

## Modeling the Pattern of Reserve Money Growth in Ghana

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**Abstract:** The role played by reserve money growth cannot be ignored in the development of a country. Thus, this study describes an empirical approach to modeling monthly reserve money growth in Ghana using SARIMA model. The result showed that ARIMA (0, 1, 1) $\times$ (0, 0, 1)<sub>12</sub> model was appropriate for modeling the reserve money growth. This model has the least AIC of 608.91, AICc of 609.18, BIC of 616.44, RMSE of 6.33, MAPE of 16.90 and MAE of 4.39, respectively. Diagnostic test of the model residuals with the ARCH LM-test and Durbin-Watson test indicates that there is no ARCH effect and autocorrelation in the residuals respectively. Finally, a twenty eight months forecast with the model showed that from the middle of the year 2011 to December, 2012, there will be an increase in the reserve money growth. Hence, we recommend that the government and other policy holders should devise appropriate measures to slow the growth since the country is not experiencing low inflation.

**Key words:** Forecast, Ghana, reserve money, SARIMA

### INTRODUCTION

The growth of reserve money cannot be ignored in the economic development of a country. The reserve money, according to the Webster's online dictionary is an aggregate of money held by the banks and public plus the deposits with the central bank. The reserve money constitutes currency in circulation, other deposits with the state bank, currency in tills and bank's deposits with the state bank. Monetary reserve plays a very significant role in settling transactions involving counter parties and for undertaking trading in foreign exchange and commodity market.

A growth in reserve money is useful as it aids in keeping prices stable as productivity increases in a country. On the other hand where a country experiences serious inflations, the money growth needs to slow to control it. Thus, in a country like Ghana where we sometimes experience double digit inflation and not much significant growth in productivity, the pattern of this reserve money growth needs to be given a close look.

To do this, we need to know what the pattern of the reserve money is likely to be with time in order to adopt appropriate measures. Myriad of researches on the pattern of economic indicators has been done using time series models. The most common time series model used is the Autoregressive Integrated Moving Average (ARIMA) model. Appiah and Adetunde (2011), forecasted the exchange rate between the Ghana cedi and the US dollar using ARIMA model. Their study revealed that ARIMA

(1, 1, 1), was appropriate for forecasting the exchange rate. Also, Alnaa and Ferdinand (2011) used ARIMA model to predict inflation in Ghana. A prediction with their ARIMA (6, 1, 6) model showed that if appropriate measures are not put in place inflation spiral could be set in motion. Aiden *et al.* (1998), used Seasonal ARIMA (SARIMA) model to forecast Irish inflation, Junttila (2001), employed SARIMA model to forecast Finish inflation and Pufnik and Kunovac (2006), used SARIMA model to forecast short term inflation in Croatia.

This study thus, aims to model and forecast the pattern of reserve money growth in Ghana. This is imperative because it helps the country to monitor the pattern of the reserve money growth in order to make appropriate policies as to when to slow the growth or to increase it.

### MATERIALS AND METHODS

This study was carried out in Ghana in January, 2012, using data on reserve money growth, from January, 2003 to August 2010. The data was obtained from the website of the Bank of Ghana. The data was model using Seasonal Autoregressive Integrated Moving Average (SARIMA) stochastic model. An ARIMA (p, d, q) model is a combination of Autoregressive (AR) which shows that there is a relationship between present and past values, a random value and a Moving Average (MA) model which shows that the present value has something to do with the past residuals. If the data has a seasonal component, then

ARIMA (p, d, q) is extended to include the seasonal component. Thus, Seasonal Autoregressive Integrated Moving Average (SARIMA) model is expressed as ARIMA (p, d, q) × (P, D, Q)<sub>s</sub>. The orders p and q are for the non-seasonal AR and MA component, respectively. The orders of the Seasonal AR and MA component are P and Q respectively. Also, the order of differencing for the seasonal and non-seasonal are D and d, respectively.

The estimation of the model consists of three steps, namely: identification, estimation of parameters and diagnostic checking.

**Identification step:** Identification step involves the use of the techniques to determine the values of p, q, P, Q, D and d. The values are determined by using Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF). For any ARIMA (p, d, q) process, the theoretical PACF has non-zero partial autocorrelations at lags 1, 2, ..., p and has zero partial autocorrelations at all lags, while the theoretical ACF has non zero autocorrelation at lags 1, 2, ..., q and zero autocorrelations at all lags. The non-zero lags of the sample PACF and ACF are tentatively accepted as the p and q parameters. To identify the orders of the seasonal component, for seasonal MA the ACF shows a significant spike at the seasonal lags while for the seasonal AR component, the PACF shows significant spike at the seasonal lags. The number of times the data was seasonally and non-seasonally differenced gives the value of D and d, respectively.

**Estimation of parameters:** The second step is the estimation of the model parameters for the tentative models that have been selected. Here, the model with minimum values of Akaike Information Criterion (AIC), modified Akaike Information Criterion (AICc), Normalized Bayesian Information Criterion (BIC), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE) and Mean Absolute Error (MAE).

