Modelling and Forecasting a monthly Market Capitalization on Equity Only

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***Abstract* — This study aimed to examine the effect of heteroskedastcity on the Nigerian Stock Exchange (NSE) monthly market capitalization as a result of daily volatility of stock prices over the years. Time series analysis using ARIMA, GARCH (1,1) and mixed ARIMA – ARCH/GARCH (1,1) models were employed to model monthly market capitalization on the floor of NSE as reported by Central Bank of Nigeria (CBN) in 2016 Statistical Bulletin Financial. Given the suspected autoregressive behaviour of the series, ARIMA model was fitted to the data and the results obtained regarding volatility of the series as evident in the residual and squared residual suggested the presence of ARCH effect in the data. However, we combine both ARIMA model and ARCH/GRACH models to capture the conditional variance in the market capitalization equity data as a result of persistence in volatility, though, not as strong as expected. Thus, the best model for the data was found to be the ARIMA-ARCH/GARCH (1,1) models which efficiently captured the volatility in monthly market capitalization equity data. The forecasted series based on the fitted models equally suggested that there could be volatility persistence in the future NSE market capitalization equity.**

Keywords - *Modelling, Volatility, Forecast, ARIMA, ARCH, GARCH, NSE, Market capitalization.*

I. Introduction

Time series analysis is a major branch in statistics that mainly focuses on analyzing data set to study the characteristics of the data and extract meaningful statistics in order to predict future values of the series. There are two methods in time series analysis, namely: frequency-domain and time-domain. The former is based mostly on Fourier transformation while the latter closely investigates the autocorrelation of the series and is of great use in Box-Jenkins and autoregressive conditional heteroskedastcity/ generalized autoregressive conditional heteroskedastcity (ARCH/GARCH) methods of modelling to perform forecast of the series [15].

Financial markets are considered to have a keen role in economic conditions for countries worldwide. In this regard one of the major aspects of the financial markets is to model and estimate financial market volatility caused by its importance as an indicator for the dynamic fluctuations in stock prices [19][20]. Thus volatility is considered to be a measure of uncertainty for changes in asset prices, and it was used earlier by Markowitz [17] as a measure of risk. During the last three decades there were continuous need to find out accurate measurement of volatility due to its vital role in pricing assets, risk and portfolio management [11][8][10]. According to Bo Sjo [2] many economic time series display time varying variance in such a way that the variance process can be modelled as an auto regressive moving average (ARMA) process.

Volatility clusters, meaning that the variance appears to be high during certain periods and low in other periods often implies an ARMA process in the variance of the process. If the previous period was characterized as high volatility the present and the near future periods are likely to have a high variance as well. Volatility clusters are typical for financial price and return series, exchange rates and inflation rates. In particular, high frequency observations likely to display volatility clustering that can be modelled by ARCH/GARCH methods. High frequency means monthly and below monthly observations.

It is typically not possible to find ARCH/GARCH in frequencies above monthly observations. The ARCH /GARCH process is often seen as a way of modelling time varying risk. Thus, instead of identifying the factors that explains time varying risk, the consequences of time varying risk can be picked-up and modelled with an ARCH/GARCH process.

The aim of this paper is to examine the behavior of NSE monthly market capitalization equity during the period from 2007-2016 which covers both the period of pre and recent global financial crisis. The modelling and forecasting the NSE monthly market capitalization equity were performed using the time-domain method.

II. Literature Review

Market capitalization (Market cap) is the market value at a point in time of the shares outstanding of a publicly traded company, being equal to the share price at that point of time multiplied by the number of shares outstanding. As outstanding stock is bought and sold in public markets, capitalization could be used as an indicator of public opinion of a company's net worth and is a determining factor in some forms of stock valuation. Market capitalization is used by the investment community in ranking the size of companies, as opposed to sales or total asset figures. It is also used in ranking the relative size of stock exchanges, being a measure of the sum of the market capitalizations of all companies listed on each stock exchange. In performing such rankings, the market capitalizations are calculated at some significant date, such as 30 June or 31 December [18].

