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Comparative Performance of Garch and Sarima Techniques in the Modeling of Nigerian Broad Money

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ABSTRACT
Money is a driving tool in any economy of a nation. As such the analysis and forecasting of Broad Money is of utmost importance to policy makers of any economy. The analysis shows the comparison of the performance of Nigerian Broad Money for GARCH and SARIMA models. In financial time series, the non-constant volatility is always high and GARCH model is better compared to the SARIMA model. The data used was collected from Central Bank of Nigeria website www.cenbank.org for 16 years (2000 - 2015). The time series were modeled using both methodologies and the analysis of the result shows that GARCH model outperform SARIMA models based on the minimum AIC. In the confines of this experiment SARIMA AIC was higher than that of GARCH, which showed that GARCH model is better than ARIMA model.

INTRODUCTION

Money is a driving tool that is very important for the economy of any nation. It acts as a transfer of value for goods and services and as a unit of value. It helps in decision making and serves as transaction balances. It also includes different financial instruments and some other types of deposits balances that can be converted to transaction money.

Broad money is the quantity of the money supply which includes more than just physical money such as currency and coins which is used in determing the availability of money in a country. The money supply is the total of all the assets in a country that consumers, producers, individuals and government can use as a form of payment or converted into demand deposits, treasury bills, debentures, ordinary shares and short-term investments which can be converted easily into money and vice versa. It is a monetary indicator usually used to check the total supply of money in the economy which is easy to track. The importance of Broad money cannot be over-emphasized. It is used by the monetary authority, Central Bank of Nigeria by the use of interest rate, direction of credits and supply of money to regulate the level of activities in the economy in order to enhance price stability, investment for employment and economic growth and development.

Monetary policy emphasizes on more effective instruments in the rate of deregulation of money market preventing money from becoming the main cause of disturbances in the country. It allows the supply of broad money to expand to meet the needs of households and companies. An effective financial policy basically depends on the ability of an Economists and Statisticians to provide a well suitable model that can be of assistance in the on-going economic processes and forecast of the future development.

LITERATURE REVIEW

A GARCH process depends on past variance and past squared observations to model for present variance. They are usually used in financial aspect because of its efficiency in modeling assets proceeds and price increase. According to Engle (1982), it is a statistical model which is used by financial institutions for estimation of the volaticity of stock returns in financial market in which volaticity can transform in becoming more volatile throughout the periods of monetary crises or world procedures and less volatile throughout periods of relative quietness and steady economic growth. GARCH models aim to reduce mistakes in forecasting and facilitate the accuracy of ongoing predictions.

A comparative study was carried out by Sparks and Yurova using the ARIMA model versus the ARCH/GARCH models on daily equity prices of time series data for large companies proved that for one-step ahead forecast, ARCH/GARCH model perform better than the ARIMA model.

The SARIMA is an offshoot of the ARIMA models. These models were put together by American Statisticians G.E.P Box and Jenkins in 1976. The Box Jenkins approach invents a systematic class of model called ARIMA (Autoregressive Integrated Moving Average) models to hold time correlated forecasting and modeling (Shumway and Stoffer, 2010). The observed data in this methodology are assumed to follow a multiplicative model. These models include the autoregressive model of order *P*, *AR* (*p*), the moving average model of order q, *MA* (*q*), the autoregressive moving average model, ARMA (*p*, *q*), the ARIMA (Autoregressive Integrated Moving Average) model and the SARIMA (Seasonal Autoregressive Integrated Moving Average). The SARIMA model is helpful in situation where the time series data shows evidence of seasonality (i.e. timely occurrence with about the same intensity periodically). Many economists and fiscal time series are recognized to show some seasonality in their behavior.

Etuk (2012), used the seasonal ARIMA model to forecast the Nigeria consumer price index data from March 1963 to December 2003, the results reveal a seasonality of Lag 12 and a seasonal MA component to the model. The model used is $(0, 1, 1) \times (0, 1, 1)_{12}$ seasonal model which shows seasonality. An Autoregressive Integrated Moving Average (ARIMA) model, $(0, 1, 1) \times (0, 1, 1)_{12}$ is fitted to the series. A visual assessment of the actual and fitted plots reveals a close accord between the two. Some other statisticians that have done extensive work on the SARIMA model include: Helman (2011), Daniel and Adebisi (2013), Etuk and Igbudu (2013), Etuk and Ojekudo (2014), Ampaw *et al.*, (2013), Etuk *et al*., (2013).

