern European (CEE) stock markets, focusing on the relationship between conditional volatility and stock returns. They concluded that in the case of CEE stock markets, ARIMA and GARCH processes provide reasonable approximations to mean and volatility dynamics. Raza et al. (2015) used GARCH family models for stock market volatility modeling and forecasting and concluded that the volatility of KSE100 Index stock returns is best handled by these family time models. Balli et al. (2015) investigated the effects of stock returns and volatility spillovers from developed markets to emerging and frontier markets. Their findings revealed that US markets have developed less volatile markets. The variance ratio results back up this claim. They did, however, broaden the range of variation among emerging markets. They also confirmed that other factors, such as portfolio investment, volume of investment, and distance, play a role in explaining these spillover effects. Galbraith et al. (2015), Bentes (2015), Johnk, Soydemir (2015), Andreou, Werker (2015), and others all support these findings. Altun (2018) forecasts value-at-risk using a two-sided Lomax distribution and GJR-GARCH models. He used daily Nasdaq-100 index data for the study period (14 March 2014–13 April 2018) and discovered that the GJR-GARCH model outperformed the two-sided Lomax distribution and aided in modeling the index's skewness and excess kurtosis. Chang et al. (2019) recently proposed a modified Grey-GARCH model to study the volatility of the daily dynamics of Nasdaq closing prices and compared their proposed model to ordinary Grey-GARCH and the standard GARCH model, concluding that Nasdaq-100 index price volatility can be best modelled and forecasted with their new model.

2.0 MATHEMATICAL PRELIMINARY

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3.1 Descriptive. Stock returns for the data used for the study was computed by taking the natural log. The mathematical equation for log returns is expressed as: - $R_t = \ln\left(\frac{I_t}{I_{t-1}}\right)$

Where R_t is stock returns at time t, I_t is stock market index at time t and I_{t-1} is stock market index at lag 1 in time t.

3.2 Karl pearson correlation measure was used to measure the degree of inter-dependence among pairs of stock returns and is given as $r = \frac{n\sum xy - (\sum x)(\sum y)}{\sqrt{n(\sum x^2) - (\sum x)^2}\sqrt{n(\sum y^2) - (\sum y)^2}}$

3.3 $ARCH(p)$

Suppose $X_1, X_2 ... X_T$ are the time series observations (exchange rates, stock values and so on) and let $F_t = (X_t, ... X_0)$ be the set of X_t up to time t, including X_t for $t \le 0$. As defined by Engle (1982), the process (X_t) is an Autoregressive conditional heteroscedasticity process of order q $\{ARCH(p)\}$, if: ($X_t / F_{t-1} \sim (0, h_t)$, with $h_t^2 = \alpha_0 + \alpha_1 X_{t-1}^2 + ... + \alpha_q X_{t-q}^2 = \alpha_0 \sum_{i=1}^{q} \alpha_i X_{t-1}^2$

3.4 $GARCH(p,q)$

GARCH model was developed by Bollerslev's in 1986 by generalization of ARCH model, it possessed two distributed lags which are used to explain variance. The $GARCH(p,q)$ model is defined by: $y_t = \sigma_t \varepsilon_t$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i y_{t-1}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2$$

where $\alpha_0 > 0, \alpha_i \ge 0, \beta_j \ge 0$ and the innovation sequence $[\varepsilon_i]_{i=-\infty}^{\infty}$ is independent and identically distributed with E(ε_0) = 0 and E(ε_0^2) = 1

3.0 DATA ANALYSIS AND INTERPRETATION
DESCRIPTIVE ANALYSIS

TABLE 1: DESCRIPTIVE STATISTIC

STATISTIC	LOW	HIGH
MEAN	21.55389	22.04959
MEDIAN	25.31000	25.85000
MAXIMUM	72.27000	72.89000
MINIMUM	0.088542	0.092014
STD. DEV.	16.72011	17.05862
SKEWNESS	0.356637	0.341713
KURTOSIS	2.511685	2.472306
JARQUE-BERA	245.7703	245.2181

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PROBABILITY	0.000000	0.000000
SUM	170146.4	174059.4
SUM SQ. DEV.	2206583.	2296835.
OBSERVATIONS	7894	7894

Figure 1 above shows that the standard deviation obtained is high implying the presence of the fluctuations in stock market returns data used; the skewness of the series is accomplished with long right tail implying that the series used is not symmetric. From the table 1 above, the stock returns data are leptokurtic or fat tailed because of the presence of large kurtosis value. The p value of Jarque-Bera test is less than zero indicating that the data is not normal, therefore, the hypothesis of normality is rejected. Thereafter the study proceeded to evaluation of stationarity status of the data for the study after which the complete data analysis was done.