The total capitalization of stock markets or economic regions may be compared with other economic indicators. The total market capitalization of all publicly traded companies in the world was US$51.2 trillion in January 2007 and rose as high as US$57.5 trillion in May 2008 before dropping below US$50 trillion in August 2008 and slightly above US$40 trillion in September 2008. In 2014 and 2015, global market capitalization was US$68 trillion and US$67 trillion, respectively. Market cap is given by the formula $MC = N \times P$, where MC is the market capitalization, N is the number of shares outstanding, and P is the closing price per share. Market cap reflects only the *equity* value of a company. It is important to note that a firm's choice of capital structure has a significant impact on how the total value of a company is allocated between equity and debt. The Nigerian Stock Exchange (NSE) was established in 1960 as the Lagos Stock Exchange. In 1977, its name was changed from the Lagos Stock Exchange to the Nigerian Stock Exchange. As at March 7, 2017, it has 176 listed companies with a total market capitalization of about N8.5 trillion. All listings are included in the Nigerian Stock Exchange All Shares index. In terms of market capitalization, the Nigerian Stock Exchange is the third largest stock exchange in Africa [18].

In financial trading, one of the central parts is to try to capture the movements of the underlying asset, which is usually known as volatility. The volatility is the conditional standard deviation of the underlying assets return. The volatility has some important features. One of the most important is that the volatility changes over time and that it is not directly visible in daily data since there is only one observation each trading day. The volatility depends on the trading in each day and between the days [22].
Awartani and Corradi [1] study the forecasting ability of different GARCH (1,1) against asymmetric GARCH models and they found that the asymmetric models perform better than the GARCH (1,1) model on one step ahead forecast and on longer time horizon. They found out that GARCH (1,1) was only defeated by models that allows for asymmetry. For other models GARCH (1,1) performed well. Goyal [12] used CRSP value weighted returns (stocks) and examine the performance for some GARCH models. The result indicated that the GARCH-M has a bad forecast and simple ARMA specification performed better in the out-of-sample test. Dana AL-Najjar [6] suggest that the symmetric ARCH /GARCH models can capture characteristics of Amman Stock Exchange (ASE), and provide more evidence for both volatility clustering and leptokurtic, whereas EGARCH output reveals no support for the existence of leverage effect in the stock returns at Amman Stock Exchange. Varun Malik [23] in his work found out that the variance of stock price in ARIMA model is unconditional variance and remains constant. ARIMA is applied for stationary series and therefore, non-stationary series should be transformed. Additionally, ARIMA and GARCH models are often used together, namely ARIMA/GARCH (1,1) model. ARCH/GARCH (1,1) is a method to measure the volatility of the series, or, more especially, to model the noise term of ARIMA model. ARCH/GARCH (1,1) incorporates new information and analyses the series based on conditional variances where users can forecast future values with up-to-date information to making money. The forecast interval for the mixed model is closer than that of ARIMA-only model [20]. As result of the above review, which is not exhaustive in itself, but have provided ideas and framework for more understanding on the behavior of financial market activities in modelling and forecasting.

III. Materials and Methods

The data used is the monthly NSE market capitalization, as reported by Central Bank of Nigeria (CBN) in 2016 Statistical Bulletin Financial Statistics Final., covering ten years period from January 2007 to December 2016.

Stationary and differencing of data series

The first step in modelling time index data is to convert the non-stationary time series to stationary one. This is important for the fact that a lot of statistical and econometric methods are based on this assumption and can only be applied to stationary time series. Non-stationary time series are erratic and unpredictable while stationary process is mean-reverting, i.e., it fluctuates around a constant mean with constant variance. In other words, this means that the probabilistic character of the series must not change over time, i.e. that any section of the time series is “typical” for

every other section with the same length. More mathematically, we require that for any, *s, t* and *k*, the observations, $x_t, x_{t+1}, \ldots, x_{t+k}$ could have just as easily occurred at times, $s, s+1, \ldots, s+k$.
In order to convert non-stationary series to stationary, differencing method can be used in which the series is lagged 1 step and subtracted from original series:

$$Y_t = Y_{t-1} + e_t, \quad \text{and} \quad e_t = Y_t + Y_{t-1}, \qquad (1)$$

In financial time series, it is often that the series is transformed by logging and then the differencing is performed. This is because financial time series is usually exposed to exponential growth, and thus log transformation can smooth out (linearize) the series and differencing will help stabilize the variance of the time series.

