TECHMIND RESEARCH
ISSN: 2292-9355
Journal of Research in Marketing
Volume 1 No.1 August 2013

Monthly Nigerian Interbank Call Rates Modeling by Seasonal Box-Jenkins Approach

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Abstract- *The realization of the monthly Nigerian interbank call rates herein referred to as IBCR and analyzed span from January 2006 to August 2013. The time plot of IBCR in Figure 1 shows an overall horizontal secular trend. There are two peaks: one between 2008 and 2009 and the other between 2011 and 2013. The two peaks are separated by a trough in 2010. Augmented Dickey Fuller (ADF) Test shows that IBCR is non-stationary. Seasonal (i.e. 12-point) differencing of IBCR yields a series called SDIBCR with basically a similar structure as IBCR, a trough between 2009 and 2010 separating two peaks (See Figure 2). The ADF seasonality test adjudges SDIBCR as still non-stationary. A non-seasonal differencing of SDIBCR yields DSDIBCR which has a horizontal trend and no discernible seasonality. It is adjudged to be stationary by the same test procedure. The correlogram of DSDIBCR in Figure 4 shows significant negative spikes at lag 12 for both the utocorrelations and partial autocorrelations. This indicates 12-monthly seasonality and the involvement of a seasonal moving average component of order one and a seasonal autoregressive component, also of order one, respectively. Based on this autocorrelation structure, four SARIMA models: $(1, 1, 1)x(1, 1, 1)_{12}$, $(1, 1, 2)x(1, 1, 1)_{12}$, $(2, 1, 1)x(1, 1, 1)_{12}$ and $(2, 1, 2)x(1, 1, 1)_{12}$ are proposed and fitted. In the Akaike's Information Criterion (AIC) sense, the SARIMA$(2, 1, 1)x(1, 1, 1)_{12}$ model is adjudged the most adequate.*

Keywords- *Interbank call rates, Money market indices, Sarima Modelling, Nigeria*

1. INTRODUCTION

Interbank call rates are money market indicators. They refer to the rates of interest charged on short-term loans made between banks. They depend on the availability of money, prevalent rates and the contract terms.A time series is said to be seasonal or to have a seasonal component if it has a tendency to fluctuate periodically. Economic and financial data like these ones are known to be seasonal as well as volatile. Prices, inflation rates, gross domestic product, foreign exchange rates, etc. are known to exhibit seasonality. Often, the 'seasons' are identifiable. For instance, Etuk(2012a) observed that daily Nigeria Naira – US Dollar exchange rates tended to have peaks on Fridays and troughs on Mondays. Martinez et al.(2011) observed that the number of reported cases of dengue in Campinas, State of Sao Paulo, Brazil tended to show a maximum in the rainy season and a minimum in the dry season. Such seasonal series may be modeled using a seasonal Box-Jenkins approach. In this work the aim is to show that Nigerian interbank call rates are seasonal of period 12 months. Moreover a seasonal autoregressive integrated moving average (SARIMA) model is proposed and fitted to the call rates. This is with a view to providing basis for possible forecasting of the series.

2. REVIEW OF LITERATURE

Amongst authors who have written extensively on the seasonality of economic and financial time series are Ismail and Mahpol(2005), Brida and Garrido(2009), Saz(2011), Prista et al.(2011), Etuk(2012b, 2014), Chikobvu and Sigauke(2012), Linlin and Xiaorong(2012), Eni and Adesola(2013), Bako et al.(2013), to mention a few. SARIMA models were proposed to capture the seasonal nature of such time series. These models have been extensively applied in the modeling of intrinsically seasonal series. A few other researchers who have concerned themselves with the study and application of such models are Helman(2011), Nadarajah and Emami(2013), Martinez et al.(2011) and Surhatono(2011). Etuk(2014) has demonstrated the likely supremacy of SARIMA models over the more general autoregressive integrated moving average (ARIMA) models for modeling seasonal series.

3. MATERIALS AND METHODS

3.1 Data

The data for this write-up are interbank call rates amongst Nigerian banks from January 2006 to August 2013. They are obtained from the website of the Central Bank of Nigeria www.cenbank.org in the *Data and Statistics* section and under the *Money Market Indicators* subsection.

