IOSR Journal of Economics and Finance (IOSR-JEF)
e-ISSN: 2321-5933, p-ISSN: 2321-5925.Volume 6, Issue 6. Ver. II (Nov. - Dec. 2015), PP 48-55
www.iosrjournals.org

An Econometric Model for Inflation Rates in the Volta Region of Ghana

Francis Okyere[1], François Mahama[2], Solomon Yemidi[3], Elikem Kofi Krampa[4]
[1] National Vocational Training Institute (NVTI), Ghana, P. O. Box MB 21, Accra, Ghana
[2,3,4] Department of Mathematics and Statistics, Ho Polytechnic, Ghana, P. O. Box, HP 217, Ho – Volta, Ghana,

Abstract : *Ghana has been challenged by high inflation rates for a long period of time. The phenomenon in many cases leaves in its trail adverse economic consequences. Therefore, forecasting inflation rates in Ghana becomes very important for government and central bank to design fiscal measures or effective monetary policies to combat any unexpected high inflation in this country. For firms and households, knowledge about the rate of inflation in future enables them to factor it into their planning so as to guard against unpleasant ramifications. This paper employs Autoregressive Integrated Moving Average (ARIMA) technique to model inflation rates in Volta region of Ghana. Using monthly inflation rates data from January 2009 to September 2015, we find that ARIMA (2,1,2) can be used to study the behavior of the data in the Volta region of Ghana regarding inflation rates. Based on the selected model, we forecasted six (6) months inflation rates for the region outside the sample period (i.e. from October 2015 to March 2016). From the out-sample forecast, we surmise that Volta region is likely to experience continuous double digit inflation rates. Hence, policy makers should re-evaluate their policies in order to determine other factors that contribute to the high inflation rates.*
Keywords - *Volta region Inflation, Forecasting, ARIMA model, Unit Root test, ARCH–LM test*

I. Introduction

Inflation can broadly be defined as the sustained increase in the general price level of goods and services in a country or a given geographical area over a period of time, usually one year. Inflation occurs when demand for goods and services exceeds their supply in the economy [25]. Price stability is a healthy monetary policy that can enhance economic growth and prosperity. It is now universally accepted that price stability is a cornerstone of modern well-functioning economies and high inflation distorts wealth redistribution in an economy, because it arbitrarily redistributes wealth among different groups of people in a society [9]. Inflation is widely discussed because it changes the purchasing power of money and real values of variables such as interest rates, wages and many others. This explains why it is a very important issue of concern to policy makers especially when it assumes a relatively high level in a country over a time period (e.g. monthly, quarterly or annually). Ghana Statistical Service [13] said the Consumer Price Index (CPI) measures the change over time in the general price level of goods and services that households acquire for the purpose of consumption, with reference to price level in 2012, the base year, which has index of 100. The general prices of goods and services are taken from the ten (10) regions of Ghana. At the regional level, inflation rates vary and this means that food and non-food inflation rates are not the same. That is why Ghana Statistical Service (GSS) releases regional inflation rates aside the national rate.

Inflation is one macroeconomic indicator that affects all other levels of the economy especially business transactions. It is, to a large extent, responsible for currency fluctuations which go a long way to influence planning in business. For this reason, it is plausible to forecast or estimate future inflation rates so that such rates are incorporated in decision affecting Volta Region in particular and the country at large.

Empirical researches have been carried out in the area of inflation rates modelling and forecasting in Ghana. Examples include (see [9]; [27]; [26]; [8]; and [6]). All these researchers attempted to model only the national inflation rate of Ghana.

Among the most effective approaches for analysing time series data is the method propounded by Box and Jenkins, the Autoregressive Integrated Moving Average (ARIMA) model. ARIMA models had been used in several field of study by these researchers (see [21]; [11]; [10]; [29]; [23]; [22]; [17]; [24] [5]; [1]; [7]; [28]; [16]; [3]; [19]; [2]; [25]; [15] and [18]).

In this study, our main objective was to model and forecast six (6) months of Volta region inflation rates of Ghana outside the sample period. The forecast is very important for regional ministers / economic policy makers to foresee ahead of time the possible future requirements to design economic strategies and effective monetary policies to combat any expected high inflation rates in the Volta region. Forecasts will also play a crucial role in business, industry, government, and institutional planning because many important decisions depend on the anticipated future values of inflation rate.

II. Materials And Method

This study was carried out in Ghana in October, 2015, using monthly Volta region inflation rates of Ghana from January 2009 to September 2015. Volta Region [14] is one of Ghana's ten administrative regions. It is to the east of Lake Volta. Its administrative capital is Ho. The region's population in 2000 was 1,635,421 and 2,118,252 in 2010 (see [4]). Agriculture/Hunting/ Forestry industry is the largest sector in the region and indeed in all the districts, except the Keta District, where fishing is the main industry. Males predominate in the Construction; Transport/Storage and Communication sectors while females predominate in the Wholesale/Retail Trade and the Hotels/Restaurant industries. The information on the employment status reveals that majority of the people in the region are self-employed (see [14]).