STATIONARITY

The study employed the following three methods in ascertaining stationarity of the series vis-a vis graphical analysis, correlogram and Unit root test (Augmented Dickey Fuller test).

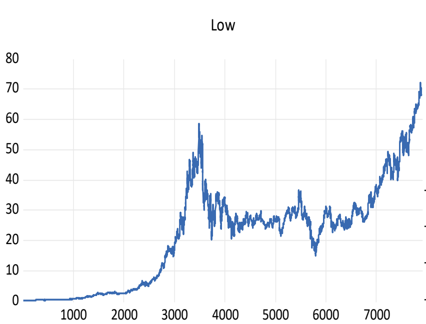
I GRAPHICAL METHODS

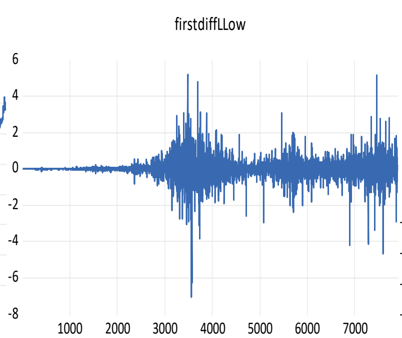
Figures 1, 2, 4 and 5 as shown in the table below (level and first difference figures) revealed that series is volatile, noisy and chaotic and as such stationarity could not be achieved. However, figures 3 and 6 (which is the second difference figures) as shown below revealed that the series is no longer volatile, chaotic or noisy and as a result stationarity is achieved at this point.

FIG. 1: LEVEL (LOW)

FIG. 2: FIRST DIFF (LOW)

FIG. 3: SECOND DIFF (LOW)





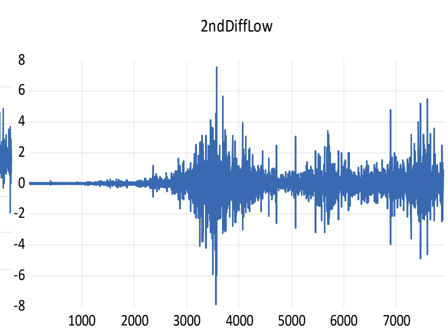


FIG. 4: LEVEL (HIGH)

FIG. 5: FIRST DIFF (HIGH)

FIG. 6: SECOND DIFF (LOW)

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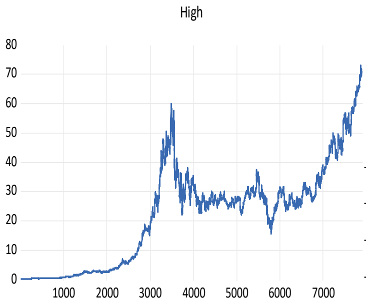

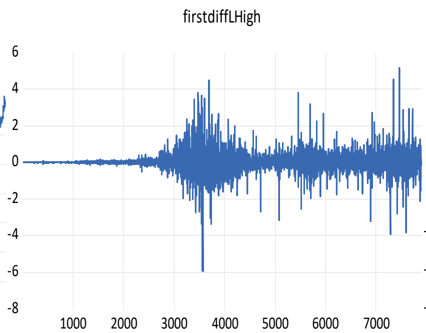

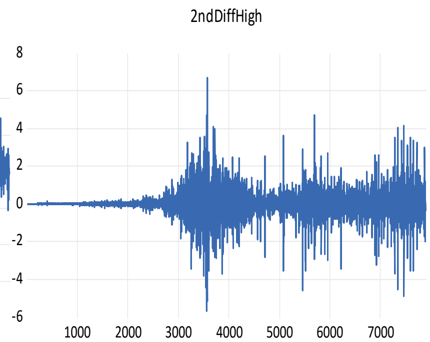

II CORRELOGRAM (HIGH)

Results of correlogram for original data and first difference (Tables 2, 3, 5 and 6) show that ACF and PACF does not decay exponentially to zero, implying that the series is volatile, noisy and chaotic showing that the series is not stationary. On the other hand, tables 4 and 7 shows that ACF and PACF decay exponentially to zero, implying that the series is no longer volatile, noisy and chaotic and stationary.