3.2 Seasonal Box-Jenkins Modelling

A time series $\{X_t\}$ is said to follow an *autoregressive moving average model of order p and q*, denoted by ARMA(p, q) if it satisfies the following difference equation

$$X_t - \alpha_1 X_{t-1} - \alpha_2 X_{t-2} - \dots - \alpha_p X_{t-p} = \varepsilon_t + \beta_1 \varepsilon_{t-1} + \beta_2 \varepsilon_{t-2} + \dots + \beta_q \varepsilon_{t-q} \quad (1)$$

where the α's and β's are constants such that the model is stationary as well as invertible and $\{\varepsilon_t\}$ is a white noise process. Let the model (1) be put as

$$A(L)X_t = B(L)\varepsilon_t \quad (2)$$

where A(L) the autoregressive(AR) operator is given by $A(L) = 1 - \alpha_1 L - \alpha_2 L^2 - \dots - \alpha_p L^p$ and B(L) the moving average(MA) operator is given by $B(L) = 1 + \beta_1 L + \beta_2 L^2 + \dots + \beta_q L^q$ and L is the backward shift operator defined by $L^k X_t = X_{t-k}$. It is well known that for the model (1) or (2) to be stationary and invertible, the zeroes of A(L) and B(L) must be outside the unit circle, respectively.

Most real-life time series are non-seasonal. Box and Jenkins(1976) proposed that for such a non-seasonal series differencing of an appropriate order could render the series stationary. Suppose d is the minimum degree of differencing necessary for stationarity of $\{X_t\}$. Let the d^{th} difference of X_t be denoted by $\nabla^d X_t$. If the series $\{\nabla^d X_t\}$ follows an ARMA(p, q), then the original series $\{X_t\}$ is said to follow an *autoregressive integrated moving average model of orders p, d and q* denoted by ARIMA(p, d, q).

Suppose $\{X_t\}$ is seasonal of period s. Box and Jenkins(1976) proposed that it be modeled by

$$A(L)\Phi(L^s)\nabla^d\nabla^D_s X_t = B(L)\Theta(L^s)\varepsilon_t \quad (3)$$

where $\Phi(L)$ and $\Theta(L)$, the respective seasonal AR and MA operators, are polynomials such the entire model is stationary as well as invertible. ∇_s is the seasonal difference operator defined by $\nabla_s = 1 - L^s$. Suppose the seasonal operators are of orders P and Q respectively. Then $\{X_t\}$ is said to follow a *multiplicative seasonal autoregressive integrated moving average model of orders p, d, q, P, D, Q and s* denoted by SARIMA(p, d, q)x(P, D, Q)$_s$ model.

3.3 Sarima Model Fitting

Sarima model estimation invariably begins with the determination of the orders p, d, q, P, D, Q and s. Seldom is it possible to determine the seasonal period s from the time plot. The correlogram of the stationary differenced series usually better depicts the period s as the lag for which there is a significant spike. Often, for stationarity it is enough to put the differencing orders equal to one each. That is, d = D = 1. The AR orders p and P, may be estimated by the non-seasonal and seasonal cut-off lags of the partial autocorrelation function(PACF) respectively. Similarly, the MA orders q and Q may be estimated by the non-seasonal and seasonal cut-off lags of the autocorrelation function(ACF) respectively. The estimation of the parameters of the model is usually done using non-linear optimization techniques because the model involves items of the white noise process. The least squares optimization technique shall be used. Based on the observed autocorrelation structure more than one model shall be proposed. The most adequate of them shall be chosen on the basis of Akaike's Information Criterion(AIC). The chosen model shall be subjected to some residual analysis with a view to ascertaining its adequacy. An adequate model should have uncorrelated and normally distributed residuals. The statistical and econometric package Eviews was used for all analytical work of this paper. It uses the least squares technique for model estimation.