**Diagnostic checking:** The estimated model must be checked to verify if it adequately represents the series. Diagnostic checks are performed on the residuals to see if they are randomly and normally distributed. Here, the residual plot versus the fitted values was used to check if the residuals are randomly scattered. An overall check of the model adequacy was made using the Ljung-Box Q statistics. Furthermore, an ARCH LM-test and Durbin Watson test were performed on the residuals of the fitted model. These tests are performed to check for homoscedasticity and autocorrelation of the residuals, respectively.

**Unit root test:** This test was performed to check whether the data was stationary. In view of this, the Augmented Dickey-Fuller test was used for the test. The test is based on the assumption that a time series data  $y_t$  follows a random walk:

$$Y_t = \rho y_{t-1} + \epsilon_t$$

where,  $\rho = 1$ , thus,  $y_{t-1}$  is subtracted from both sides.  $\Delta y_t = \beta y_{t-1} + \epsilon_t$  and  $\beta = \rho - 1$ . The null hypothesis is  $H_0: \beta = 0$  and therefore  $\rho = 1.0$  against the alternative that  $H_0: \beta < 0$  and  $\rho < 1$ .

## RESULTS AND DISCUSSION

Figure 1, shows the time series plot of the data, given an overview about the series. The series shows a periodic pattern over a period of time. From Fig. 1, it can be seen that data was not stationary. This can be affirmed from the slow decay in the ACF of the series and a very significant spike at lag 1 of the PACF with marginal spikes at few other lags as shown in Fig. 2. Also, from Fig. 2 the significant spike at lag 12 of the PACF is an indication of seasonal variation in the data set.

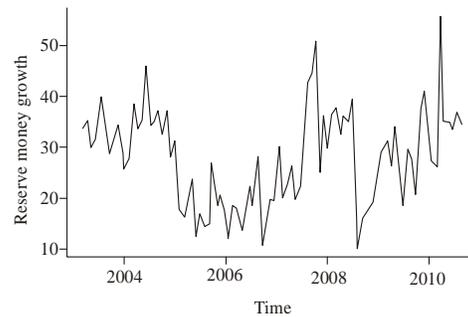


Fig. 1: Time series plot of the data

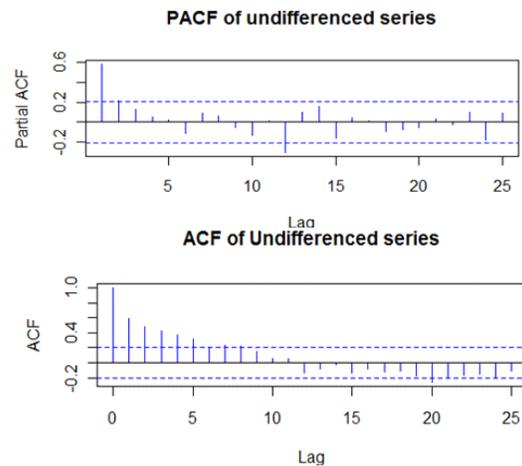


Fig. 2: ACF and PACF of the actual data

Table 1: Augmented Dickey-Fuller test statistics

Order of differencing	ADF test statistics	p-value
0	- 2.3412	0.4356
1	- 5.1306	0.01

Table 2: Different ARIMA (p, 1, q)×(P, 0, Q)<sub>12</sub> models fitted

Model type	AIC	AICc	BIC	RMSE	MAPE	MAE
ARIMA (1, 1, 0)(0, 0, 1) <sub>12</sub>	613.15	613.43	620.69	6.46	17.58	4.53
ARIMA (0, 1, 1)(0, 0, 1) <sub>12</sub>	608.91*	609.18*	616.44*	6.33*	16.9*	4.39*
ARIMA (1, 1, 1)(0, 0, 1) <sub>12</sub>	610.10	610.57	620.15	6.36	17.11	4.39
ARIMA (2, 1, 0)(0, 0, 1) <sub>12</sub>	613.00	614.14	623.72	6.45	17.31	4.49
ARIMA (2, 1, 1)(0, 0, 1) <sub>12</sub>	611.29	612.00	623.84	6.27	17.16	4.38

\*: Best based on that selection criterion

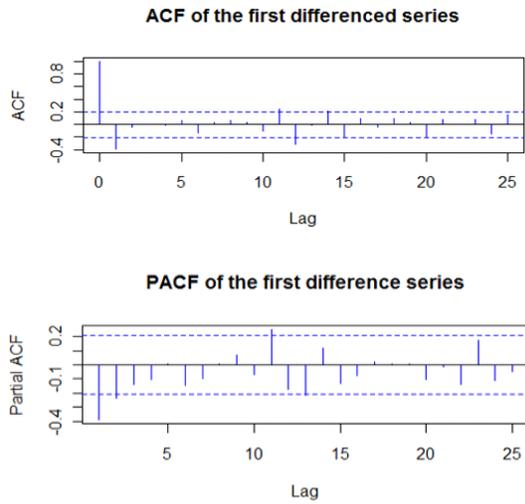


Fig. 3: ACF and PACF of the differenced series

Table 3: Estimates of ARIMA (0, 1, 1)×(0, 0, 1)<sub>12</sub> model

Type	Coefficient	Standard error	t-statistics	p-value
MA (1)	0.5215	0.1058	4.929	0.000
SMA (1)	0.6557	0.1377	4.762	0.001

Furthermore, the ADF test shown in Table 1 shows that the series was not stationary. Thus, the data was differenced and tested. As shown in Table 1, the ADF test indicates that the data was stationary after the non-seasonal first difference.

