

Time Series Analysis of Currency in Circulation in Nigeria

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Abstract

This paper discussed the levels and trend of Currency In Circulation (CIC) in Nigeria. The relevance of this study lies in the fact that it could help monitor the CIC and give early warning signals about any economic crisis that may due to inflation. Monthly data on CIC in Nigeria for the period January 2010 to December 2014 was obtained from the Central Bank of Nigeria (CBN) statistical bulletin. The CIC data was Seasonally non Seasonally differenced to remove Seasonality and the trend. The appropriate model that best described the pattern in the series was the Multiplicative Seasonal Autoregressive Moving Average (SARIMA) model, SARIMA (0,1,0)_x(0,1,1)₁₂.

Keywords: Currency in Circulation, Liquidity, Moving average process, Variance stability

1.0 Introduction

Currency in circulation (CIC) is the outstanding amount of notes and coins circulated in the economy and they are the most liquid monetary aggregate.(Albert;2013). CIC accounts for approximately seventy percent of reserve in Nigeria (Alvan;2014). The key determinant of CIC is the cash demand of both the public and the banking system. The variation in currency circulation are vital indicators for monetization and demonetization of the economy (Albert ;2014). Currency in circulation increased on annual basis between the years 2009 to 2013 while the ratio of CIC to GDP decreased from 2009 to 2013 (CBN annual statistical bulletin 2013). The share of the currency in circulation in money supply and its ratio in nominal Gross Domestic Product (GDP) revealed its relative importance in any economy (Simwaka 2006; Stavreski; 1998). A lot of studies involving CIC have been carried out by researchers.

Alvan (2014) modeled and forecasted CIC in Nigeria for liquidity management in Nigeria using the VAR and VEC models. He observed that exchange rate, interbank rate, seasonality, holiday and elections were significant in explaining demand for currency.

Albert et al. (2013) fitted a predictive model for monthly CIC in Ghana. They proposed ARIMA (0,1,1)(0,1,1)₁₂ model as being appropriate for modeling CIC in Ghana.

Dheerasinghe (2006) modeled the CIC in Sri Lanka with monthly, weekly and daily data using time series models.

Alberto et al (2012) modeled the daily banknotes in circulation in the context of liquidity management of European central bank.

2.0 Methodology

The data used for this study are secondary data on CIC in Nigeria over the period January 2006 to December 2014. The data was collected from CBN annual economic reports. In analyzing the data we employed Multiplicative Seasonal Autoregressive Moving Average Model. Stationarity is a basic requirement for the application of Box Jenkins methodology. The mean function, variance function of a stationary time series are constant over time. It then follows that a time series is non stationary if at least one of its mean and variance is dependent on time. A stationary time series with time varying mean can be converted into a stationary time series when the time series has a stochastic trend. The mth order difference of the series takes the form

$$\nabla^m X_t = X_t - X_{t-m}$$

For seasonal differences, we have

$$\nabla_D^S X_t = X_t - X_{t-s}$$

Where S is the seasonal length. The seasonal length for monthly data is S = 12.

The order of differencing can be determined by visual inspection of the time series plot, Continuous inspection of the time series plot of the differenced series and plot of the ACF after each stage. Stationary time series are expected to have constant variance over time. When the variance is not stable, an appropriate transformation can be applied to stabilize the variance

(Iwueze et al,2013).For seasonal time series with period “s”, Box & Jenkins (1976) have generalized the autoregressive integrated moving average (ARIMA) model and defined a general multiplicative seasonal model in the form

Where B is the back shift operator on the index of the time series such that

$$B^s X_t = X_{t-s}, \text{ s is the number of seasons; } \theta_0 \text{ is a constant;}$$

$$\phi_p(B) = 1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_p B^p$$

$$\theta_p(B) = 1 - \theta_1 B^s - \theta_2 B^{2s} - \dots - \theta_p B^{ps}$$

$$\theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - \dots - \theta_q B^q$$

$$\theta_Q(B^s) = 1 - \theta_s B^s - \theta_{2s} B^{2s} - \dots - \theta_{Qs} B^{Qs};$$

$\{E_t\}$ is a purely random process with zero mean and variance σ^2 .