4. RESULTS

The time plot of the data IBCR in Figure 1 in Appendix shows an overall horizontal trend and two peaks, one between 2008 and 2009 and the other between 2011 and 2013, separated by a trough in 2010. Twelve-point differencing of IBCR produces the series SDIBCR which has two peaks, one from 2007 to 2009 and the other from 2011 to 2012(See Figure 2 in Appendix). Separating these peaks is a trough. Non-seasonal differencing of SDIBCR yields the series DSDIBCR. Its time plot in Figure 3 in Appendix shows a horizontal trend. Seasonality is not discernible. The Augmented Dickey Fuller (ADF) Test Statistic for IBCR, SDIBCR and DSDIBCR are of values -2.4, -2.1, and -6.6, respectively. With the 10%, 5% and 1% critical values at -2.6, -2.9 and -3.5 respectively, the ADF test adjudges both IBCR and SDIBCR as non-stationary, but DSDIBCR as stationary. The correlogram of DSDIBCR in Figure 4 has significant negative spikes at lag 12 for both the ACF and the PACF. This shows that the series is 12-monthly seasonal and there are seasonal autoregressive and moving average components of order one each. Hereby proposed are the Sarima models of orders $(1, 1, 1)x(1, 1, 1)_{12}$, $(1, 1, 2)x(1, 1, 1)_{12}$, $(2, 1, 1)x(1, 1, 1)_{12}$ and $(2, 1, 2)x(1, 1, 1)_{12}$, with AIC values of 5.14, 5.37, 5.10 and 5.43, respectively. The best model, with the least AIC, is the $(2, 1, 1)x(1, 1, 1)_{12}$ model. The estimation of the model is summarized in Table 1 in appendix. The correlogram of the residuals is in Figure 5 in Appendix and their histogram is in Figure 6 in Appendix. Figure 5 in Appendix shows that the residuals are uncorrelated and Figure 6 in Appendix shows that they are normally distributed. Hence the model chosen is adequate. .

5. CONCLUSION

It has been demonstrated that Nigerian monthly interbank call rates follow a Sarima(2, 1, 1)x(1, 1, 1)$_{12}$ model. On the basis of this model forecasts may be obtained.

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Author's Biography with Photo

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ISSN: 2292-9355
Journal of Research in Marketing
Volume 1 No.1 August 2013