TABLE 2: CORRELOGRAM HIGH (LEVEL)

Date: 09/04/21 Time: 11:03
Sample: 1 7894
Included observations: 7894

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob</th></tr>
<tr><td>|*******</td><td>|*******</td><td>1</td><td>0.999</td><td>0.999</td><td>7882.0</td><td>0.000</td></tr>
<tr><td>|*******</td><td>| |</td><td>2</td><td>0.998</td><td>-0.051</td><td>15749.</td><td>0.000</td></tr>
<tr><td>|*******</td><td>| |</td><td>3</td><td>0.997</td><td>0.016</td><td>23600.</td><td>0.000</td></tr>
<tr><td>|*******</td><td>| |</td><td>4</td><td>0.996</td><td>0.006</td><td>31437.</td><td>0.000</td></tr>
<tr><td>|*******</td><td>| |</td><td>5</td><td>0.995</td><td>-0.008</td><td>39259.</td><td>0.000</td></tr>
<tr><td>|*******</td><td>| |</td><td>6</td><td>0.994</td><td>-0.006</td><td>47065.</td><td>0.000</td></tr>
<tr><td>|*******</td><td>| |</td><td>7</td><td>0.993</td><td>-0.008</td><td>54857.</td><td>0.000</td></tr>
<tr><td>|*******</td><td>| |</td><td>8</td><td>0.992</td><td>0.002</td><td>62632.</td><td>0.000</td></tr>
<tr><td>|*******</td><td>| |</td><td>9</td><td>0.991</td><td>0.003</td><td>70393.</td><td>0.000</td></tr>
<tr><td>|*******</td><td>| |</td><td>10</td><td>0.990</td><td>0.001</td><td>78139.</td><td>0.000</td></tr>
<tr><td>|*******</td><td>| |</td><td>11</td><td>0.989</td><td>-0.002</td><td>85869.</td><td>0.000</td></tr>
<tr><td>|*******</td><td>| |</td><td>12</td><td>0.988</td><td>-0.005</td><td>93584.</td><td>0.000</td></tr>
<tr><td>|*******</td><td>| |</td><td>13</td><td>0.987</td><td>-0.002</td><td>101284</td><td>0.000</td></tr>
<tr><td>|*******</td><td>| |</td><td>14</td><td>0.986</td><td>-0.007</td><td>108969</td><td>0.000</td></tr>
<tr><td>|*******</td><td>| |</td><td>15</td><td>0.985</td><td>-0.024</td><td>116637</td><td>0.000</td></tr>
<tr><td>|*******</td><td>| |</td><td>16</td><td>0.983</td><td>0.002</td><td>124288</td><td>0.000</td></tr>
<tr><td>|*******</td><td>| |</td><td>17</td><td>0.982</td><td>0.016</td><td>131925</td><td>0.000</td></tr>
<tr><td>|*******</td><td>| |</td><td>18</td><td>0.981</td><td>-0.016</td><td>139545</td><td>0.000</td></tr>
<tr><td>|*******</td><td>| |</td><td>19</td><td>0.980</td><td>0.008</td><td>147149</td><td>0.000</td></tr>
<tr><td>|*******</td><td>| |</td><td>20</td><td>0.979</td><td>-0.013</td><td>154737</td><td>0.000</td></tr>
<tr><td>|*******</td><td>| |</td><td>21</td><td>0.978</td><td>0.005</td><td>162309</td><td>0.000</td></tr>
<tr><td>|*******</td><td>| |</td><td>22</td><td>0.977</td><td>0.011</td><td>169865</td><td>0.000</td></tr>
<tr><td>|*******</td><td>| |</td><td>23</td><td>0.976</td><td>0.023</td><td>177407</td><td>0.000</td></tr>
<tr><td>|*******</td><td>| |</td><td>24</td><td>0.975</td><td>0.015</td><td>184934</td><td>0.000</td></tr>
<tr><td>|*******</td><td>| |</td><td>25</td><td>0.974</td><td>-0.002</td><td>192447</td><td>0.000</td></tr>
<tr><td>|*******</td><td>| |</td><td>26</td><td>0.973</td><td>0.024</td><td>199945</td><td>0.000</td></tr>
<tr><td>|*******</td><td>| |</td><td>27</td><td>0.972</td><td>-0.000</td><td>207431</td><td>0.000</td></tr>
<tr><td>|*******</td><td>| |</td><td>28</td><td>0.971</td><td>0.003</td><td>214903</td><td>0.000</td></tr>
</table>