MATERIALS AND METHODS

The data for this analysis are Monthly Nigerian Broad Money from 2000-2015 collected from the website of Central Bank of Nigeria website. (E-views) software was used.

The Garch Model

GARCH means Generalized Autoregressive Conditional Heteroskedasticity. It is an econometric term invented in 1982 by Robert F. Engle. It is used where volatility is a crucial issue. Volatility is the degree of variation of data overtime as measured by the standard deviation.

The GARCH (P, Q) models involved the residual of a time series regression. The model is given by;

Let $Y_t = C + \varepsilon_t$

C is the deterministic part and the residual is modeled as

$\varepsilon_t = \sqrt{\sigma_t}\, Z_t$.

$E(\varepsilon_t) = 0$

$\varepsilon_t^2 = \sigma_t^2 Z_t^2$.

$E(\varepsilon_t^2) = \sigma_t^2$ and

$E(Z_t^2) = \sigma_t^2$.

Where, σ_t^2 is the conditional variance given as

$\sigma_t^2 = \omega + \alpha_1 E_{t-1}^2 + \alpha_2 E_{t-2}^2 + \alpha_3 E_{t-3}^2 + \ldots + \alpha_q E_{t-q}^2 + \beta_1 \sigma_{t-1}^2 + \beta_2 \sigma_{t-2}^2 + \beta_3 \sigma_{t-3}^2 + \ldots\ldots + \beta_p \sigma_t - p^2$

Where in the original model Z_t have the unit normal density $Z_t \sim N$ (0:1).

The Sarima Model

The SARIMA methodology is a multiplicative model that is widely used by statisticians for analyzing time series data. It was invented by G.E.P. Box and Jenkins in 1976. It is preferred because of its high degree of accuracy. When the data to be analyzed is seasonal, the SARIMA (p,d,q) ×(P,D,Q)s is used. A non-seasonal ARIMA model is classified as an 'ARIMA' (p, d, q) model.

$\Phi_P(B^s)\,\phi_p(B)\,\nabla_s^D\,\nabla^d x_t = \mu + \Theta_Q(B^s)\theta_q(B)W_t$,

$\varphi_p(B) = 1 - \varphi_1 B - \varphi_2 B^2 \ldots. \varphi_p B^p$ (non-seasonal AR component)

$\Phi(B^s) = 1 - \Phi_1 B^s - \Phi_p B^{2s} \ldots. - \Phi_p B^{ps}$(seasonal AR component)

$\theta_q(B) = 1 + \theta_1 B + \theta_2 B^2 \ldots. + \theta_q B^q$(non-seasonal MA component)

$\varphi q(B^s) = 1 + \varphi_1 B^s + \varphi_2 B^{2s} \ldots. + \varphi_q B^{qs}$(seasonal MA component)

$W_t = (1 - B)^d (1 - B)^D y_t$

Where, w, is the usually refers to as the Gaussian white noise processes.

RESULTS

First, SARIMA technique was used for the analyses of the data and in doing this, a time plot is first constructed which is given in Figure 1.1.

FIGURE 1: NMCS

Figure 1.1: Time Plot of Nigerian Broad Money

A proper look at the plot shows the presence of a trend. In this case, we shall conduct an Augmented Dickey-Fuller (ADF) test to check if the data is stationary. The result is shown in Table 1.1 below.

Table 1.1: Augmented Dickey-Fuller Unit Root Test on NMCS

Null hypothesis: NMCS has a unit root				
Exogenous Constant				
Lag Length 0 (Automatic –based on SIC maxlag = 14)				
			t-Statistics	Prob *
Augmented Dickey-Fulley test statistics			1,437756	0.9991
Test critical values	1% level		-3.464643	
	5% level		-2.876515	
	10% level		-2.574831	
*MacKinnon (1996) one sided p-value				
Augmented Dickey-Fuller Test Equation				
Dependent Variable D(NBD)				
Method: Least Square				
Date: 05/14/17 Time 16.31				
Sample (adjusted 2000M02 2016M02				
Included observations 194 after adjustments				
Variables	Coefficient	Std. Error	t-Statistics	Prob.
NMCS (-1)	0.005854	0.003970	1.455396	0.1472
C	0.056729	0.039459	1.449940	0.1487
R-squared	0.010819	Mean dependent var.		0.101571
Adjusted R-square	0.005585	S.D dependent var.		0.335524
S.E of regression	0.334586	Akaike info criterion		0.658570
Sum squared resid	21.15812	Schwarz criterion		0.692625
Log likelihood	-60.89340	Hannah-Quinn criter.		0.672364
F-statistic	2.067142	Durbin-Watson stat.		1.941331
Prob(F-statistic)	0.152157			