APPENDIX

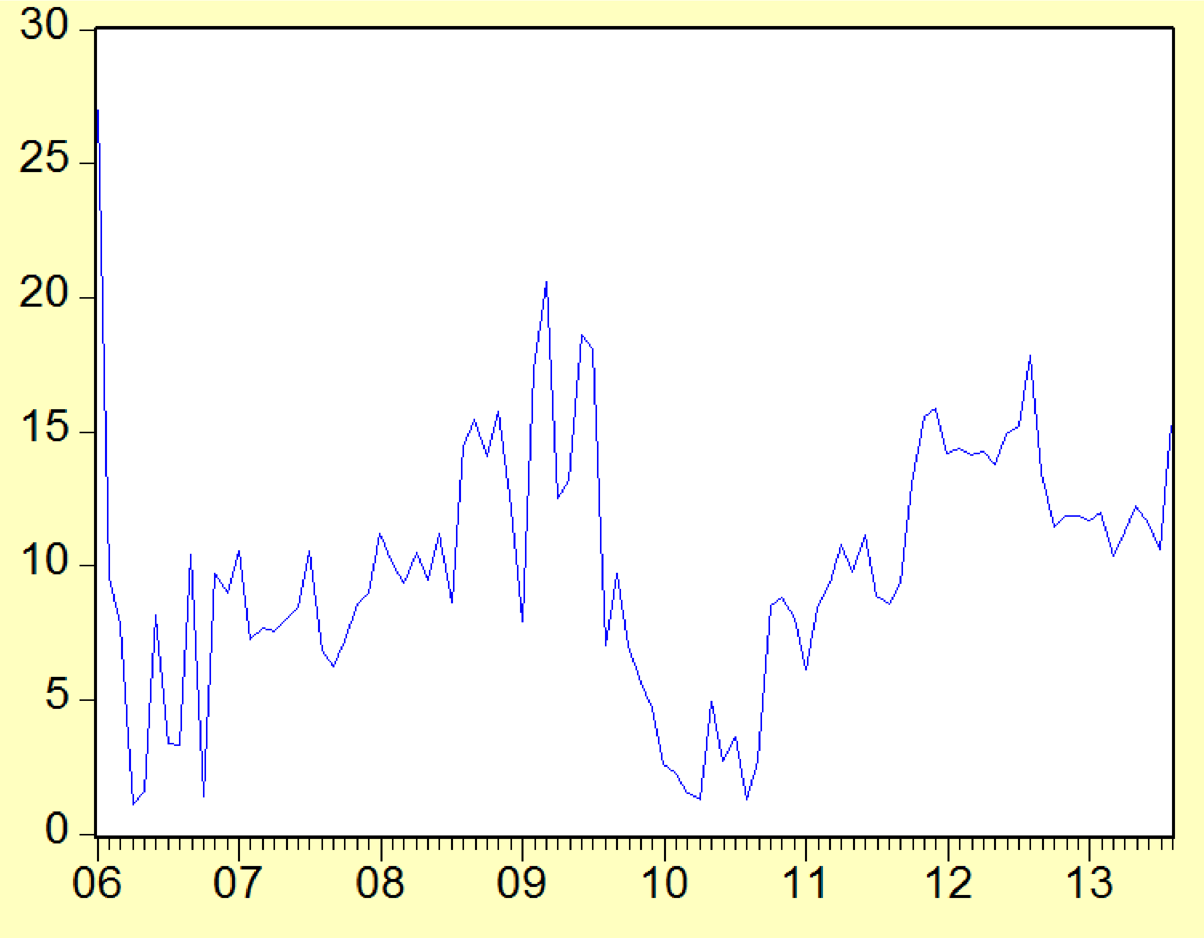

FIGURE 1: IBCR

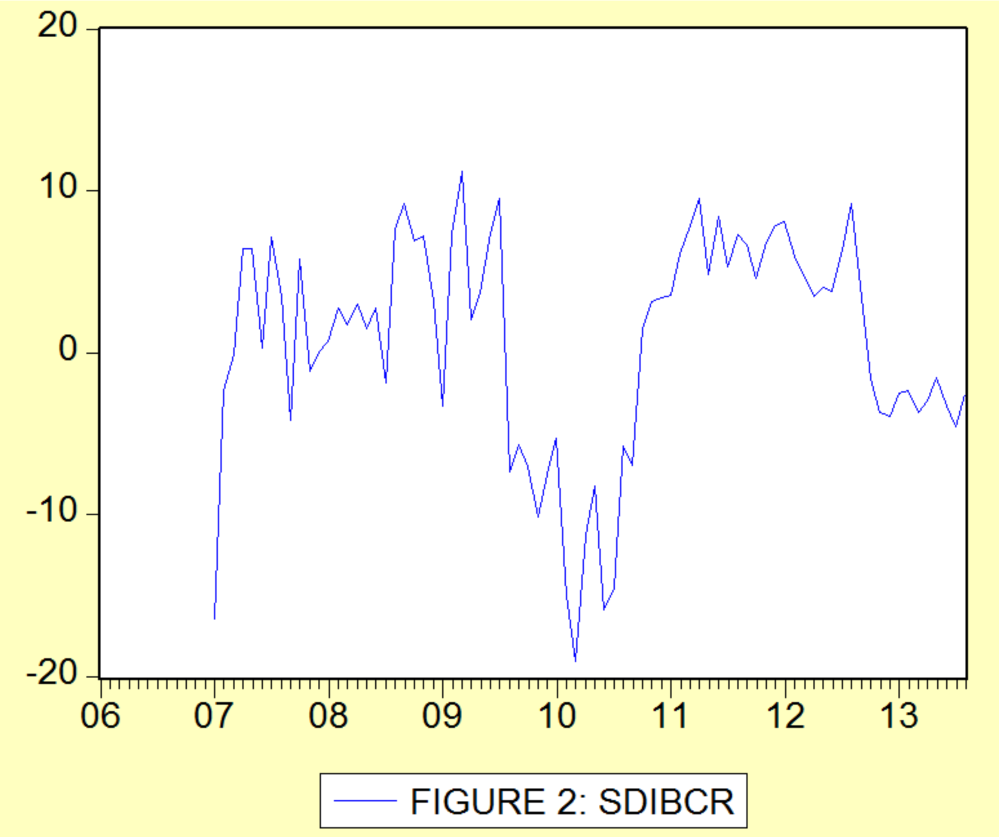
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FIGURE 2: SDIBCR