Examining the distribution of financial data

*A. **Skewness***

The third central moment tells us how symmetrical a distribution gathers around its mean. Rather than working with the third central moment directly, it is, by convention, standardized. Skewness is defined as follows:

$$Skew = \frac{E[(X-\mu)^3]}{\sigma^3} \qquad (2)$$

Any random variable with a symmetric distribution will have Skew = 0. Values greater than zero indicate positive skewness, i.e. distributions that have a heavy tail on the right hand side also value less than 0 indicates a left-skewed distribution.

*B. **Kurtosis***

The kurtosis is the standardized fourth central moment. Similar to the variance, it measures how spread out a distribution is, but it puts more weight on the tails. The exact definition is:

$$Kurt_{EX} = \frac{E[(X-\mu)^4]}{\sigma^4} \qquad (3)$$

It is important to note that the kurtosis is not very meaningful for skewed distributions, because it will measure both asymmetry and tail weight. Hence, it is an indicator that is aimed at symmetric distributions. Its minimal value is 1, and is achieved for any random variable that only takes two distinct values with probability 1/2. The normal distribution has Kurt =3 ; that value is independent of the location and scale parameters μ and σ^2 . Distributions with heavier tails than the Gaussian, and thus Kurt > 0 are called leptokurtic. In financial analysis, an asset with leptokurtic log returns needs to be taken seriously. It means that big losses (as well as big gains) can occur, and one should be prepared for it [16].

Testing Normality:

*A.**Jarque-Bera Test***

The Jarque-Bera[13] test of normality compares the sample skewness and kurtosis to 0 and 3, their values under normality. The test statistic is:

$$JB = \frac{n}{24}(4 * Skew^2 + Kurt_{EX}^2) \sim \chi_2^2 \qquad (4)$$

*B.**Shapiro-Wilk Test***

The Shapiro-Wilk [21] test is a test of normality in frequentist statistics and given as

$$W = \frac{(\sum_i^n a_i x_i)^2}{\sum_i^n (x_i - \bar{x})^2} \qquad (5)$$

$x_{(i)}$ = ith order statistic i.e. smallest number in the sample
a_i= constants generated from the covariance, variance and mean of the sample size n from normally distributed sample.
x_i=random variables.

Volatility Models:

Based on previous studies, there is empirical evidence that financial log returns feature volatility clustering. There are periods where the prices change more substantially, and others where the market is more quiet and the movements are relatively little. Hence, the magnitude of financial log-returns is usually serially correlated. The Random Walk model cannot accommodate for time-varying volatility, neither in its Gaussian formulation nor with heavy-tailed increments. Hence, there is a need for approaches to take care of the situation which is in ARCH/GARCH class of models [7].

*A. **ARCH model***

In order to properly assess the effect of a model on dataset it is important to decide which model should be used [14], therefore the right ARCH model that should be estimated has to be identified. Recall that the ARCH (m) model is

$$u_t = \sigma_t z_t \qquad (6)$$

Where Z_t is a White Noise with mean zero and unit variance i.e. $Z_t \sim NIID(0, 1)$

$$\sigma_t^2 = \omega + \alpha_1 u_{t-1}^2 + \cdots + \alpha_q u_{t-q}^2 \qquad (7)$$

For Variance to be positive, we have:

$$\omega > 0, \alpha_1, \ldots, \alpha_{q-1} \geq 0, \alpha_q > 0$$

For Stationarity:

$$\alpha_1 + \ldots + \alpha_q < 1$$

The two parameters ω and α are the model coefficients. By construction, the conditional variance of ARCH (1) process behaves just like AR (1) model. Therefore one can exploit the use of Autocorrelation Function (ACF) of squared log returns and the Partial Autocorrelation Function (PACF) to identify the order of the appropriate ARCH model.
However, a small number of term u^2_{t-1} is often not sufficient, square of residual are still often correlated. Also, for a larger number of terms, these are often not significant or the constrains on parameter are not satisfied. These problems are solve by GARCH [3][7].