The test statistic above shows that the data is non-stationary as such we take the first difference to make it stationary. A plot of the first difference is shown in figure 1.2.

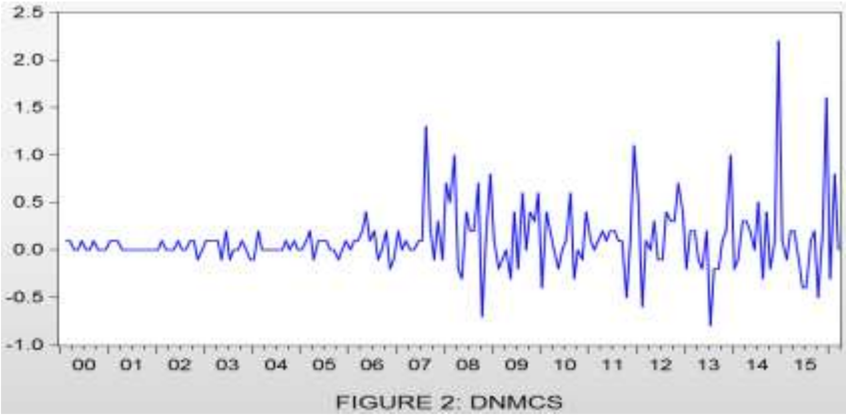


Figure 1.2: Time Plot of Differenced Series

A look at the time plot above shows that the first difference of the Nigerian Broad Money is a stationary data. An Augmented Dickey Fuller (ADF) test was conducted to confirm the stationary of the data. The result of the test is shown in table 1.2 below.

Table 1.2: Augmented Dickey-Fuller Test Result for Differenced Series

Null Hypothesis: DNMCS has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-14.47369	0.0000
Test critical values:	1% level	-3.464280	
	5% level	-2.876356	
	10% level	-2.574746	

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

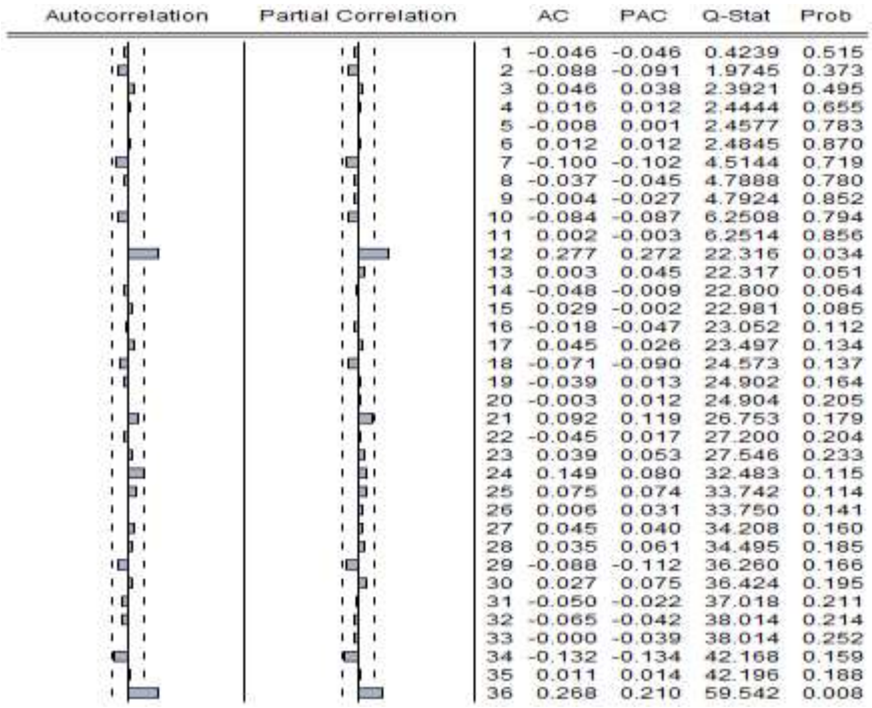
Augmented Dickey-Fuller Test Equation
Dependent Variable: D(DNMCS)
Method: Least Squares
Date: 07/24/16 Time: 09:10
Sample (adjusted): 2000M03 2016M03
Included observations: 193 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DNMCS(-1)	-1.046406	0.072297	-14.47369	0.0000
C	0.107375	0.025415	4.224924	0.0000