The variables $\{W_t\}$ are formed from the original series $\{X_t\}$ by differencing to remove both trend and seasonality using

$$W_t = (1-B)^d (1-B^s)^D X_t \dots \dots \dots (2.2)$$

The values of the integers d and D do not usually need to exceed one. Equation (2.1) is called a Multiplicative Seasonal Autoregressive Integrated Moving average (SARIMA) model of order (p,d,q)x(P,D,Q)₁₂

3.0 Results and Discussion

In this section we analyze CIC using Box and Jenkins procedure.

The time plot of Nigeria CIC in figure 1 showed that the series exhibited an increasing trend and is not be stationary. Observation of the ACF in Figure 2 showed that the series was not stationary. The partial autocorrelation function also showed large values at lags 12, 24 and 36 which implied that the series had a seasonal component. We differenced to remove the trend in the series and improve on stability of the variance.

A time plot of the non seasonal and seasonally differenced series is displayed in figure 3. The plot indicated a horizontal trend just like the non seasonally differenced data. We then plot and examine the autocorrelation function of the non seasonal and seasonally differenced series.

The autocorrelation function of the seasonally differenced series suggested that the model could be a seasonal moving average model. All the values of the autocorrelation function also lie within the 95 percent confidence interval. It also fluctuates about zero with negative spike at 12 which also confirms stationarity in the mean and variance. We also examined the partial autocorrelation function of the seasonally differenced series.

From the partial autocorrelation function displayed in figure 4 and we observe a significant negative spike at lag 12. Using the significant lags of the ACF and PACF and the respective seasonal lags tentative model for the currency in circulation will be identified. We then go into model estimation based on the observed characteristics of the autocorrelation and partial autocorrelation functions.

3.1 Model Estimation

The MINITAB software was used in estimating the parameters of the model.

SARIMA (0,1,0)(0,1,1)₁₂ the P and T values can be seen to be significant at 5% level. The fitted model can be expressed in terms of lag operator as

$$Y_t = Y_{t-1} + Y_{t-12} - Y_{t-13} - 0.7842E_{t-12} + E_t$$

Table 1: Final Estimates of Parameters

Type	Coef	SE Coef	T	P
SMA 12	0.7842	0.1733	4.53	0.000

3.2 Diagnostic Checking.

We examined the suitability of the selected model by looking at the residuals

The time plot of the residual also depicts a series with constant variance and without trend. We further examined the autocorrelation function of the residuals. The ACF of the residuals as displayed in figure 5 showed that the error terms are uncorrelated and follow white noise process.

3.3 Forecasting

The following Forecasts were made using the fitted model.

Month	Forecast	Lower	Upper
JAN	1825.01	1741.96	1908.07
FEB	1772.96	1655.50	1890.41
MAR	1820.24	1676.39	1964.10
APR	1809.08	1642.97	1975.19
MAY	1787.55	1601.83	1973.26
JUN	1774.23	1570.79	1977.67
JUL	1790.60	1570.86	2010.34
AUG	1794.14	1559.23	2029.06
SEP	1803.72	1554.56	2052.88
OCT	1871.14	1608.50	2133.77
NOV	1908.73	1633.27	2184.19
DEC	2088.54	1800.84	2376.25

Table 4.11: 2015 Monthly Forecasts for Money in Circulation.

3.4 Conclusion

The study primarily sought to investigate the currencies in circulation in Nigeria and to forecast future growth in currencies in circulation using ARIMA modeling. The major conclusion has been that the way that the data is made stationary in its mean is the most important factor determining post-sample forecasting accuracies. Most importantly, when the trend in the data is identified and extrapolated using the same procedure as other methods that have been found to be more accurate in empirical studies then ARIMA models perform consistently better than these methods, although the differences are small and non-statistically significant. In the course of study, an ARIMA model is developed and used to forecast future net currency circulation in Nigeria. Based on forecasts it is believed that the forecasts and the comments presented in this research would be helpful to policy makers in Nigeria for future volume of currencies in circulation policy planning.