B. ***GARCH model***

According to Javed and Mantalos [14], numerous studies that investigate model selection for the GARCH models find that the "performance of the GARCH (1,1) model is satisfactory". They claim that the first lag is sufficient to capture the movements of the volatility.

$$\sigma_t^2 = \omega + \alpha_1 u_{t-1}^2 + \cdots + \alpha_q u_{t-q}^2 + \beta_1 \sigma_{t-1}^2 + \ldots + \beta_p \sigma_{t-p}^2 \quad (8)$$

For Variance to be positive, we have:

$$\omega > 0, \alpha_1, \ldots, \alpha_{q-1} \geq 0, \alpha_q > 0$$

$$\beta_1, \ldots, \beta_{p-1} \geq 0, \beta_p > 0$$

For Stationarity:

$$(\alpha_1 + \ldots + \alpha_q) + (\beta_1 + \ldots + \beta_p) < 1$$

The popular GARCH (1,1) which is satisfactory will be adopted for the analysis.
A fitting routine is available with function garch() in library(tseries). It works based on the assumption that we have a pure ARCH process $u_t = \sigma_t Z_t$ with Gaussian White Noise innovations Z_t and mean zero, $\mu=0$. As an alternative to this iterative approach, we can use function garchFit() from the fGarch package. It allows for simultaneous estimation of the mean and the model parameters.

IV. Results

Descriptive Statistics

Based on the monthly NSE market cap equity (mceq) describe in Figure 1 (a), we observe that the series has a trend. This is typical for financial time series. In addition, as we can see the mean of this series is obviously non constant over time; hence it is to be considered as a non-stationary time series. Again, the evolution of the trend will be near-impossible to predict.

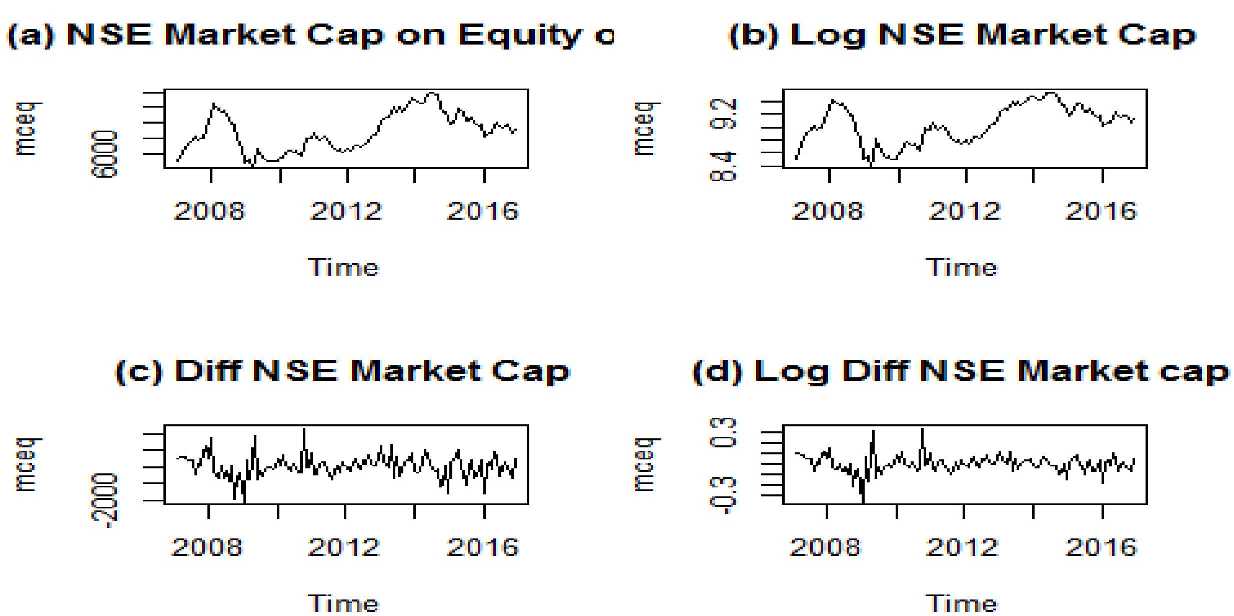

Figure 1: Plots of (a) actual Mcap; (b) Log Mcap; (c) differencing Mcap; and (d) Log of differencing Mcap.