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Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
|*******	| |	29	0.970	0.021	222362	0.000
|*******	| |	30	0.969	0.012	229808	0.000
|*******	| |	31	0.968	0.013	237242	0.000
|*******	| |	32	0.968	0.001	244665	0.000
|*******	| |	33	0.967	-0.010	252075	0.000
|*******	| |	34	0.966	-0.007	259473	0.000
|*******	| |	35	0.965	0.005	266859	0.000
|*******	| |	36	0.964	0.014	274233	0.000

TABLE 3: CORRLOGRAM HIGH (FIRST DIFFERENCE)

Date: 09/04/21 Time: 11:05
Sample (adjusted): 2 7894
Included observations: 7893 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
|* |	|* |	1	0.130	0.130	133.78	0.000
| |	| |	2	-0.030	-0.048	140.98	0.000
| |	| |	3	-0.025	-0.015	145.91	0.000
| |	| |	4	0.009	0.013	146.59	0.000
| |	| |	5	0.007	0.002	146.98	0.000
| |	| |	6	-0.025	-0.026	151.72	0.000
| |	| |	7	0.007	0.015	152.07	0.000
| |	| |	8	0.008	0.004	152.62	0.000
| |	| |	9	-0.006	-0.008	152.89	0.000
| |	| |	10	-0.002	0.001	152.93	0.000
| |	| |	11	0.011	0.012	153.96	0.000
| |	| |	12	0.031	0.028	161.77	0.000
| |	| |	13	0.012	0.006	162.91	0.000
| |	| |	14	0.038	0.040	174.55	0.000
| |	| |	15	0.008	-0.001	175.08	0.000
| |	| |	16	-0.021	-0.020	178.53	0.000
| |	| |	17	-0.027	-0.020	184.36	0.000
| |	| |	18	-0.030	-0.026	191.72	0.000
| |	| |	19	0.023	0.028	195.92	0.000
| |	| |	20	-0.008	-0.016	196.46	0.000
| |	| |	21	-0.041	-0.037	209.73	0.000
| |	| |	22	-0.038	-0.029	221.46	0.000
| |	| |	23	-0.010	-0.006	222.29	0.000
| |	| |	24	-0.001	-0.005	222.29	0.000
| |	| |	25	-0.053	-0.054	244.68	0.000
| |	| |	26	-0.003	0.009	244.74	0.000
| |	| |	27	-0.001	-0.008	244.74	0.000
| |	| |	28	-0.027	-0.029	250.36	0.000
| |	| |	29	-0.037	-0.028	261.50	0.000
| |	| |	30	-0.032	-0.022	269.43	0.000
| |	| |	31	0.008	0.009	269.92	0.000
| |	| |	32	0.024	0.023	274.42	0.000
| |	| |	33	-0.009	-0.014	275.00	0.000
| |	| |	34	-0.024	-0.019	279.67	0.000
| |	| |	35	-0.019	-0.010	282.38	0.000
| |	| |	36	0.031	0.037	289.87	0.000