References

- Iwueze I.S., Nwogu E.C., Valentine Nlebedim, Uses of Buys-Ballot Table in Times Series Analysis, *CBN journal of Applied Statistics*, 2013,111-128.
- Alvan Ikoku (2014), Modeling and Forecasting Currency in Circulation for Liquidity Management in Nigeria. *CBN journal of Applied Statistics*, 2014, Vol 5 No 1.
- Albert Luguterah, Suleman Nasiru and Lea Anzagra, A Predictive model for Monthly Currency Circulation in Ghana. *Journal of Mathematical Theory and Modeling* 2013.
- Albertho C., Gonzalo C., Astrid H and Fernando N. (2002) Modeling the daily Banknotes in Circulation the context of Liquidity Management of European Central Bank. <http://www.ecb.int>.
- Central Bank of Nigeria Annual Economic Report (2013)
- Dheerasinghe (2006)

Appendix

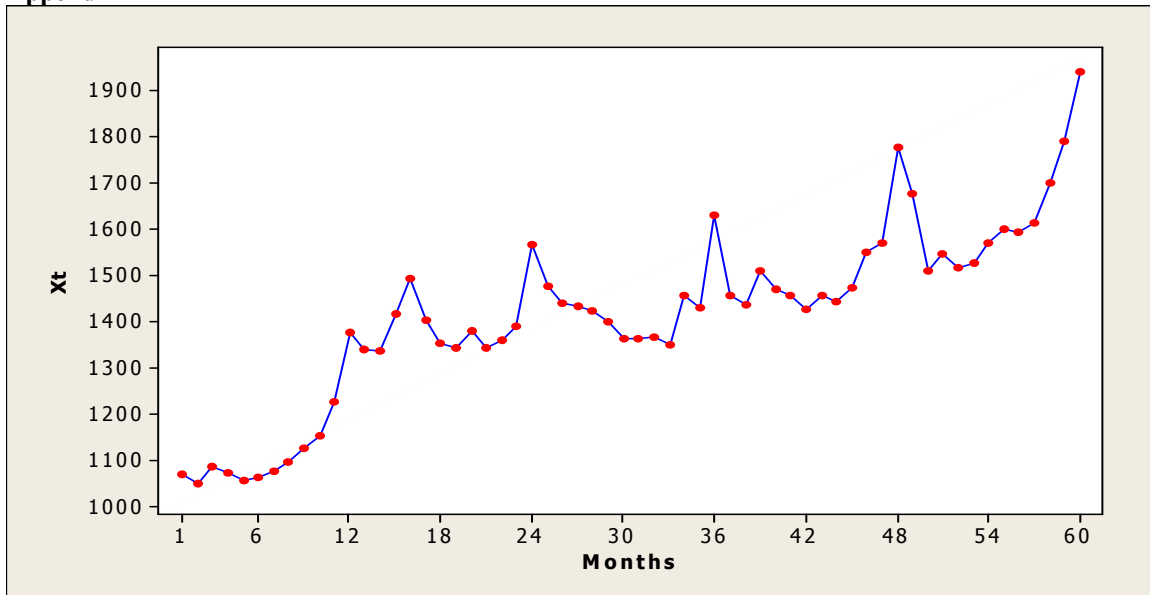


Figure 1: Time Series Plot of Currency In Circulation

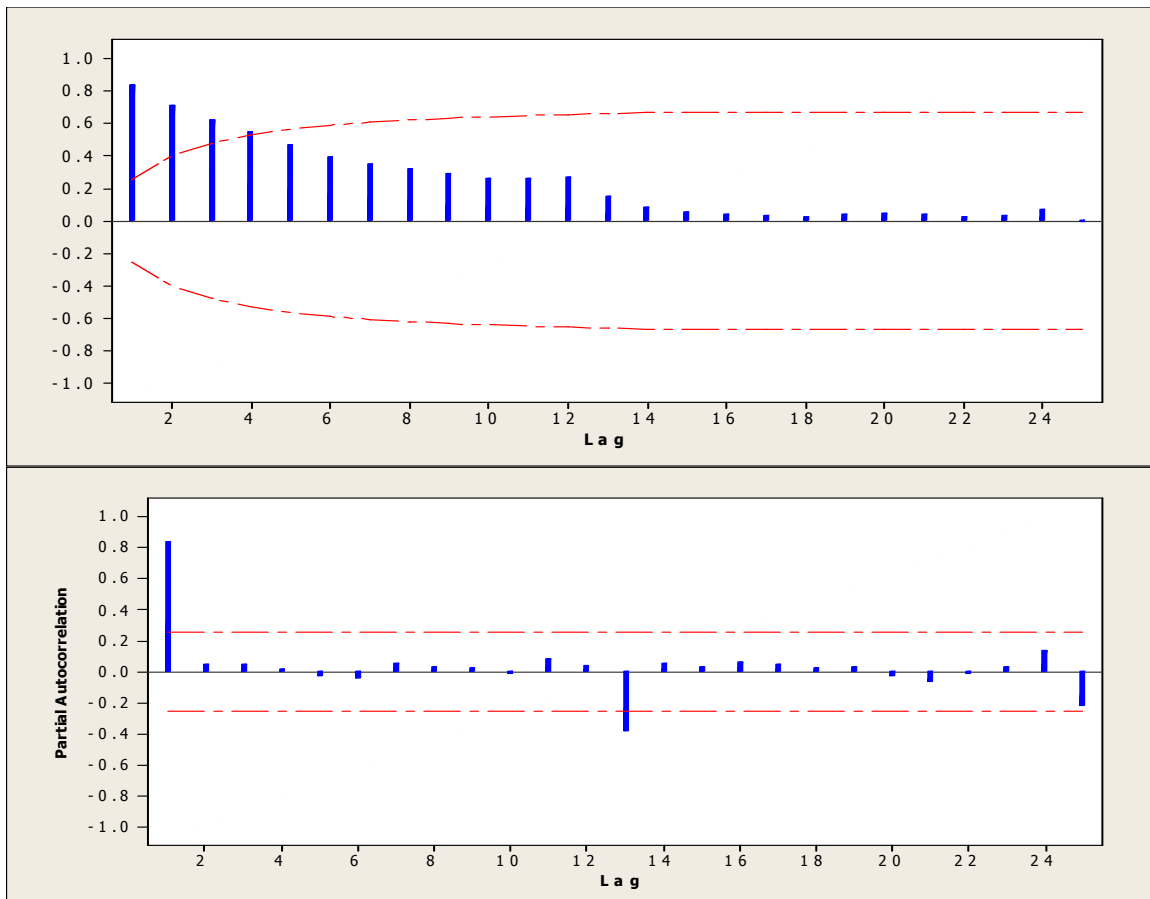


Figure 2: ACF and PACF Plot of Currency in Circulation

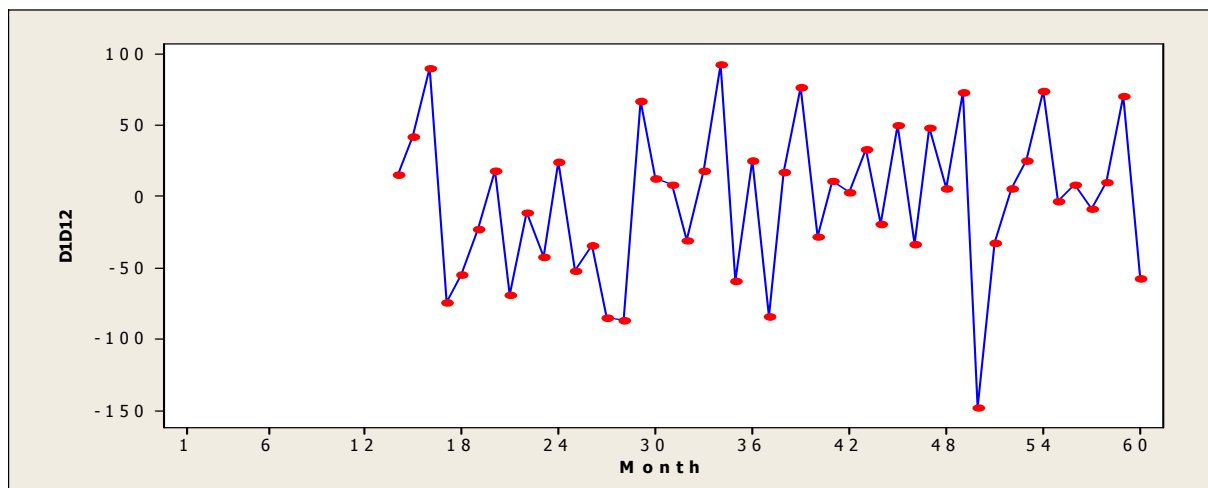


Figure 3: Time Series Plot of Seasonal and Non-Seasonal First Differenced Series.

