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GARCH AND SARIMA MODELING OF NIGERIAN NARROW MONEY

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Abstract
The study was on Generalized Autoregressive Conditional Heteroscedastic (GARCH) and Seasonal Autoregressive Integrated Moving Average (SARIMA) Modeling of Nigerian Narrow Money. It was aimed at examining the behavior of the monthly data of Nigerian Narrow Money from January 2000 to February 2018 and to construct a suitable GARCH model for the series. Information retrieved from the CBN website in Nigeria. A non-constant volatility was evident in the data, as is typical of financial time series. We found and applied the Generalized Autoregressive Conditional Heteroscedastic GARCH and Seasonal Autoregressive Integrated Moving Average (SARIMA) models to analyze the time series. The findings demonstrated that compared to the GARCH(1,1) model, the SARIMA model had a larger AIC. Since the GARCH(1,1) model provided a lower Akaike Information Criterion (AIC), it is superior for this series.

Keywords: GARCH, SARIMA, Modeling, Narrow Money

Introduction

The term "money" encompasses a broad range of concepts used for buying and selling products and services as well as paying off debts. As well as being a medium of trade, standard of delayed payment, unit of account, and measure of worth, money serves as a store of value. Coins and banknotes are the two main forms of money. It must be rare, as that is a feature of money. To keep its purchasing power from dwindling, the money supply should not be excessive. This is why monetary policy exists: to manage the money supply. When the government wants to accomplish broad economic goals, it employs monetary policy, which consists of the precise steps done by the Central Bank to control the money supply, value, and cost, CBN (2016a). Among other macroeconomic goals, achieving price stability and lowering the unemployment rate are crucial. Like other central banks, the Central Bank of Nigeria (CBN) uses the money supply to accomplish its monetary policy aim. Narrow money and wide money are the two components that make up the money supply, according to the CBN. If all of the money in circulation is physical currency, demand deposits, and other liquid assets kept by financial institutions, then this money supply is narrow. It is the most accessible account such as savings accounts. Narrow money comprises the currencies in circulation and demand deposits. In Nigeria, it is often denoted by M1 and regarded as the liquid component of the money supply. On the other hand, broad money is the total value of money in the economy, plus narrow money. It is a broader measure of money supply. Broad money is longer-term time deposits; it is denoted as M2 in Nigeria, CBN (2016b).

Thus, Broad Money (M2) = Narrow money (M1) + Quasi-Money (QM),
where quasi–money includes savings deposits, time deposits and foreign currency deposits.

The Generalized Autoregressive Conditional Heteroskedastic (GARCH) Model

Using historical variances and future variance forecasts as inputs, this linear model may foretell future variances. After developing the ARCH model, Bollerslev expanded it to a GARCH in 1986 (Engle, 2001). GARCH uses the values of the past squared observations and past variances (Engle, 1982; Engle, 2001).
A GARCH (1,1) is given as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 X_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

The GARCH model is the ARMA equivalent of ARCH. It has an autoregressive component. The GARCH model is the most commonly used financial time series model, which has inspired more sophisticated models (The Pennsylvania State University, 2018). The conditional variance, GARCH (p,q) in general is given as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 X_{t-1}^2 + \alpha_2 X_{t-2}^2 + \cdots + \alpha_q X_{t-q}^2 + +\beta_1 \sigma_{t-1}^2 + \beta_2 \sigma_{t-2}^2 + \cdots + \beta_p \sigma_{t-p}^2.$$

This can be written as:

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

where α_i and β_j are parameters of the model,

$$X_t = \sigma_t Z_t, \qquad Z_t \sim N(0,1),$$ (Stock &Watson, 2012).

Nigerian board money was the subject of a study by Pepple and Etuk (2017) that compared the effectiveness of two models: GARCH and SARIMA. For this data modelling, they turned to the SARIMA and GARCH methods. The analytical findings demonstrated that the GARCH model outperformed the SARIMA model.

Research on the modelling and assessment of volatility in the Jordanian stock market was carried out by AL-Najjar (2016). He investigated the Amman Stock Exchange's (ASE) stock return volatility using the ARCH, GARCH, and Exponential GARCH (EGARCH) models. In contrast to EGARCH, which failed to provide any evidence of a leverage effect in stock returns, his research indicated that ARCH/GARCH models might better capture ASE features and give stronger evidence for volatility clustering and leptokurtic. An improved model for the series was determined to be GARCH (1,1). When it came to capturing the volatility of the Malaysian stock market, Lim and Sek (2013) compared the performances of GARCH-type models. They used both the symmetric and asymmetric GARCH. Using data from January 1990 to December 2010, they compared three metrics: mean squared error, root mean squared error, and mean absolute percentage error. The findings showed that the two GARCH-type models were distinct from one another. During times before and after crises, symmetric GARCH performed better, but asymmetric GARCH was the favoured model.