The Volta inflation rates data was obtained from Ghana Statistical Service and we used R Studio Software for the data analysis. The data was modeled using Autoregressive Integrated Moving Average (ARIMA) 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. These models are fitted to time series data either to better understand the data or to predict future points in the series.

2.1 Autoregressive Integrated Moving Average (ARIMA) Model

A time series Y_t is said to follow Autoregressive Integrated Moving Average (ARIMA) model if the *d*th differences $\nabla^d Y_t$ follow a stationary ARMA model. There are three important values which characterize an ARIMA process [20]:

- *p*, the order of the autoregressive component
- *d*, the number of differencing needed to arrive at a stationary ARMA(*p*, *q*) process
- *q*, the order of the moving average component

The general form of the ARIMA (*p*,*d*,*q*) is represented by a backward shift operator as

$$\phi(B)(1-B)^d Y_t = \theta(B)e_t \tag{1}$$

where the AR and MA characteristic operators are

$$\phi(B) = \left(1-\phi_1 B-\phi_2 B^2-...-\phi_p B^p\right) \tag{2}$$

$$\theta(B) = \left(1-\theta_1 B-\theta_2 B^2-...-\theta_q B^q\right) \tag{3}$$

and

$$(1-B)^d Y_t = \nabla^d Y_t \tag{4}$$

where

ϕ is the parameter estimate of the Autoregressive component

θ is the parameter estimate of the Moving Average component

∇^d is the difference operator

B is the backward shift operator

e_t is a purely a random process with mean zero and $\mathrm{var}(e_t) = \sigma_e^2$

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

2.2 Model Identification

Identification step involves the use of the techniques to determine the values of *p*, *d*, and *q*, 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 $p+1, p+2, ..., p+n$, while the theoretical ACF has non zero autocorrelation at lags 1, 2, …, *q* and zero autocorrelations at all lags $q+1, q+2, ..., q+n$

2.2.1 Unit Root Test of Stationarity

Determining whether the time series is stationary or not is a very important concept before making any inferences in time series analysis. Therefore, Phillips Perron (PP) test has been used to check the stationarity of the series. The test is based on the assumption that a time series data y_t follows a random walk.

$$y_t = \rho y_{t-1} + e_t \tag{5}$$

where ρ is the characteristic root of an AR polynomial and e_t is purely a random process with mean zero and variance σ^2.

2.3 Estimation of Model Parameters

After identifying the possible ARIMA models, the maximum likelihood method was used to estimate the model parameters.

2.4 Diagnostic Checking

The next step is to select the best model among all the identified models. For this, residual diagnostics and the model with the maximum value of log-likelihood and minimum values of modified Akaike Information Criterion (AICc), Bayesian Information Criterion (BIC), Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) was considered as the best model. Under the residual diagnostics, Ljung-Box Q statistic is used to check whether the residuals are random or not.

2.5.1 Akaike Information Criterion (AIC)

The Akaike's Information Criterion (AIC) says select the ARIMA(*p, d, q*) model which minimizes,

$$AIC = -2\ln L + 2k \qquad (6)$$

where $\ln L$ is the natural logarithm of the estimated likelihood function and $k = p + q$ is the number of parameters in the model. The AIC is an estimator of the expected Kullback-Leibler divergence, which measures the closeness of a candidate model to the truth. The smaller this divergence, the better the model.

A problem arises in that AIC is a biased estimator of the expected KL divergence in ARIMA(*p, d, q*) models. An alternative AIC statistic which corrects for this bias is,

$$AICc = AIC + \frac{2(k+1)(k+2)}{n-k-2} \qquad (7)$$

2.4.2 Bayesian Information Criterion (BIC)

The Bayesian Information Criterion (BIC) says select the ARIMA(*p, d, q*) model which minimizes,

$$BIC = -2\ln L + 2k\ln(n) \qquad (8)$$

where $\ln L$ is the natural logarithm of the estimated likelihood function and $k = p + q$ is the number of parameters in the model and *n* is total observations.

Both AIC and BIC require the maximization of the log likelihood function and when we compared AICc to BIC, BIC offers a stiffer penalty for over parameterized models.

An overall check of the model adequacy was made using the modified Box-Pierce ***Q*** statistic. The test statistic is given by:

$$Q_m = n(n+2)\sum_{k=1}^{n}\left(n-k\right)^{-1} r_k^2 \approx x_{m-r}^2 \qquad (9)$$

where:

r_k^2 = the residuals autocorrelation at lag k

n = the number of residual

m = the number of time lags included in the test.