TABLE 4: CORRELOGRAM HIGH SECOND DIFFERENCE

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Date: 09/04/21 Time: 11:17
Sample (adjusted): 3 7894
Included observations: 7892 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
***| |	***| |	1	-0.408	-0.408	1313.0	0.000
*| |	**| |	2	-0.095	-0.314	1384.5	0.000
| |	**| |	3	-0.017	-0.260	1386.7	0.000
| |	*| |	4	0.021	-0.198	1390.2	0.000
| |	*| |	5	0.017	-0.142	1392.5	0.000
| |	*| |	6	-0.036	-0.159	1402.6	0.000
| |	*| |	7	0.017	-0.128	1404.9	0.000
| |	*| |	8	0.009	-0.103	1405.5	0.000
| |	*| |	9	-0.010	-0.102	1406.4	0.000
| |	*| |	10	-0.006	-0.102	1406.6	0.000
| |	*| |	11	-0.004	-0.107	1406.7	0.000
| |	*| |	12	0.023	-0.077	1410.8	0.000
| |	*| |	13	-0.026	-0.104	1416.2	0.000
| |	| |	14	0.033	-0.057	1424.6	0.000
| |	| |	15	-0.001	-0.036	1424.6	0.000
| |	| |	16	-0.013	-0.035	1426.0	0.000
| |	| |	17	-0.002	-0.029	1426.0	0.000
| |	*| |	18	-0.033	-0.079	1434.5	0.000
| |	| |	19	0.049	-0.032	1453.3	0.000
| |	| |	20	0.001	-0.011	1453.3	0.000
| |	| |	21	-0.020	-0.020	1456.5	0.000
| |	| |	22	-0.015	-0.043	1458.3	0.000
| |	| |	23	0.011	-0.042	1459.2	0.000
| |	| |	24	0.036	0.007	1469.2	0.000
| |	| |	25	-0.059	-0.057	1497.0	0.000
| |	| |	26	0.028	-0.037	1503.1	0.000
| |	| |	27	0.016	-0.016	1505.2	0.000
| |	| |	28	-0.009	-0.018	1505.8	0.000
| |	| |	29	-0.010	-0.023	1506.5	0.000
| |	| |	30	-0.019	-0.053	1509.5	0.000
| |	| |	31	0.013	-0.064	1510.9	0.000
| |	| |	32	0.028	-0.025	1517.0	0.000
| |	| |	33	-0.010	-0.019	1517.7	0.000
| |	| |	34	-0.012	-0.028	1518.9	0.000
| |	*| |	35	-0.025	-0.072	1523.9	0.000
| |	| |	36	0.039	-0.040	1535.8	0.000

TABLE 5: CORRELOGRAM LOW (LEVEL)

Date: 09/04/21 Time: 14:25
Sample: 1 7894
Included observations: 7894

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
|*******	|*******	1	0.999	0.999	7881.3	0.000
|*******	| |	2	0.998	-0.038	15747.	0.000
|*******	| |	3	0.997	0.002	23596.	0.000
|*******	| |	4	0.996	0.020	31430.	0.000
|*******	| |	5	0.995	-0.006	39249.	0.000

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Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
|*******	| |	6	0.994	0.000	47053.	0.000
|*******	| |	7	0.993	-0.014	54841.	0.000
|*******	| |	8	0.992	0.002	62614.	0.000
|*******	| |	9	0.991	0.002	70370.	0.000
|*******	| |	10	0.990	-0.007	78111.	0.000
|*******	| |	11	0.988	0.004	85837.	0.000
|*******	| |	12	0.987	-0.005	93547.	0.000
|*******	| |	13	0.986	0.009	101241	0.000
|*******	| |	14	0.985	-0.005	108920	0.000
|*******	| |	15	0.984	-0.021	116583	0.000
|*******	| |	16	0.983	-0.004	124229	0.000
|*******	| |	17	0.982	0.017	131860	0.000
|*******	| |	18	0.981	0.008	139475	0.000
|*******	| |	19	0.980	-0.027	147074	0.000
|*******	| |	20	0.979	-0.002	154657	0.000
|*******	| |	21	0.978	-0.001	162223	0.000
|*******	| |	22	0.977	0.017	169774	0.000
|*******	| |	23	0.976	0.028	177310	0.000
|*******	| |	24	0.975	0.011	184832	0.000
|*******	| |	25	0.974	-0.003	192339	0.000
|*******	| |	26	0.973	0.007	199832	0.000
|*******	| |	27	0.972	0.006	207311	0.000
|*******	| |	28	0.971	0.010	214776	0.000
|*******	| |	29	0.970	0.027	222229	0.000
|*******	| |	30	0.969	0.002	229669	0.000
|*******	| |	31	0.968	0.014	237096	0.000
|*******	| |	32	0.967	-0.004	244512	0.000
|*******	| |	33	0.966	-0.010	251915	0.000
|*******	| |	34	0.965	0.010	259305	0.000
|*******	| |	35	0.965	0.003	266684	0.000
|*******	| |	36	0.964	0.005	274050	0.000

TABLE 6: CORRELOGRAM LOW (FIRST DIFFERENCE)