R-squared	0.523082	Mean dependent var	-0.000518
Adjusted R-squared	0.520585	S.D. dependent var	0.487500
S.E. of regression	0.337544	Akaike info criterion	0.676067
Sum squared resid	21.76176	Schwarz criterion	0.709877
Log likelihood	-63.24044	Hannan-Quinn criter.	0.689759
F-statistic	209.4878	Durbin-Watson stat	2.008190
Prob(F-statistic)	0.000000		

Correlogram of the First Differences

The correlogram of the first difference of the Nigerian Broad Money shows a spike at lag 12. This shows the presence of a seasonal moving average (MA) of order 1. The correlogram of the first difference is given in Figure 1.3. The correlogram of the first difference is given in Figure 1.3.



Lag	AC	PAC	Q-Stat	Prob
1	-0.046	-0.046	0.4239	0.515
2	-0.088	-0.091	1.9745	0.373
3	0.046	0.038	2.3921	0.495
4	0.016	0.012	2.4444	0.655
5	-0.008	0.001	2.4577	0.783
6	0.012	0.012	2.4845	0.870
7	-0.100	-0.102	4.5144	0.719
8	-0.037	-0.045	4.7888	0.780
9	-0.004	-0.027	4.7924	0.852
10	-0.084	-0.087	6.2508	0.794
11	0.002	-0.003	6.2514	0.856
12	0.277	0.272	22.316	0.034
13	0.003	0.045	22.317	0.051
14	-0.048	-0.009	22.800	0.064
15	0.029	-0.002	22.981	0.085
16	-0.018	-0.047	23.052	0.112
17	0.045	0.026	23.497	0.134
18	-0.071	-0.090	24.573	0.137
19	-0.039	0.013	24.902	0.164
20	-0.003	0.012	24.904	0.205
21	0.092	0.119	26.753	0.179
22	-0.045	0.017	27.200	0.204
23	0.039	0.053	27.546	0.233
24	0.149	0.080	32.483	0.115
25	0.075	0.074	33.742	0.114
26	0.006	0.031	33.750	0.141
27	0.045	0.040	34.208	0.160
28	0.035	0.061	34.495	0.185
29	-0.088	-0.112	36.260	0.166
30	0.027	0.075	36.424	0.195
31	-0.050	-0.022	37.018	0.211
32	-0.065	-0.042	38.014	0.214
33	-0.000	-0.039	38.014	0.252
34	-0.132	-0.134	42.168	0.159
35	0.011	0.014	42.196	0.188
36	0.268	0.210	59.542	0.008

Figure 1.3: Correlogram of the First Differences

Estimation of the SARIMA (0,1,0)(0,0,1)$_{12}$ Model

A look at the correlogram above suggests that the SARIMA model that suits the data is SARIMA (0, 1, 0) (0, 0, 1)$_{12}$ model.

Recall that the SARIMA model is given by:

$\varphi_p(B)\ \Phi_p(B^s)\ W_t = \mu + \theta_q(B)\ \Theta_q(B^s)e_t$

From the identified model, there is no non-seasonal AR and MA component. Also, there is no seasonal AR component. Thus, the model becomes:

$W_t = \mu + \Theta_q(B^s)\ e_t$

and the resulting equation is:

$1\text{-}B\ (X_t) = \mu + (1 + \Theta_1 B^{12})\ e_t$

$X_t - X_{t\text{-}1} = e_t + \Theta_1 B^{12}\ e_t + \mu$

$X_t - X_{t\text{-}1} = \mu + e_t + \Theta_1\ e_{t-12}$

$X_t = \mu + X_{t\text{-}1} + e_t + \Theta_1\ e_{t-12}$

The estimation of the SARIMA (0, 1, 0) (0, 0, 1)$_{12}$ model and the result is given in table 1.3. From the result, the AIC is 0.631776.