When the *p*-value associated with the ***Q*** is large the model is considered adequate, else the whole estimation process has to start again in order to get the most adequate model. Here all the tests were performed at the 95% confidence interval.

Furthermore, an ARCH LM-test was performed on the residuals to check the presence of ARCH effect.

III. Results And Discussion

Inflation has been one of the macroeconomic problems confronting Ghana for a long period of time. It has been one of the contributing factors to the fast depreciation of the Ghanaian Cedi.

In this research we analyze eighty-one (81) monthly observations of Volta region inflation rate of Ghana from January 2009 to September 2015. The data was obtained from Ghana Statistical Service. Figure 1 describes the features of the data.

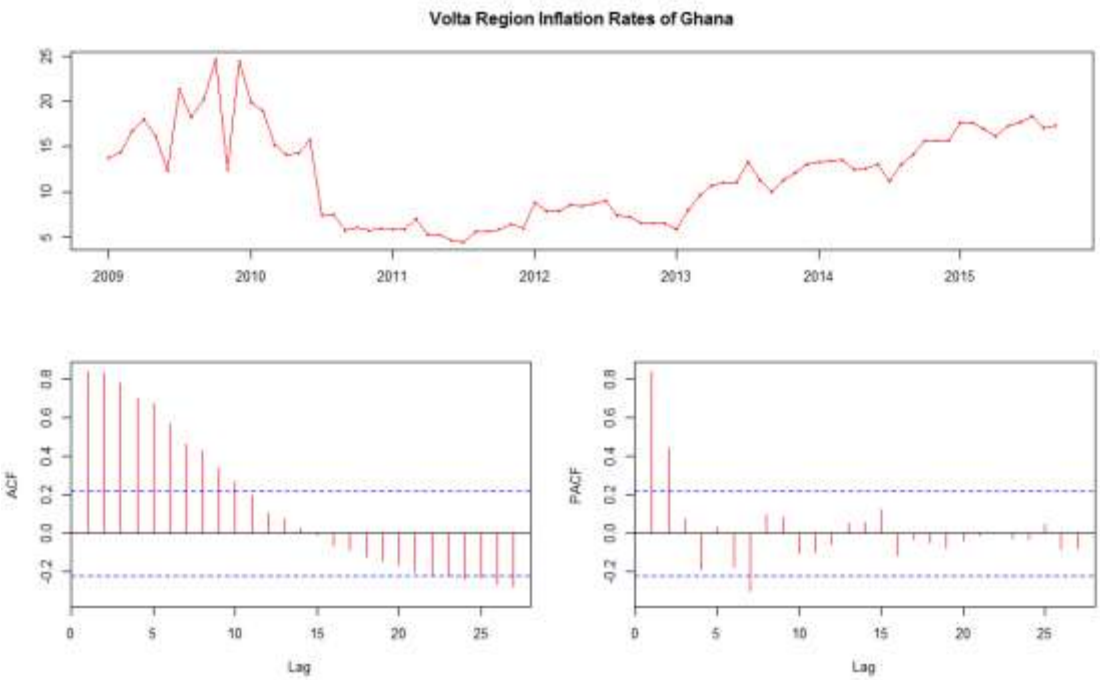

FIGURE 1: Time series plot, ACF and PACF plot for monthly Volta region inflation rates

From Fig. 1, it can be confirmed that the inflation volatility. The volatility in Volta region's inflation series can be attributed to several economic factors. The mean and variance ought to be adjusted to form stationary series, so that the values vary more or less uniformly about a fixed level over time. This is also seen from the ACF plot of the series in Fig. 1, which shows a slow decline. Also, PACF plot has a very significant spike at lag 1. The Phillips Perron (PP) test further confirms this observation. The first difference achieved stationarity as shown in Table 1.

TABLE 1: Unit Root test for Volta region inflation rates of Ghana

Order of Difference	PP test statistic	p-value
0	-7.9050	0.6523
1	-115.7321	0.0100

The next step in the model building procedure is to determine the order of the AR and MA for non-seasonal components. Cryer and Chan [20] suggested the term $2(p+q+1)$ or $2(p+q)$ serves as a penalty function to help ensure selection of parsimonious models and to avoid choosing model with too many parameters.

This can be suggested by the sample ACF and PACF plots based on the Box-Jenkins approach. From Fig. 2, ACF tails off at lag 1 and the PACF spikes at lag 1 suggesting that $q=1$ *and* $p=1$ would be needed to describe these data as coming from a non-seasonal moving average and autoregressive process respectively. Again, we had a significant spike at lag 5 of both ACF and PACF plot but it may be due to random influence. To ensure parsimonious model and checking parameter inadequacy or over fitting, we reduced/added parameters to tentative model of ARIMA(1,1,1).