Date: 09/04/21 Time: 14:32
Sample (adjusted): 2 7894
Included observations: 7893 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
|* |	|* |	1	0.099	0.099	77.198	0.000
| |	| |	2	-0.023	-0.033	81.361	0.000
| |	| |	3	-0.034	-0.028	90.329	0.000
| |	| |	4	-0.008	-0.003	90.873	0.000
| |	| |	5	-0.011	-0.012	91.838	0.000
| |	| |	6	0.000	0.001	91.839	0.000
| |	| |	7	0.009	0.008	92.454	0.000
| |	| |	8	-0.000	-0.003	92.455	0.000
| |	| |	9	0.009	0.009	93.043	0.000

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Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
| |	| |	10	-0.008	-0.010	93.550	0.000
| |	| |	11	-0.002	0.000	93.582	0.000
| |	| |	12	0.005	0.006	93.814	0.000
| |	| |	13	0.020	0.019	97.068	0.000
| |	| |	14	0.035	0.031	106.52	0.000
| |	| |	15	0.000	-0.005	106.52	0.000
| |	| |	16	0.004	0.008	106.67	0.000
| |	| |	17	-0.039	-0.039	118.98	0.000
| |	| |	18	-0.015	-0.006	120.69	0.000
| |	| |	19	-0.001	0.000	120.69	0.000
| |	| |	20	-0.006	-0.009	120.94	0.000
| |	| |	21	-0.036	-0.036	131.02	0.000
| |	| |	22	-0.034	-0.029	140.16	0.000
| |	| |	23	-0.014	-0.011	141.70	0.000
| |	| |	24	-0.001	-0.001	141.71	0.000
| |	| |	25	-0.014	-0.018	143.32	0.000
| |	| |	26	-0.011	-0.010	144.29	0.000
| |	| |	27	-0.012	-0.013	145.35	0.000
| |	| |	28	-0.058	-0.059	171.61	0.000
| |	| |	29	-0.008	0.003	172.06	0.000
| |	| |	30	-0.016	-0.019	174.11	0.000
| |	| |	31	0.008	0.010	174.60	0.000
| |	| |	32	0.034	0.031	183.76	0.000
| |	| |	33	-0.027	-0.036	189.73	0.000
| |	| |	34	-0.034	-0.025	198.85	0.000
| |	| |	35	-0.003	0.007	198.91	0.000
| |	| |	36	0.022	0.021	202.65	0.000

TABLE 7: CORRELOGRAM LOW (SECOND DIFFERENCE)

Date: 09/04/21 Time: 14:32
Sample (adjusted): 3 7894
Included observations: 7892 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
***| |	***| |	1	-0.432	-0.432	1475.8	0.000
| |	**| |	2	-0.062	-0.306	1505.8	0.000
| |	**| |	3	-0.020	-0.254	1509.0	0.000
| |	*| |	4	0.016	-0.195	1510.9	0.000
| |	*| |	5	-0.008	-0.174	1511.4	0.000
| |	*| |	6	0.002	-0.154	1511.4	0.000
| |	*| |	7	0.010	-0.124	1512.2	0.000
| |	*| |	8	-0.010	-0.121	1513.0	0.000
| |	*| |	9	0.014	-0.091	1514.5	0.000
| |	*| |	10	-0.013	-0.092	1515.8	0.000
| |	*| |	11	-0.001	-0.090	1515.8	0.000
| |	*| |	12	-0.004	-0.094	1515.9	0.000
| |	*| |	13	0.000	-0.098	1515.9	0.000
| |	| |	14	0.027	-0.056	1521.7	0.000
| |	| |	15	-0.022	-0.065	1525.3	0.000
| |	| |	16	0.027	-0.017	1531.0	0.000
| |	| |	17	-0.038	-0.049	1542.4	0.000
| |	| |	18	0.006	-0.053	1542.7	0.000
| |	| |	19	0.010	-0.041	1543.5	0.000
| |	| |	20	0.014	-0.014	1545.1	0.000
| |	| |	21	-0.018	-0.022	1547.6	0.000
| |	| |	22	-0.010	-0.040	1548.4	0.000