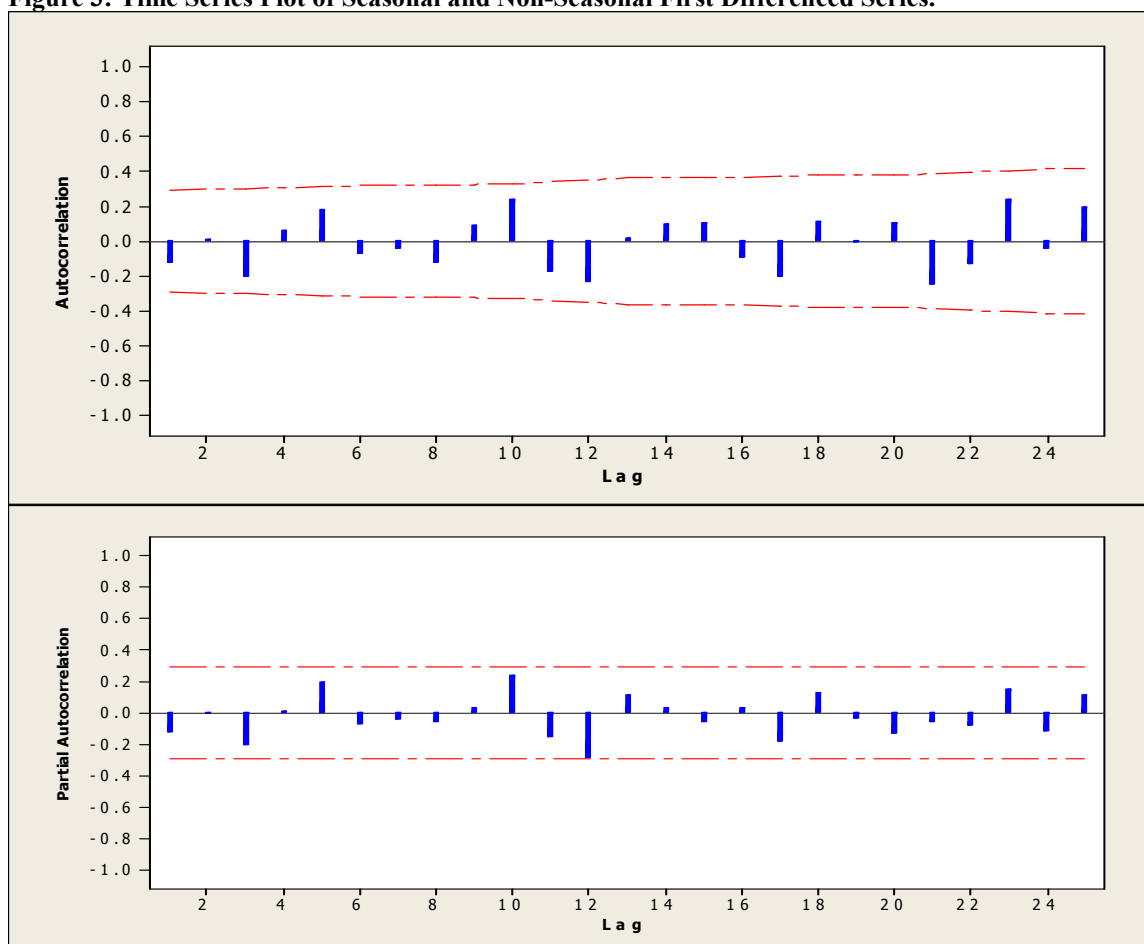


Figure 4: ACF and PACF plot Seasonal and Non Seasonal First Differenced Series.