Also, the rapid decay in the ACF and the PACF of the differenced data as shown in Fig. 3 indicates that the data was stationary after the first non-seasonal differencing. From Fig. 3, there was significant spike at lag 12 of the ACF which suggests that a seasonal moving average component needs to be added to our model. Hence, different ARIMA (p, 1, q)×(P, 0, Q)<sub>12</sub> models were fitted to the data and the best model selected based on the minimum values of AIC, AICc, BIC, RMSE, MAPE and MAE.

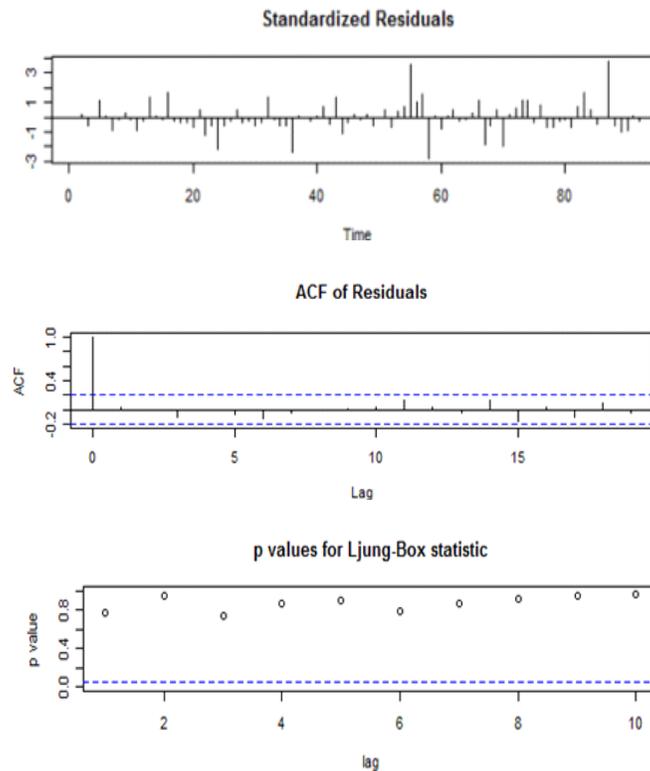


Fig. 4: Diagnostic plots of the residuals of ARIMA (0, 1, 1)×(0, 0, 1)<sub>12</sub> model

Table 4: Diagnostic test statistics

Test type	Test statistics	p-value
ARCH LM-test	34.0947	0.7325
Durbin-Watson	1.94	0.3864

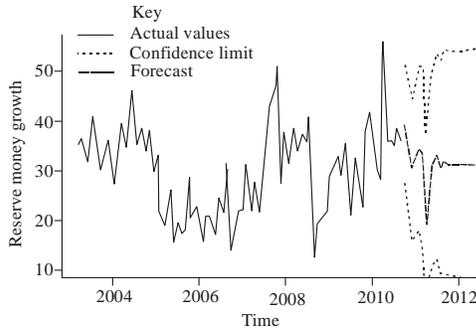


Fig. 5: Twenty eight months forecast of reserve money growth with ARIMA (0, 1, 1)×(0, 0, 1) model

From Table 2, ARIMA (0, 1, 1)×(0, 0, 1)<sub>12</sub> was the best model based on the selection criterion used. The parameters of this model were then estimated. As shown in Table 3, all the parameters are very significant. In addition, the model was diagnosed to see how well it fits the data. It can be seen from Fig. 4 that the ACF of the residuals shows that the residuals are white noise although there was a significant spike at lag 0 of the ACF which could be due to random factor. Furthermore, the plot of the Ljung-Box p-values in Fig. 4 shows that the model is adequate for representing the data as they are above 0.05 value indicated by the blue line. Also, the ARCH LM-test and the Durbin-Watson test of the residuals in Table 4 indicate that there was no ARCH effect and autocorrelation in the residuals of the model respectively at the 0.05 level of significance.

Finally, we made a twenty eight months forecast with our model. As shown in Fig. 5, there was a decrease in the reserve money growth from September 2010 till the middle of 2011 where we experience a surge in the growth of the reserve money.

## CONCLUSION

In this study, we modeled the reserve money growth of Ghana with ARIMA (0, 1, 1)×(0, 0, 1)<sub>12</sub> model. Our forecast showed a decrease in the pattern of the reserve money growth from September 2010 and continues surge from the middle of the year 2011 to December 2012. The decrease in the pattern of the reserve money growth was good for a country experiencing double digit inflation with no significant growth in productivity. Hence, we advice government and policy holders to slow down the growth rate because increase in the growth of the reserve money would lead high prices of commodities in the country, thus increasing inflation.

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