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|	|	23	0.004	-0.048	1548.5	0.000
|	|	24	0.015	-0.030	1550.2	0.000
|	|	25	-0.009	-0.037	1550.9	0.000
|	|	26	0.002	-0.032	1550.9	0.000
|	|	27	0.025	0.012	1556.0	0.000
|	|	28	-0.053	-0.050	1578.5	0.000
|	|	29	0.032	-0.027	1586.8	0.000
|	|	30	-0.018	-0.054	1589.4	0.000
|	*|	31	-0.001	-0.072	1589.4	0.000
|	|	32	0.049	-0.003	1608.1	0.000
|	|	33	-0.030	-0.015	1615.5	0.000
|	|	34	-0.021	-0.046	1618.9	0.000
|	|	35	0.004	-0.057	1619.1	0.000
|	|	36	0.016	-0.048	1621.1	0.000

UNIT ROOT

Tables 8, 9, 11 and 12 show that at level and first difference the series was not stationary and at second difference it becomes stationary.

TABLE 8: UNIT ROOT HIGH (LEVEL)

Null Hypothesis: HIGH has a unit root
Exogenous: Constant
Lag Length: 2 (Automatic - based on SIC, maxlag=35)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.104403	0.9472
Test critical values:	1% level	-3.431002	
	5% level	-2.861713	
	10% level	-2.566904	

*MacKinnon (1996) one-sided p-values.

TABLE 9: FIRST DIFFERENCE HIGH

Null Hypothesis: D(HIGH) has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=35)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-61.44972	0.0001
Test critical values:	1% level	-3.431002	
	5% level	-2.861713	
	10% level	-2.566904	

*MacKinnon (1996) one-sided p-values.

TABLE 10: SECOND DIFFERENCE HIGH

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Null Hypothesis: D(HIGH,2) has a unit root
Exogenous: Constant
Lag Length: 35 (Automatic - based on SIC, maxlag=35)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-26.21097	0.0000
Test critical values:	1% level	-3.431006	
	5% level	-2.861714	
	10% level	-2.566904	

*MacKinnon (1996) one-sided p-values.

TABLE 11: UNIT ROOT LOW (LEVEL)

Null Hypothesis: LOW has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=35)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.275667	0.9261
Test critical values:	1% level	-3.431002	
	5% level	-2.861713	
	10% level	-2.566904	

*MacKinnon (1996) one-sided p-values.

TABLE 12: UNIT ROOT LOW (FIRST DIFFERENCE)

Null Hypothesis: D(LOW) has a unit root
Lag Length: 0 (Automatic - based on SIC, maxlag=35)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-80.43592	0.0001
Test critical values:	1% level	-3.431002	
	5% level	-2.861713	
	10% level	-2.566904	

*MacKinnon (1996) one-sided p-values.

TABLE 13: UNIT ROOT LOW (SECOND DIFFERENCE)

Null Hypothesis: D(LOW,2) has a unit root
Exogenous: Constant
Lag Length: 35 (Automatic - based on SIC, maxlag=35)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-26.35103	0.0000
Test critical values:	1% level	-3.431006	
	5% level	-2.861714	
	10% level	-2.566904	

*MacKinnon (1996) one-sided p-values.

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TABLE 14: ARMA ESTIMATION OF HIGH

Dependent Variable: DATE
Method: Least Squares
Date: 09/04/21 Time: 14:46
Sample: 1 7894
Included observations: 7894

Variable	Coefficient	Std. Error	t-Statistic	Prob.
HIGH	20795.92	179.6510	115.7573	0.0000

R-squared	18144.29531	Mean dependent var	730788.8
Adjusted R-squared	18144.29531	S.D. dependent var	3303.292
S.E. of regression	444968.2	Akaike info criterion	28.84952
Sum squared resid	1.56E+15	Schwarz criterion	28.85040
Log likelihood	-113868.1	Hannan-Quinn criter.	28.84982
Durbin-Watson stat	0.000450		

TABLE 15: ARMA ESTIMATION OF LOW

Dependent Variable: DATE
Method: Least Squares
Date: 09/04/21 Time: 14:50
Sample: 1 7894
Included observations: 7894

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOW	21231.65	183.9052	115.4489	0.0000

R-squared	18205.26154	Mean dependent var	730788.8
Adjusted R-squared	18205.26159	S.D. dependent var	3303.292
S.E. of regression	445715.1	Akaike info criterion	28.85287
Sum squared resid	1.57E+15	Schwarz criterion	28.85376
Log likelihood	-113881.3	Hannan-Quinn criter.	28.85318
Durbin-Watson stat	0.000506		