Estimation Result of the SARIMA model

Dependent Variable: DNMCS
Method: Least Squares
Date: 07/24/16 Time: 09:22
Sample (adjusted): 2000M02 2016M03
Included observations: 194 after adjustments
Convergence achieved after 6 iterations
MA Backcast: 1999M02 2000M01

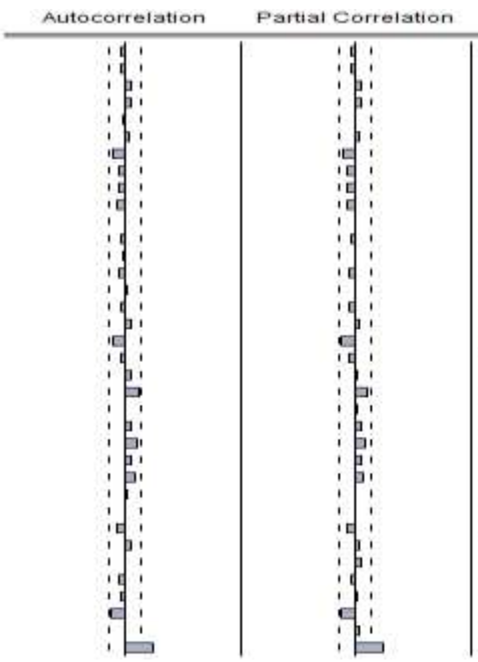
Variable	Coefficient	Std. Error	t-Statistic	Prob.
MA(12)	0.367269	0.071157	5.161353	0.0000

R-squared	0.030391	Mean dependent var	0.102577
Adjusted R-squared	0.030391	S.D. dependent var	0.336153
S.E. of regression	0.331005	Akaike info criterion	0.631776
Sum squared resid	21.14593	Schwarz criterion	0.648620
Log likelihood	-60.28225	Hannan-Quinn criter.	0.638597
Durbin-Watson stat	1.974518		

Inverted MA Roots	.89+.24i	.89-.24i	.65-.65i	.65-.65i
	.24-.89i	.24+.89i	-.24+.89i	-.24-.89i
	-.65-.65i	-.65+.65i	-.89+.24i	-.89-.24i

Correlogram of Residuals of the SARIMA Model

The model was found to be adequate as the residuals were uncorrelated. The *MA*(12) coefficient is 0.367269. The correlogram of the residuals of the model is given in Figure 1.4.



	AC	PAC	Q-Stat	Prob
1	-0.041	-0.041	0.3331	
2	-0.045	-0.046	0.7261	0.394
3	0.057	0.054	1.3760	0.503
4	0.046	0.048	1.7914	0.617
5	-0.011	-0.002	1.8169	0.769
6	0.031	0.032	2.0135	0.847
7	-0.102	-0.106	4.1212	0.660
8	-0.066	-0.074	4.9993	0.660
9	-0.054	-0.073	5.5894	0.693
10	-0.068	-0.074	6.5529	0.684
11	-0.004	0.002	6.5569	0.767
12	-0.044	-0.039	6.9526	0.803
13	-0.015	0.001	6.9998	0.858
14	-0.051	-0.057	7.5405	0.872
15	0.011	-0.003	7.5663	0.911
16	-0.038	-0.054	7.8673	0.929
17	0.060	0.039	8.6354	0.928
18	-0.112	-0.125	11.365	0.837
19	-0.036	-0.061	11.643	0.865
20	0.041	0.011	12.014	0.885
21	0.116	0.107	14.957	0.779
22	-0.003	0.020	14.959	0.825
23	0.046	0.042	15.424	0.843
24	0.098	0.097	17.591	0.779
25	0.061	0.049	18.424	0.782
26	0.089	0.077	20.217	0.735
27	0.014	0.001	20.263	0.779
28	0.001	-0.002	20.264	0.820
29	-0.076	-0.078	21.584	0.800
30	0.043	0.039	22.003	0.820
31	0.001	0.043	22.004	0.854
32	-0.063	-0.031	22.928	0.852
33	-0.034	0.022	23.197	0.872
34	-0.128	-0.126	27.073	0.756
35	0.003	0.041	27.075	0.795
36	0.248	0.261	41.893	0.197