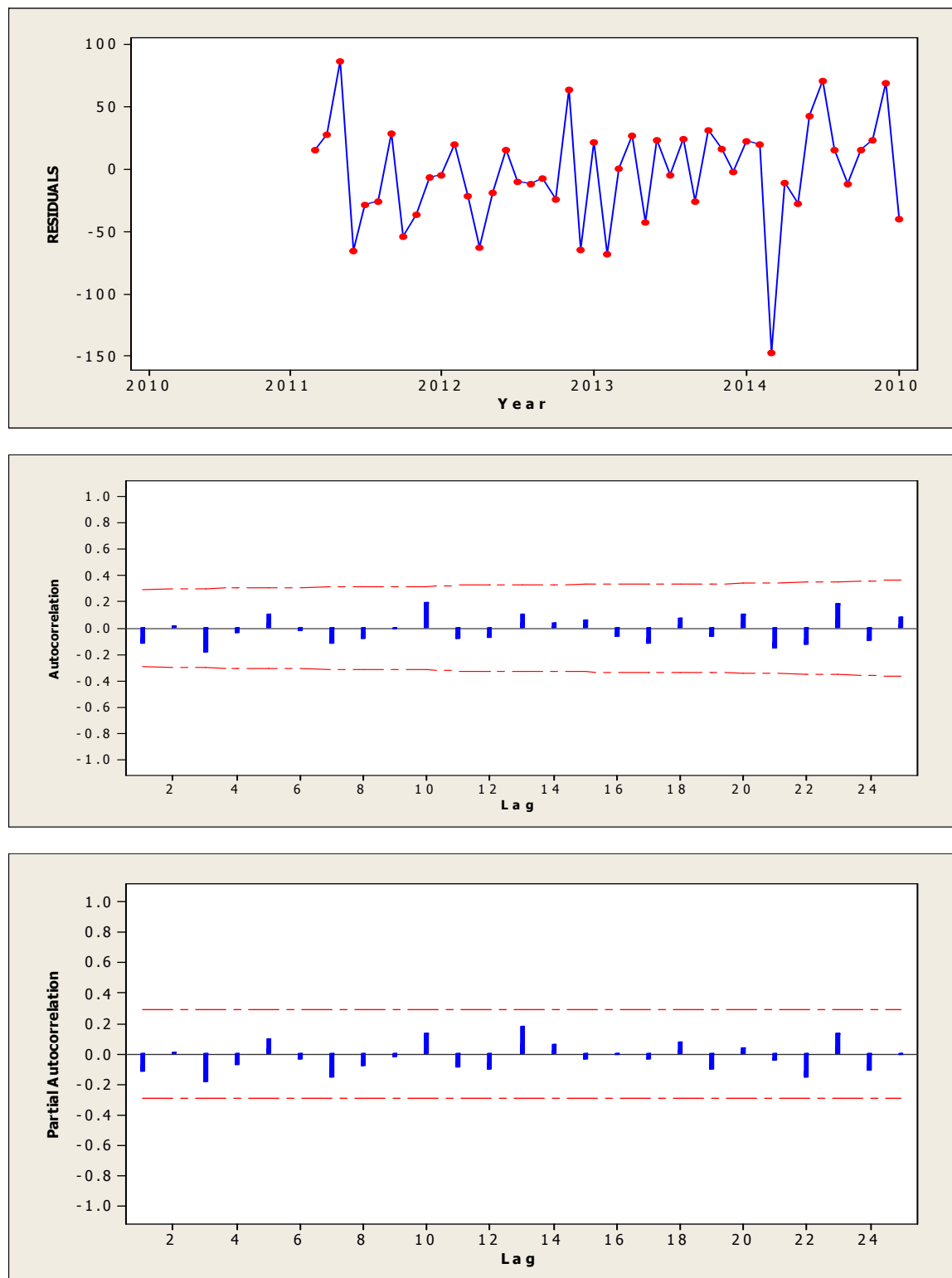


Figure 5: Diagnostic Plot of Multiplicative SARIMA $(0,1,0) \times (0,1,1)_{12}$