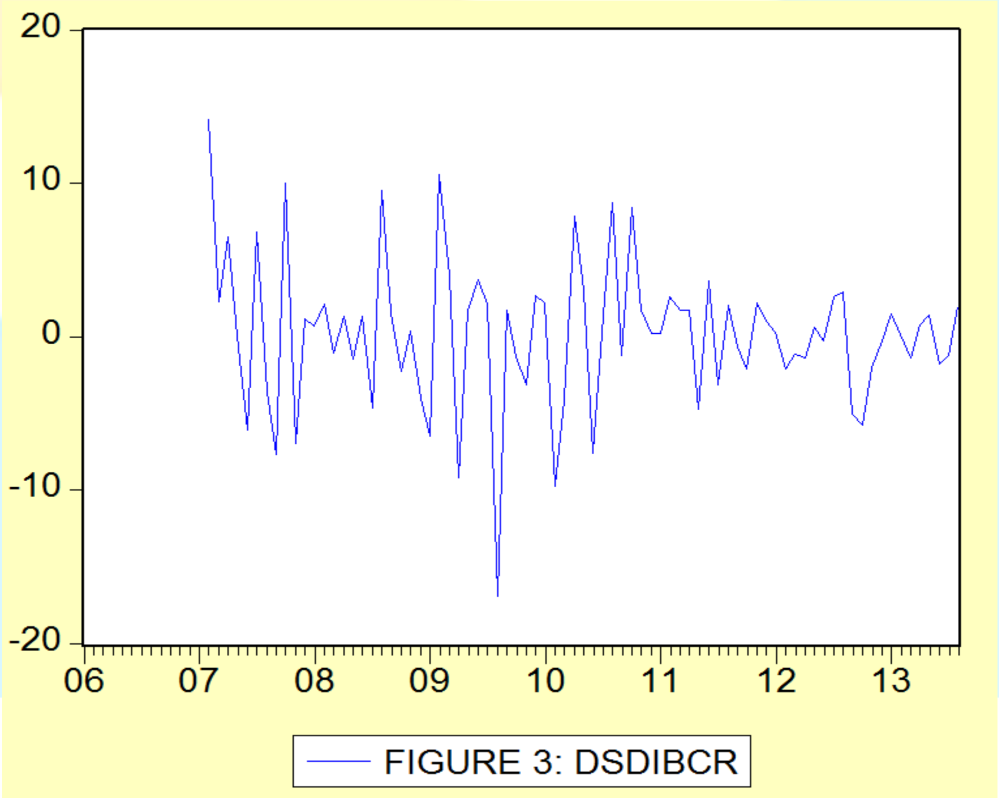
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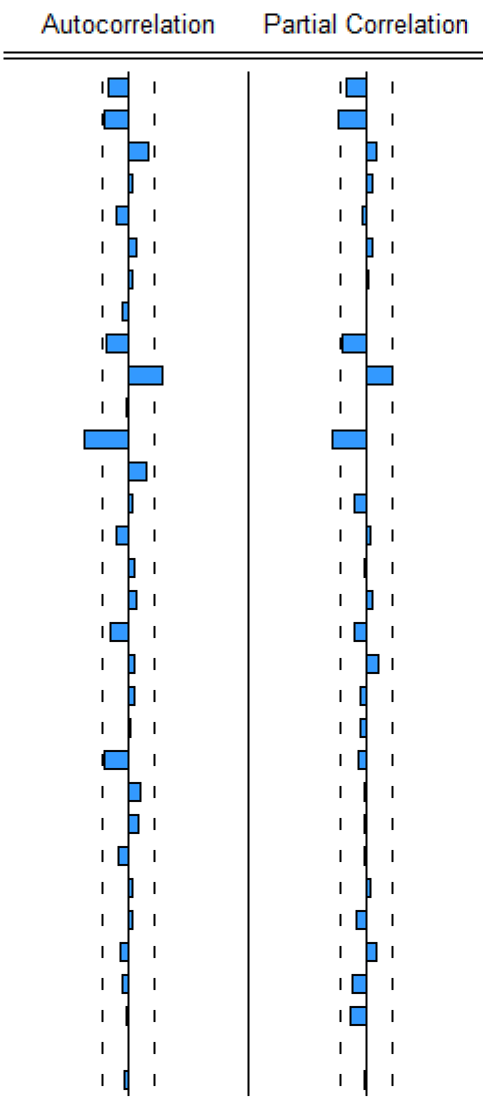
FIGURE 3: DSDIBCR