Table 1: Descriptive Statistics of the NSE Market Cap on Equity Series

Mean	*variance*	*Standard Deviation*	*JB (p-value)*	*Min*	*Max*	*skewness*	*kurtosis*	*Shapiro-Wilk (p-value)*
8850.227	6274701	2504.935	2.2e-16	4484	14028	0.2088	-1.0061	3.996e-06

Visual inspection of Figure 1 (a) reveals that at the beginning of the sample period, 2007 displayed relatively low equities and rises rapidly over 12,000 in billion naira up to early part of 2008 and it started to experience a significant drop in equity through 2009.After this drastic falls as a results of crashed in stock prices culminated with global financial meltdown, market cap begins to gradually increase again as stock prices stabilize and begins to rise, it peaked around the mid- year of 2014 and begin to decline again possibly due to recent recession. Similar trend was observed in Figure 1 (b), the log of market cap during the same periods. After first differencing, the visual inspection of the plots in Figure 1 (c) and (d) indicates that market cap series oscillates around the mean value for all the series, the return series are relatively calm, i.e. the fluctuations is small for most of the observations. However, it is difficult to tell from visual inspection if any of these series exhibit clustering behavior, but, with the application of conditional volatility model, this can be accounted for.

From Table 1, the positive mean returns of 8850.227 for NSE market cap implies that on the average, investors recorded gains more than losses during the periods under review. The standard deviation with 2504.935 shows that market cap equities experiences high variability. The skewness indicates that the market cap equities distribution is positively skewed which implies that it rises more than it drops, reflecting the renewed confidence in the NSE activities. The market cap equity returns series shows evidence of heavy tails since the kurtosis is negative implies that big losses (as well as big gains) are not likely to occur, i.e. stability. The p-value of both Jarque-Bera statistic and Shapiro-Wilk'statistic for log of market cap equity returns shows that the return series are not normally distributed.

Unit Root test

Table 2: Unit root test results

Augmented Dickey-Fuller Test
data: diff.logmcap
Dickey-Fuller = -4.5881, Lag order = 4, p-value = 0.01
alternative hypothesis: stationary

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

ACF/PACF of Market Cap Equity Returns Series

Based on the behavior of ACF and PACF plots in Figure 2, an indication of autoregressive pattern is clearly show.

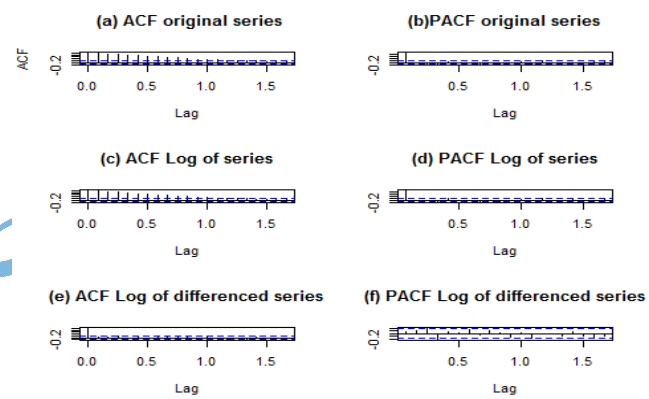

Figure 2: Plots of ACF and PACF of the actual series

The ACF values show a geometrically declined pattern and only the first PACF value is significant indicating that the possible model could be ARCH (1). Hence, different AR, MA, and ARMA models are fitted to the return series by varying the order combinations using Akaike information criterion (AIC) to obtain the optimal order which is arima(1,1,3) . The mean equations were estimated using the model in Table 3. The forecast of the fitted model is depicted in Figure 3 (a) and Q-Q plot of series showing heavy tails while the Figure 4 (a) and (b) shows both the lower and upper bounds of the actual data and fitted series which follows similar pattern and closely related.

Table 3: ARIMA model

```
arima(x = logmcap, order = c(1, 1, 3))

Coefficients:
          ar1     ma1     ma2     ma3
      -0.4922  0.5975  0.2101  0.3301
s.e.   0.1919  0.1822  0.1124  0.0884

sigma^2 estimated as 0.006556:  log likelihood =
130.09,  aic = -250.18
```

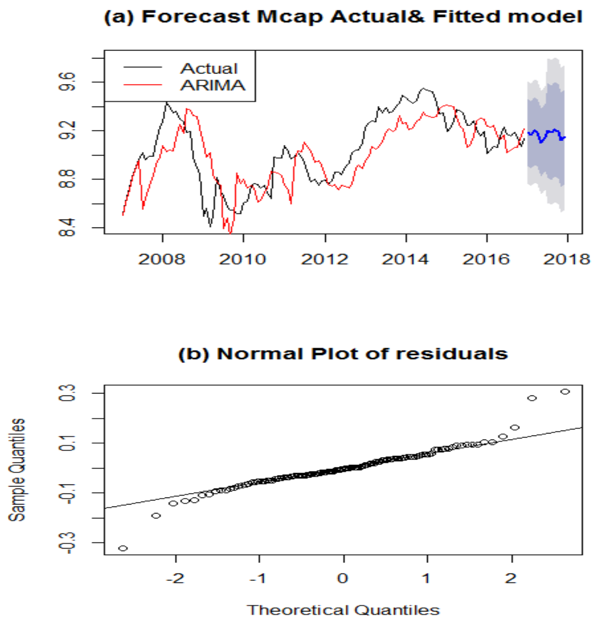

Figure 3: (a) Plot of forecast of the fitted model and actual Mcap. (b) Q-Q plot of residual series