Figure1.4: Correlogram of the Residual

THE GARCH MODEL

The first step is to check if the series can be analyzed using the GARCH model, then the time plot of the data is looked upon which shows spots of increased vibration sprinkled throughout the series .In order to make the variance to be constant we generate a new series which is the log of the original series. Let this new series be LNMCS. A line graph of DLNMC (which is the first difference of LNMCS) is given below:

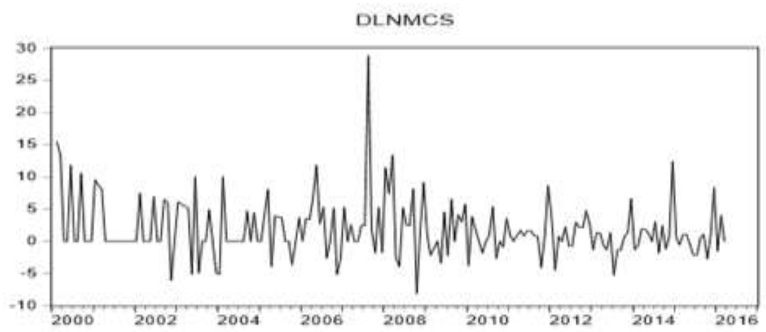


Figure 1.5: Time plot of First difference of LNMCS

From the line graph, volatility clustering is obvious. Next we estimate an AR (1). Since our objective is to check for volatility clustering and interoscedasticity in the data series, we carry out a check for ARCH effects using the ARCH LM Test. The test result of this test is given in the table below:

Table 1.4: ARCHLM Test Result for NMCS

Heteroskedasticity Test: ARCH

F-statistic	0.208703	Prob. F(5,182)	0.9585
Obs*R-squared	1.071774	Prob. Chi-Square(5)	0.9566

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 05/14/17 Time: 17:56
Sample (adjusted): 2000M08 2016M03
Included observations: 188 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	17.81745	5.200422	3.426154	0.0008
RESID^2(-1)	-0.016631	0.073981	-0.224805	0.8224
RESID^2(-2)	0.002736	0.073543	0.037202	0.9704
RESID^2(-3)	-0.024342	0.073533	-0.331031	0.7410
RESID^2(-4)	-0.025361	0.073580	-0.344664	0.7307
RESID^2(-5)	0.062783	0.072815	0.862227	0.3897

R-squared	0.005701	Mean dependent var	17.84669
Adjusted R-squared	-0.021615	S.D. dependent var	56.71145
S.E. of regression	57.32108	Akaike info criterion	10.96661
Sum squared resid	597998.5	Schwarz criterion	11.06990
Log likelihood	-1024.861	Hannan-Quinn criter.	11.00846
F-statistic	0.208703	Durbin-Watson stat	2.002483
Prob(F-statistic)	0.958511		

The F statistics and T^*R^2 indicate the presence of ARCH in the data. This totally justifies the use of GARCH model. Next we specify the GARCH (1, 1) model and carry out the analysis. This analysis was carried out using the e-views software.

Estimation of the Model

Using e-view software, the estimation output of the GARC (1, 1) is given in Table 1.5

Dependent Variable: DNMCS
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 07/24/16 Time: 09:30
Sample (adjusted): 2000M02 2016M03
Included observations: 194 after adjustments
Convergence achieved after 46 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.044259	0.011858	3.732406	0.0002
Variance Equation				
C	-6.98E-06	4.60E-05	-0.151579	0.8795
RESID(-1)^2	-0.019847	0.004322	-4.592187	0.0000
GARCH(-1)	1.050086	0.008763	119.8296	0.0000

R-squared	-0.030254	Mean dependent var	0.102577
Adjusted R-squared	-0.030254	S.D. dependent var	0.336153
S.E. of regression	0.341200	Akaike info criterion	-0.129605
Sum squared resid	22.46850	Schwarz criterion	-0.062226
Log likelihood	16.57168	Hannan-Quinn criter.	-0.102321
Durbin-Watson stat	2.030843		

From the above, the estimate of the parameters is:

C = 0.044259

w = -6.98E – 06

α = -0.019847

β = 1.050086

Substituting these values into the tentative model, we arrive at an equation for model given as:

$Y_t = 0.044259 - 6.98E\,(06) - 0.019847\ y_{t-1}^2 + 1.050086\,\sigma_{t-1}^2$

The correlogram of the residuals of the GARCH (1, 1) model is given in the Figure 1.6 below:

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.041	-0.041	0.3275	0.567
		2	-0.087	-0.088	1.8118	0.404
		3	0.010	0.003	1.8317	0.608
		4	0.093	0.087	3.5784	0.466
		5	0.014	0.024	3.6200	0.605
		6	0.138	0.157	7.4638	0.280
		7	-0.087	-0.075	9.0099	0.252
		8	-0.011	-0.001	9.0344	0.339
		9	-0.047	-0.073	9.4959	0.393
		10	0.018	-0.016	9.5594	0.480
		11	0.034	0.035	9.8005	0.548
		12	0.183	0.182	16.792	0.158
		13	0.040	0.107	17.122	0.194
		14	-0.101	-0.070	19.271	0.155
		15	0.046	0.050	19.724	0.183
		16	0.051	-0.020	20.274	0.208
		17	0.104	0.093	22.596	0.163
		18	-0.066	-0.097	23.540	0.171
		19	-0.019	0.004	23.619	0.211
		20	0.067	0.096	24.595	0.217
		21	0.086	0.081	26.230	0.198
		22	-0.080	-0.048	27.643	0.188
		23	0.075	0.036	28.881	0.184
		24	0.109	0.108	31.519	0.139
		25	0.109	0.098	34.174	0.104
		26	-0.025	0.021	34.311	0.127
		27	0.060	0.039	35.143	0.135
		28	0.021	0.014	35.242	0.163
		29	-0.021	-0.083	35.341	0.194
		30	0.030	0.026	35.546	0.223
		31	0.021	0.013	35.644	0.259
		32	-0.059	-0.077	36.459	0.269
		33	0.015	-0.010	36.514	0.309
		34	-0.145	-0.149	41.520	0.176
		35	0.030	0.039	41.739	0.201
		36	0.244	0.180	56.064	0.018

Figure 1.6: Correlogram of the residuals of the GARCH (1, 1) Model

DISCUSSSION

First, the series was analyzed using the ARIMA model. The series was first tested for stationarity. The test statistic was 1.437756. The statistics is less than the absolute value of the test critical value at 1% level, 5% level and 10% level. This shows that the series is not stationary. As a result, there need to be a regular differencing of the series. After the differencing, an augmented Dickey- Fuller test was conducted again for stationarity. This time, the new series DNMC was found to be stationary. A correlogram of the differenced series was constructed and the ACF created a spike at lag 12 which represents a seasonal moving average model of lag 1. There is also a spike at lag 12 on the PACF of the differenced series. Two tentative models were tested. They are SARIMA (0, 1, 0), $(0, 0, 1)_{12}$ and SARIMA (0, 1, 0), $(1, 0, 1)_{12}$. The AIC of the first model was less than that of the second model, hence we use the second model. The estimated $MA_{(12)}$ coefficient for this model D 0.367269.

The equation for this model is

$X_t = \mu + X_{t-1} + e_t + \Theta_1\, e_{t-12}$

With this equation, estimates for the series can be gotten.

The AIC obtained for this model is 0.631776,

Next the GARCH (1, 1) is used. First we observed the time plot and detect the presence of a non-constant variance. This is observed throughout the series. GARCH models may be suggested by an ARMA type look to the ACF and PACF of the squared series.

As a result of the presence of a non-constant variance, a log transform of the series is taken. The log of the series was test for stationarity and it proved to be non-stationary. Then it was differenced and the differenced series is stationary. Next, a check for volatility clustering and heteroscedasity in the data series is carried out. This is the ARCH test. To do this, an AR model was carried out and the residual was tested using the ARCH test. The *f*-statistics and T^*R^2 Indicates the presence of ARCH in the data. This justified the use of the GARCH model. A GARCH (1, 1) model was then carried out using e-views software and the equation is:

$Y_t = 0.044259 - 6.98E(-06) - 0.019847\, y_{t-1}^2 + 1.050086\, \sigma_{t-1}^2$

The AIC for this model is – 0.129605

CONCLUSION

In conclusion, comparing the two models, the AIC for the SARIMA model is 0.631776 while that of the GARCH model is -0.129605. The GARCH (1, 1), is a better model than SARIMA model because the AIC is smaller here than that of the SARIMA model and it provides a more real –world context when trying to predict the prices and rates of financial instruments.

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