Abdul Razak et al. (2018), who analyzed and predicted the money in circulation in Malaysia from 1998 to 2016, found similar results. They evaluated the accuracy of their predictions using the ARCH and GARCH models, with the RMS error serving as the metric of choice. The GARCH model was determined to be more suitable than the ARCH model. The series was best suited by GARCH (1,1). Since ARIMA models provide higher AIC and BIC values for their data, Awogbemi et al. (2015) also suggested using GARCH and ARCH models to analyze financial time series. Following the modelling of volatility in Financial Time Series derived from the Nigerian Inflation Rate, this proposal was made. To determine how well GARCH models characterized and predicted volatility in copper price returns from July 21, 1993, to March 22, 2012, Godwin (2012) conducted an analysis. The conventional GARCH (1,1) model, he discovered and determined, was better adequate for the prediction.

The study was aimed at examining the supply of Nigerian Narrow Money from January 2000 to February 2018 and to statistically fit a suitable GARCH (p,q) model to the series. To achieve this, the study focused on the following:

1. examining the data for the supply of Nigerian Narrow Money
2. constructing a suitable GARCH (p,q) model for the process.

Materials and Methods

The data used are monthly data of Nigerian Narrow Money from January 2000 to February 2018. All of the information came from the CBN website in Nigeria, CBN (2017). For all calculations, the E-views statistics program was used. GARCH and SARIMA models are used for the study. To identify the appropriate model for the series, the Box and Jenkins (1976) methodology was used. This methodology has three important iterative steps, which include model identification, model parameter estimation and model diagnosis.

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Results

Figure 1 below shows the time plot of the Nigerian Narrow Money (NNMY), in Billions Naira from January 2000 to February 2018.

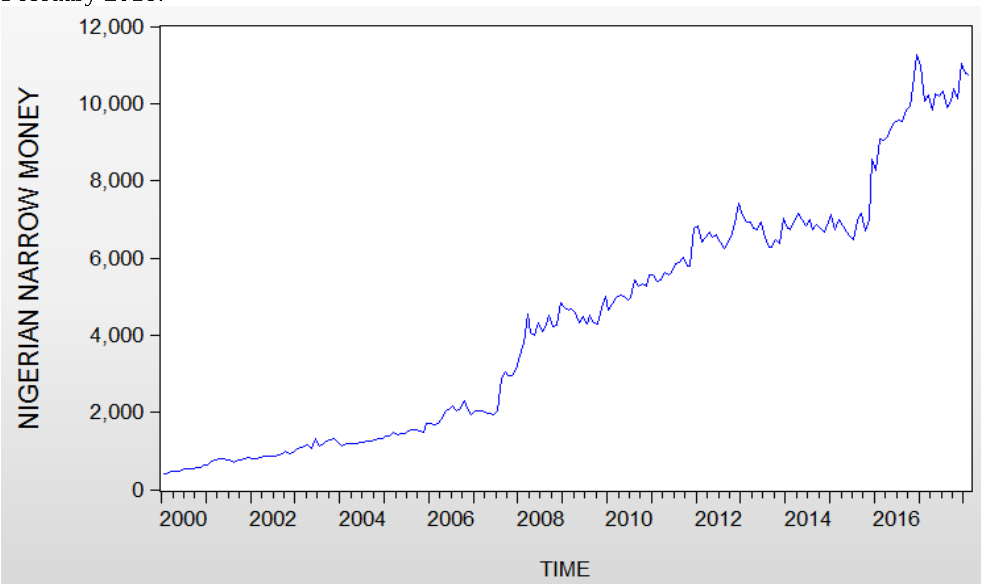

Figure 1: Time Plot of Nigerian Narrow Money (NNMY)

A proper examination of the plot indicates spots of increased variation that is not constant throughout the series.

To make the mean and the variance constant, the differencing of the series was done and the differenced series plotted. See Fig. 2 below.