	AC	PAC	Q-Stat	Prob
1	-0.172	-0.172	2.4214	0.120
2	-0.202	-0.238	5.7978	0.055
3	0.172	0.097	8.2933	0.040
4	0.039	0.049	8.4237	0.077
5	-0.110	-0.041	9.4652	0.092
6	0.080	0.057	10.025	0.124
7	0.037	0.024	10.149	0.180
8	-0.052	0.000	10.392	0.239
9	-0.182	-0.212	13.414	0.145
10	0.291	0.223	21.242	0.019
11	-0.024	0.002	21.295	0.030
12	-0.381	-0.299	35.176	0.000
13	0.156	0.006	37.543	0.000
14	0.030	-0.100	37.632	0.001
15	-0.114	0.034	38.936	0.001
16	0.047	-0.009	39.163	0.001
17	0.076	0.052	39.762	0.001
18	-0.154	-0.113	42.245	0.001
19	0.048	0.101	42.492	0.002
20	0.050	-0.051	42.761	0.002
21	0.010	-0.054	42.772	0.003
22	-0.212	-0.069	47.825	0.001
23	0.108	-0.013	49.152	0.001
24	0.086	-0.011	50.003	0.001
25	-0.097	-0.019	51.116	0.002
26	0.036	0.038	51.274	0.002
27	0.033	-0.087	51.407	0.003
28	-0.060	0.082	51.862	0.004
29	-0.055	-0.129	52.245	0.005
30	-0.015	-0.146	52.273	0.007
31	0.003	-0.003	52.275	0.010
32	-0.037	-0.016	52.460	0.013

FIGURE 4: CORRELOGRAM OF DSDIBCR

TABLE 1: ESTIMATION OF SARIMA(2, 1, 1)X(1, 1, 1)$_{12}$ MODEL

Dependent Variable: DSDIBCR
Method: Least Squares
Date: 01/08/14 Time: 15:01
Sample(adjusted): 2008:04 2013:08
Included observations: 65 after adjusting endpoints
Convergence achieved after 55 iterations
Backcast: 2007:03 2008:03

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	-0.088397	0.254833	-0.346882	0.7300
AR(2)	-0.339752	0.133322	-2.548360	0.0135
AR(12)	-0.247248	0.132795	-1.861878	0.0678
AR(13)	0.034583	0.153588	0.225168	0.8227
AR(14)	-0.130274	0.118736	-1.097168	0.2772
MA(1)	-0.095938	0.230944	-0.415418	0.6794
MA(12)	-0.862715	0.059166	-14.58120	0.0000
MA(13)	0.076232	0.239748	0.317968	0.7517

R-squared	0.625841	Mean dependent var	-0.065538
Adjusted R-squared	0.579891	S.D. dependent var	4.504276
S.E. of regression	2.919483	Akaike info criterion	5.095508
Sum squared resid	485.8327	Schwarz criterion	5.363125
Log likelihood	-157.6040	F-statistic	13.62021
Durbin-Watson stat	1.960757	Prob(F-statistic)	0.000000

Inverted AR Roots	.86+.23i	.86 -.23i	.63+.62i	.63 -.62i
	.22 -.82i	.22+.82i	.06+.72i	.06 -.72i
	-.27+.86i	-.27 -.86i	-.66 -.63i	-.66+.63i
	-.88 -.23i	-.88+.23i		
Inverted MA Roots	.99	.86+.49i	.86 -.49i	.49 -.86i
	.49+.86i	.09	.00 -.99i	.00+.99i
	-.49 -.86i	-.49+.86i	-.85+.49i	-.85 -.49i
	-.99			