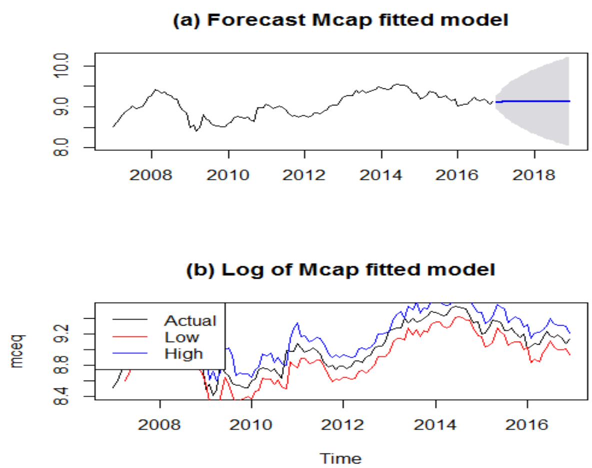

Figure 4: (a) Plot of the Mcap forecast of the fitted model. (b) Plot showing both the lower and upper bounds of actual fitted series.

Test for ARCH Effect

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

Table 4:White Neural Network Test

data: logmcap
X-squared = 2.4019, df = 2, p-value = 0.3009

From Table 4, the p-value suggests there is no evidence to conclude that there is presence of ARCH effect in the return series at both 5% and 1% significant level. Thus, no rejection of the null hypothesis of ARCH effect in the series. This result provide justification for the application of conditional volatility models without ARCH effect in the model.

ARIMA-ARCH/GARCH Model

From the Figure 5, the plots of squared residuals plot show cluster of volatility at some points in time, ACF seems to die down and PACF cuts off after lag 2 even though some remaining lags are significant. The residuals therefore show some patterns that might be modelled. ARCH/GARCH is necessary to model the volatility of the series. As indicated by its name, this method concerns the conditional variance of the series.

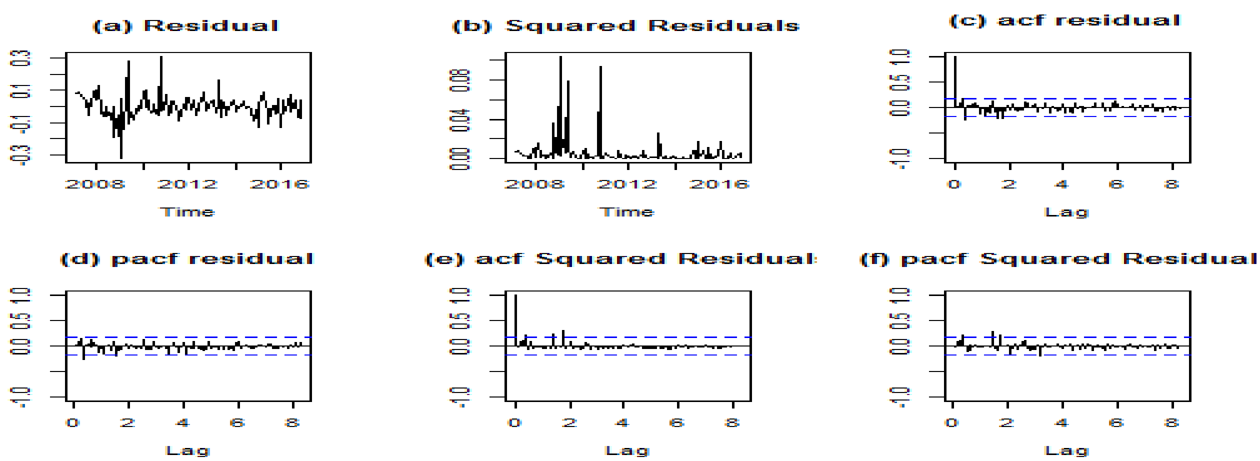

Figure 5. Plots of ACF and PACF of residual.