FORECAST ANALYSIS OF GARCH (LOW AND HIGH)

FIGURE 7: FORECAST ANALYSIS (HIGH) FIGURE 8: FORECAST ANALYSIS OF GARCH(LOW)

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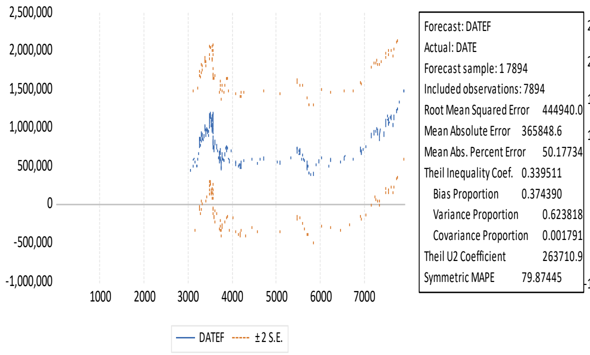

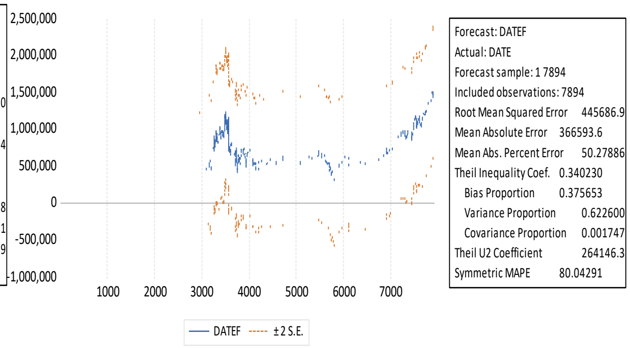

FORECAST ANALYSIS

GARCH (1,1) model forecast performance for the stock returns obtained was analysed using mean absolute error (MAE), root mean square error (RMSE), mean absolute percentage error (MAPE) and Theil inequality coefficient. The results obtained are as shown in the figure 16 below:

TABLE 16: FORECAST ANALYSIS

SERIES / INDICES	LOW	HIGH
RMSE	445686.9	444940.0
MAE	366593.6	365848.6
MAPE	50.27886	50.1773
THEIL U	0.34023	0.33951
BIAS PRO	0.37565	0.37439
VAR. PRO	0.62260	0.62381
COV. PRO	0.00174	0.00179

The value of Theil-U inequality obtained for the series are 0.3402 for high and 0.3395 showing that the model fit is good. Looking at the bias proportion which are 0.3757 and 0.3744, the variance proportion 0.6226 and 0.6238. These two indices imply that the series under study has a little or no bias error. The variance proportion is a bit close to one implying a better fit. The covariance proportion tends to zero implying that this model will be very good for use for forecasting purpose.

4.0 SUMMARY OF MAJOR FINDINGS AND RECOMMENDATIONS

The study looked at univariate analysis of volatility of asset returns using GARCH model. The data used was a secondary data collected from yahoo finance with seven thousand eight hundred and ninety-four observations. From the data, it was discovered that at level and first difference, for all the stationarity indices used (Graph, Correlogram and Unit root test), the series was not stationary but at the second difference, it was stationary. We proceeded to the data analysis stage where $GARCH(1,1)$ model was chosen as it produced the least Akaike Information Criterion (AIC) value. Thereafter, we subjected the result obtained to forecasting evaluation indices where it was discovered that Theil-U produced a very good fit, the bias and the variance proportion are almost zero and covariance proportion is very close

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to unity. All pointing to the fact that the model $GARCH(1,1)$ will have a very good forecasting ability.

In view of the above, the following policy recommendations are made that a large-scale study should be encouraged so as to further verifying the reliability of result so obtained, the government of all nations should endavoure to improve the conditions of all various stock sectors so as to improve their productivity and service delivery for the customers, the issue of fraud in the sector should be looked into so that customers will have more confidence in trading in stock sector. and lastly, a more advance model like GARCH, Bilinear, SETAR Models and Hybrid Models like BL-GARCH, STAR-GARCH, ANN-STAR, ARMA-STAR and other hybrids may as well be used to investigate the reliability of the result so obtained.

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