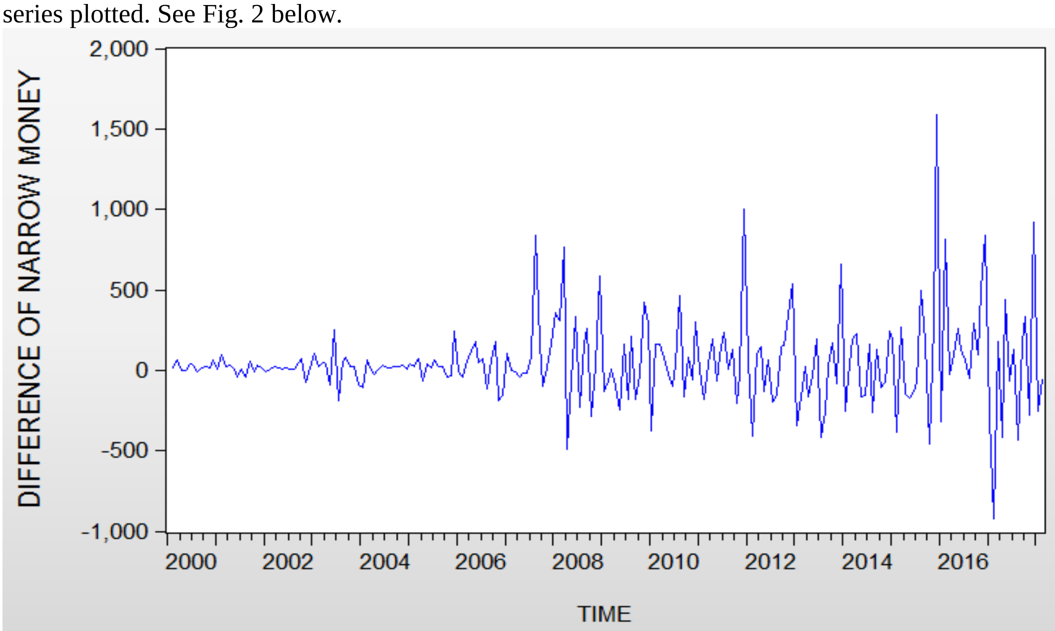

Figure 2: Time Plot of Difference of Narrow Money (DNNMY)

From the plot, it is obvious that there is a presence of volatility clustering, a property of the variance model.

Stationarity Test

Next, the stationarity test for the differenced series was conducted. To check this stationarity, an Augmented Dickey-Fuller (ADF) test was done. The result is shown in Table 1 below.

Table 1: Stationarity Test for DNNMY

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

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-16.93636	0.0000
Test critical values:	1% level	-3.460596	
	5% level	-2.874741	
	10% level	-2.573883	

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

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(DNNMY)
Method: Least Squares
Date: 04/26/18 Time: 11:27
Sample (adjusted): 2000M03 2018M02
Included observations: 216 after adjustments

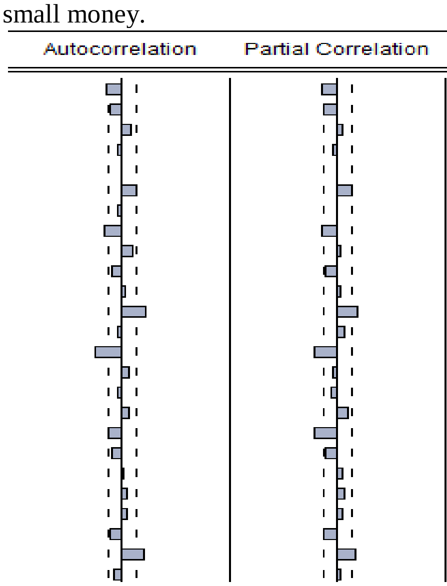
Variable	Coefficient	Std. Error	t-Statistic	Prob.
DNNMY(-1)	-1.145721	0.067649	-16.93636	0.0000
C	54.76862	18.00920	3.041147	0.0027

R-squared	0.572718	Mean dependent var	-0.305556
Adjusted R-squared	0.570721	S.D. dependent var	397.3323
S.E. of regression	260.3295	Akaike info criterion	13.97099
Sum squared resid	14503093	Schwarz criterion	14.00224
Log likelihood	-1506.867	Hannan-Quinn criter.	13.98362

A look at the time plot of the different series shows that the series is stationary. The results of the ADF test also confirm that the differenced series of the Nigerian Narrow Money is stationary.

Correlogram of the First Difference

Pulses at lag 12 are seen in the Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF) graphs of the Nigerian Narrow Money's initial difference. A 1-order seasonal autoregressive moving average is evident from this. Below in Figure 3, you can see the ACF and PACF graphs representing the disparity in Nigerian small money.