Table 5: ARIMA-ARCH/GARCH Model Results

Coefficient(s):						
mu	ar1	ma1	omega	alpha1	beta1	shape
0.4876153	0.9472732	0.1186404	0.0012776	0.1000592	0.7221413	3.7645687

Std. Errors: based on Hessian				
	Estimate	Std. Error	t value	Pr(>|t|)
mu	0.487615	0.238878	2.041	0.04122 *
ar1	0.947273	0.026303	36.014	2e-16 ***
ma1	0.118640	0.089080	1.332	0.182915
omega	0.001278	0.001238	1.032	0.301954
alpha1	0.100059	0.089748	1.115	0.264899
beta1	0.722141	0.217452	3.321	0.0008 ***
shape	3.764569	1.239019	3.038	0.0023 **

Information Criterion Statistics:			
AIC	BIC	SIC	HQIC
-2.253419	-2.090816	-2.259738	-2.187385

V. Discussion

In this section, we discuss the performance of the combined ARIMA-ARCH/GARCH model as employed. As selected earlier, ARIMA model for NSE Log market cap series is ARIMA (1, 1, 3), this is combined with ARCH/GARCH model since the series failed the ARCH effect test. The fitted model using `garchFit()` gives the results in the Table 5 above..

First, we note that `garchFit()` allows for simultaneous estimation of μ , of which we make use here. The result is given as mu in the output, with a result that should be similar (but not equal) to the arithmetic mean in the log market cap returns is significantly different from zero i.e. it has influence on the model. The coefficient of *ar1* estimate which is lagged value of the change in market cap is very much significantly different from the zero. The moving average parameter estimate, *ma1* is not significantly different from the zero indicating that the ARMA (1,1) in garchFit() model may fit the data by over parameterizing. The *omega* parameter and *apha1* parameter which are estimates of unconditional variance and *lag1* ARCH respectively, are not significantly different from zero. This support that there is no reasonable amount of ARCH effect in the market cap series. The coefficient of beta1 is the first (lag 1) GARCH parameter and it is significant which implies that there is presence of GARCH effect in market cap series which can be used to capture the conditional variance (volatility). The *shape* parameter which is positive and significant indicates that the distribution of the conditional variance is skewed not normal.

In the model, *apha1* reflects the influence of random deviations in the previous period on σ_t, whereas *beta1* measures the part of the realized variance in the previous period that is carried over into the current period. The sizes of the parameters *apha1* and *beta1* determine the short-run dynamics of the resulting volatility time series. Large GARCH error coefficients, *apha1*, mean that volatility reacts intensely to market movements which is not the case here. Large GARCH lag coefficients, *beta1*, indicate that shocks to conditional variance take a long time die out, so volatility is 'persistent' which is the case we have here.

If *apha1* is relatively high and *beta1* is relatively low then volatilities tend to be more offensive which is not the case here as well since *apha1*=0.1 and *beta1*=0.72. The estimates of *omega* is positive and considerably smaller, this is due to the changing conditional variances over time and their eventual contribution to unconditional variances.

Our results also indicate that the persistence in volatility, as measured by the sum of *apha1* and *beta1* in the GARCH (1,1) model, up to 0.82 with an average of 0.41, suggesting a weak presence of ARCH and GARCH effects, thus is made due to less ARCH presence in the series. This also suggests that current volatility of market cap equity can be explained by past volatility that tends to reflect over time.

Consequently, the ARIMA-ARCH/GARCH (1,1) models can be said to have been quite successful in taking into account the autocorrelation in the volatility in monthly market cap equity. Finally, the Figure 4 (a) and (b) suggests persistence in volatility in the future NSE market cap equity because of the bounds associated with the forecasts.

VI. Conclusion

Our analytical and empirical results aimed at examining the behavior of NSE monthly market capitalization equity in R environment during the period that covers pre and recent global financial crisis.

Using time series analysis to modelling as well as forecast the NSE market cap equity, the results shows that ARIMA model fitted the series to some reasonable extent based on the behavior of ACF and PACF plots which shows an indication of autoregressive pattern.