	AC	PAC	Q-Stat	Prob
1	-0.008	-0.008	0.0049	
2	0.015	0.015	0.0197	
3	-0.044	-0.044	0.1544	
4	0.096	0.095	0.8111	
5	0.021	0.023	0.8417	
6	0.048	0.044	1.0134	
7	0.092	0.101	1.6469	
8	0.004	-0.003	1.6481	
9	-0.176	-0.182	4.0564	0.044
10	0.045	0.043	4.2186	0.121
11	-0.199	-0.226	7.4148	0.060
12	0.062	0.042	7.7342	0.102
13	-0.036	-0.003	7.8405	0.165
14	-0.150	-0.199	9.7737	0.135
15	0.015	0.099	9.7935	0.201
16	-0.128	-0.120	11.247	0.188
17	-0.062	-0.080	11.598	0.237
18	-0.094	-0.031	12.423	0.258
19	0.077	0.062	12.983	0.294
20	0.025	-0.020	13.045	0.366
21	-0.012	0.092	13.060	0.443
22	-0.049	-0.106	13.300	0.503
23	-0.060	-0.082	13.672	0.551
24	-0.221	-0.209	18.847	0.277
25	0.124	0.000	20.510	0.249
26	-0.112	-0.137	21.909	0.236
27	0.025	-0.076	21.980	0.285
28	-0.058	-0.020	22.382	0.320

FIGURE 5: CORRELOGRAM OF SARIMA(2, 1, 1)X(1, 1, 1)$_{12}$ RESIDUALS

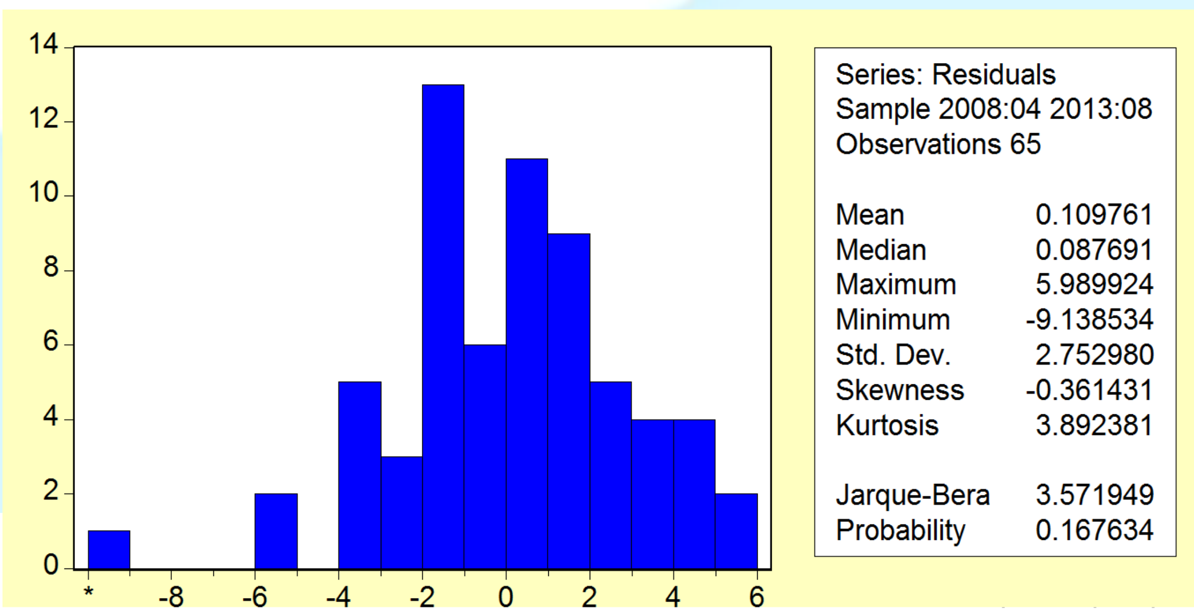


FIGURE 6: HISTOGRAM OF SARIMA(2, 1, 1)X(1, 1, 1)$_{12}$ RESIDUALS