	AC	PAC	Q-Stat	Prob
1	-0.146	-0.146	4.6659	0.031
2	-0.115	-0.139	7.5695	0.023
3	0.085	0.048	9.1899	0.027
4	-0.046	-0.042	9.6564	0.047
5	-0.002	0.001	9.6571	0.086
6	0.151	0.143	14.809	0.022
7	-0.044	0.007	15.251	0.033
8	-0.160	-0.142	21.062	0.007
9	0.102	0.037	23.442	0.005
10	-0.097	-0.106	25.610	0.004
11	0.034	0.034	25.872	0.007
12	0.225	0.198	37.590	0.000
13	-0.030	0.073	37.795	0.000
14	-0.255	-0.205	53.053	0.000
15	0.080	-0.032	54.558	0.000
16	-0.026	-0.063	54.719	0.000
17	0.071	0.101	55.927	0.000
18	-0.127	-0.225	59.778	0.000
19	-0.097	-0.099	62.019	0.000
20	0.018	0.060	62.097	0.000
21	0.053	0.068	62.768	0.000
22	0.049	0.048	63.356	0.000
23	-0.101	-0.117	65.880	0.000
24	0.215	0.180	77.299	0.000
25	-0.079	0.030	78.835	0.000

Figure 3: ACF and PACF of DNNMY

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Estimation of SARIMA Models

Two SARIMA models for the series are suggested by looking at the ACF and PACF above. This calls for comparing the suggested SARIMA models with the GARCH model. The models in question are SARIMA(1,1,0)x(1,0,1)12 and SARIMA(0,1,0)x(1,0,1)12. It is provided as a SARIMA model.:

$$\phi_p(B)\Phi_p(B^s)\omega_t = \mu + \theta_q(B)\Theta_q(B^s)\,\epsilon_t.$$

where $\phi_p(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p,$

$$\Phi_p(B^s) = 1 - \Phi_{1,s}B^s - \Phi_{2,s}B^{2s} - \cdots - \Phi_{p,s}B^{ps},$$

$$\theta_q(B) = 1 + \theta_1 B + \theta_2 B^2 + \cdots + \theta_q B^q,$$

$$\Theta_q(B^s) = 1 + \Theta_{1,s}B^s + \Theta_{2,s}B^{2s} + \cdots + \Theta_{q,s}B^{qs}.$$

Comparing the two SARIMA models, we take a look at the Akaike Information Criterion (AIC) of both models. The AIC of the SARIMA(1,1,0)x(1,0,1) model is 13.85292 while that of the SARIMA(0,1,0)x(1,01,)$_{12}$ model is 13.10216, a value less than the former. For this reason, SARIMA(0,1,0)x(1,0,1)$_{12}$ model was used.

Table 2 below shows the results of the estimation of the SARIMA(0,1,0)x(1,0,1)$_{12}$ model.

Table 2: Estimation of the SARIMA(0,1,0)x(1,0,1)$_{12}$ Model

Dependent Variable: DNNMY
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 04/26/18 Time: 11:32
Sample: 2000M02 2018M02
Included observations: 217
Convergence achieved after 19 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(12)	0.934070	0.080347	11.62544	0.0000
MA(12)	-0.751009	0.126612	-5.931604	0.0000
SIGMASQ	57455.28	4137.724	13.88572	0.0000

R-squared	0.158633	Mean dependent var	47.62212
Adjusted R-squared	0.150770	S.D. dependent var	261.9240
S.E. of regression	241.3726	Akaike info criterion	13.85038
Sum squared resid	12467795	Schwarz criterion	13.89710
Log likelihood	-1499.766	Hannan-Quinn criter.	13.86925
Durbin-Watson stat	2.250793		

Inverted AR Roots	.99	.86+.50i	.86-.50i	.50+.86i
	.50-.86i	.00+.99i	-.00-.99i	-.50+.86i
	-.50-.86i	-.86+.50i	-.86-.50i	-.99
Inverted MA Roots	.98	.85+.49i	.85-.49i	.49+.85i
	.49-.85i	.00+.98i	-.00-.98i	-.49-.85i
	-.49+.85i	-.85-.49i	-.85+.49i	-.98

Estimation of the GARCH(1,1) Model

The clustering of volatility is plain to see on the graph of the differenced series. The existence of a variance model was confirmed in the data when a clustering effect assessment was performed. Therefore, the GARCH model is appropriate. To estimate the parameters, the GARCH(1,1) model was used and the analysis was run. For the Nigerian Narrow Money, the outcomes of the GARCH(1,1) model estimate are shown in Table 4 below..