After fitting ARIMA model, the volatility observed in the residual and squared residual suggest the presence of ARCH effect, but failure of the ARCH effect test thus leaves us to assume that there is little or no ARCH effect in that data series. However, using garchFit() function in R to combine both ARIMA model and ARCH/GRACH model, the model was able to capture the conditional variance in market cap equity data series because it shows that there is persistence in volatility though not as strong as expected. Hence, the ARIMA-ARCH/GARCH (1,1) models can be said to have captured the volatility in monthly market cap equity.

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References

[1] Awartani, A. M. B. and Corradi, V. (2005). Predicting the volatility of the S&P-500 stock index via GARCH models: the role of asymmetries. International Journal of Forecasting. 21, page 167-183

[2] Bo Sjo (2011) Estimation And Testing For Arch And Garch- Modelling the volatility of the Electrolux stock. Revised January 6, 2011

[3] Bollerslev, Tim (1986). Generalized Autoregressive Conditional Heteroskedasticity. Journal of Econometrics. 31 (3): 307–327.

[4] Christian P. Robert George Casella (2010). Introducing Monte Carlo Methods with R, Springer, ISBN 978-1-4419-1575-7.

[5] Cohen Y., Cohen J.Y. (2008) Statistics and Data with R: An applied approach through examples, John Wiley Sons, Ltd. ISBN: 978-0-470-75805.

[6] Dana AL-Najjar (2016) Modelling and Estimation of Volatility Using ARCH/GARCH Models in Jordan's Stock Market. Asian Journal of Finance & Accounting ISSN 1946-052X 2016, Vol. 8, No. 1

[7] Engle, Robert F. (1982). "Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation". Econometrica. 50 (4): 987–1007. JSTOR 1912773.

[8] Ezzat, H. (2012). The Application of GARCH and EGARCH in Modelling the Volatility of Daily Stock Returns during Massive Shocks: The Empirical Case of Egypt. Munich Personal RePEC Archive. Retrieved from http://mpra.ub.uni-muenchen.de/50530/

[9] Ghulam Ali (2013) ,EGARCH, GJRGARCH, TGARCH, AVGARCH, NGARCH, IGARCH and APARCH Models for Pathogens at Marine Recreational Sites, Journal of Statistical and Econometric Methods, vol. 2, no. 3.

[10] Gökbulut, R., & Pekkaya, M. (2014). Estimating and Forecasting Volatility of Financial Markets Using Asymmetric GARCH Models: An Application on Turkish Financial Markets. International Journal of Economics and Finance, 6(4), 23-33.

[11] Goudarzi, H., & Ramanarayanan, C.S. (2011). Modeling Asymmetric Volatility in the Indian

Stock Market. International Journal of Business and Management, 6(3), 221-231.
[12] Goyal, A. (2000). Predictability of Stock Return Volatility from GARCH Models. http://www.hec.unil.ch/agoyal/docs/Garch.pdf .
[13] Jarque Carlos M., Bera Anil K. (1980) Efficient tests for normality, homoscedasticity and serial independence of regression residuals. Economic letters. 6 (3): 255-259.
[14] Javed, F. & Mantalos, P. (2013). GARCH-Type Models and Performance of Information Criteria. Communications in statistics. Simulation and computation. 42(8), page 1917-1933.
[15] Ly Pham (2013) Time Series Analysis with ARIMA – ARCH/GARCH model in R L-Stern Group
[16] Marcel Dettling (2017) Notes for the WBL-Course Statistical Analysis of Financial Data,ETH Zurich
[17] Markowitz, Harry. (1952). Portfolio Selection. The Journal of Finance, 7(1), 77-91.
[18] NSE Fact Sheet (2017) https://en.wikipedia.org/wiki/Nigerian_Stock_Exchange
[19] Raja, M., & M. Selvam, (2011). Measuring the time varying volatility of futures and options. International Journal Applied Economic Finance, 5, 18-29.
[20] Ruey S. Tsay (2005) Analysis of Financial Time Series, Second Edition, A John Wiley & Sons, Inc., Publications.
[21] Shapiro S.S, Wilk M.B. (1965) An analysis of variance test for normality (complete sample). Biometrika.52(3-4):591-611.
[22] Tsay, R. (2005). Analysis of Financial Time Series. 2nd ed. New Jersey. John Wiley & Sons.
[23] arun Malik (2017) Arima/Garch (1,1) modelling and forecasting for age stock price using r. Elk asia pacific journal of marketing and retail management issn 2349-2317