Table 4: Estimation of the GARCH(1,1) for DNNMY

Dependent Variable: DNNMY
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 04/26/18 Time: 11:33
Sample (adjusted): 2000M02 2018M02
Included observations: 217 after adjustments
Failure to improve likelihood (non-zero gradients) after 208 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(1) + C(2)*RESID(-1)^2 + C(3)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
	Variance Equation			
C	16.40073	21.63306	0.758133	0.4484
RESID(-1)^2	-0.061324	0.013204	-4.644197	0.0000
GARCH(-1)	1.081944	0.016206	66.76022	0.0000

R-squared	-0.033210	Mean dependent var	47.62212
Adjusted R-squared	-0.028449	S.D. dependent var	261.9240
S.E. of regression	265.6236	Akaike info criterion	13.10216
Sum squared resid	15310628	Schwarz criterion	13.14888
Log likelihood	-1418.584	Hannan-Quinn criter.	13.12103
Durbin-Watson stat	2.216937		

From the results above, the parameters are estimated as:
$\alpha_0 = 16.40073$, $\alpha_1 = -0.061324$ and $\beta_1 = 1.081944$.
Recall that GARCH(1,1) model is given as $\sigma_t^2 = \alpha_0 + \alpha_1 X_{t-1}^2 + \beta_1 \sigma_{t-1}^2$. Substituting these estimated values into the tentative model, we have the equation for the model:
$\sigma_t^2 = 16.40073 - 0.061324 X_{t-1}^2 + 1.081944 \sigma_{t-1}^2$
Recall that the graph of the ACF and PACF indicated the presence of the SARIMA model, hence the comparison. Therefore, using AIC, the GARCH(1,1) model is seen to be a better model than the SARIMA model.

Discussion

The data were first examined using the time plot, which indicated the presence of volatility. The series was then tested for stationarity. At the 1%,5%, and 10% confidence levels, the test statistic was -16.93636, which was below the test critical threshold. The findings demonstrated that the Nigerian Narrow Money (NNMY) series was not stationary, which is why the series needed to be differentiated. The differenced Nigerian Narrow Money (DNNMY) was determined to be stationary after the initial differencing, according to an Augmented Dickey-Fuller test for stationarity. The differenced series (DNNMY) were plotted in a correlogram. At lag 12, the ACF showed a surge. The model shown here is a lag 1 seasonal moving average. A spike at lag 12 was also seen by the PACF of the differenced dataset. The SARIMA(1,1,0)x(1,0,1)12 and SARIMA(0,1,0)x(1,0,1)12 models were evaluated as preliminary SARIMA options. The SARIMA(0,1,0)x(1,0,1)12 model has an AIC of 13.85038, which is lower than the SARIMA(1,1,0)x(1,0,1)12 model's 13.85292 value. To that end, we turned to the second model.

The coefficients for this model were estimated to be $AR_{(12)} = 0.934070$, $MA_{(12)} = -0.751009$ and $\sigma_t^2 = 57455.28$. The AIC for this model is 13.85038.

Next, the GARCH(1,1) model was estimated. Observing the time plot, the presence of non-constant variance was detected throughout the series. Because of this non-constant variance, a log transform was taken. The series was differenced and tested for stationarity, which proved to be stationary after the first difference. The presence of ARCH was also indicated which justified the use of the GARCH model. The GARCH(1,1) model was checked using E-views statistical software.

The GARCH(1,1) model equation is:
$\sigma_t^2 = 16.40073 - 0.061324X_{t-1}^2 + 1.081944\sigma_{t-1}^2$.
The AIC for this model is 13.10216 which is less than that of the SARIMA model. This shows that GARCH(1,1) is a better model for the differenced Nigerian Narrow Money (DNNMY) data.

Conclusion

The study applied a time series approach to model the Nigerian Narrow Money. Monthly data from January 2000 to February 2018 were collected and analyzed. The behaviour of the data showed a non-constant variation of trend. This behaviour was used to consider different models that could fit the series. Different SARIMA and GARCH models were considered. Comparing the SARIMA and GARCH (1,1) models, we find that the former has an AIC of 13.85038 and the latter of 13.10216. Since the AIC of the conventional GARCH (1,1) model is lower than that of the SARIMA model, it may be stated that it is a superior model for the Nigerian Narrow Money.

Recommendations

1. GARCH (1,1) should be adopted as a better model for the analysis and modelling of Nigerian Narrow Money.
2. To keep the money supply from being too high or too low, the Central Bank of Nigeria should implement stringent monetary policies.

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