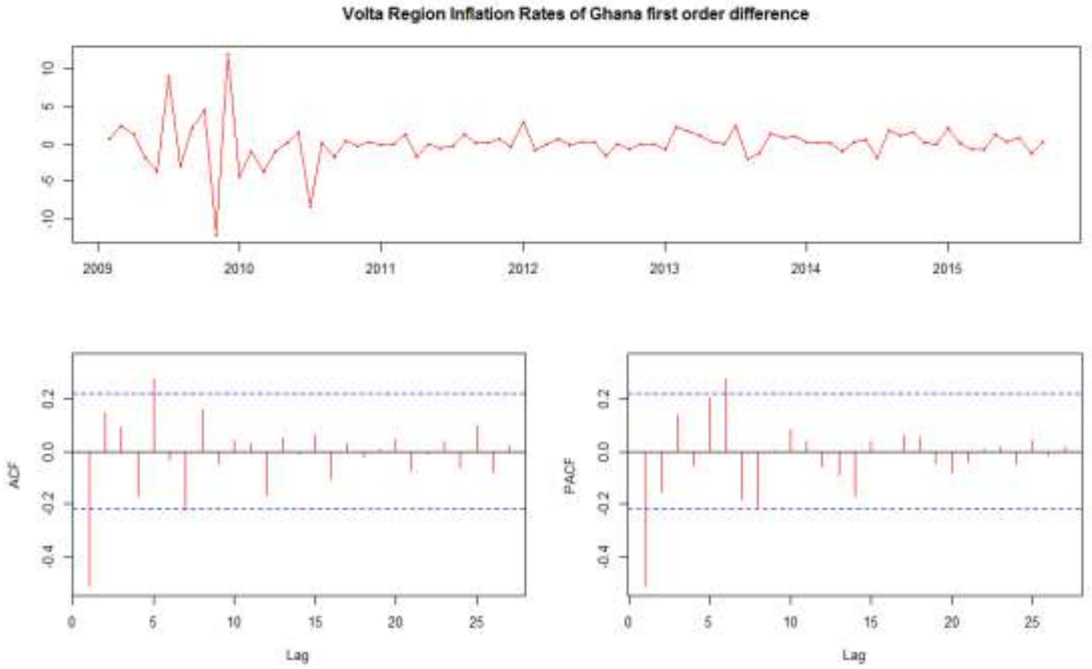

FIGURE 2: Volta Region Inflation Rates of Ghana first order difference

TABLE 2: Selection of Best $ARIMA(p,1,q)$ Model

Model	AIC	AICc	BIC	RMSE	MAE
ARIMA(0,1,1)	371.81	372.03	376.63	2.39	1.54
ARIMA(1,1,0)	369.15	369.30	373.91	2.35	1.52
ARIMA(1,1,1)	369.90	370.22	373.05*	2.33	1.54
ARIMA(2,1,1)	369.63	370.16	379.15	2.30	1.52
ARIMA(2,1,2)	362.52*	363.33*	374.43	2.09*	1.42*
ARIMA(3,1,1)	372.68	373.83	386.97	2.28	1.50

Note *Based on selected best model

After the models have been identified, the procedure for choosing these models relies on choosing the model with the minimum AIC, AICc, BIC, RMSE and MAE. The models are presented in Table 2 & 3, with their corresponding values of AIC, AICc, BIC, RMSE and MAE. Among those possible models, comparing their AIC, AICc, BIC, RMSE and MAE as shown in Table 2 & 3, ARIMA (2,1,2) was chosen as the appropriate model that fits the data well, despite BIC chose ARIMA(1,1,1), the rest of the selection criterions were in favor of ARIMA (2,1,2).

From our derived models, using the method of maximum likelihood the estimated parameters of the models with their corresponding standard error is shown in Table 3. Based on these model selection criteria (AIC, AICc, BIC, RMSE and MAE) and white noise variance estimate σ_e^2, we conclude that all the coefficients of the ARIMA(2,1,2) model are significantly different from zero and the estimated values satisfy the stability condition.

TABLE 3: Parameter estimates of ARIMA(2,1,2)

Model	Component	Parameter	Coefficient	Std. Error	P-value
ARIMA(2,1,2)	AR(1)	ϕ_1	0.4499	0.1057	0.000010
	AR(2)	ϕ_2	-0.4486	0.1069	0.000013
	MA(1)	θ_1	-1.1066	0.0584	0.000000
	MA(2)	θ_2	1.0000	0.0882	0.000000
	Log-likelihood	-176.26	RMSE	2.09	
	AIC	362.52	MAE	1.42	
	AICc	363.33	σ_e^2	4.44	
	BIC	374.43			

In time series modeling, the selection of a best model fit to the data is directly related to whether residual analysis is performed well. One of the assumptions of ARIMA model is that, for a good model, the residuals must follow a white noise process. That is, the residuals have zero mean, constant variance and also uncorrelated. From Fig. 3, the standardized residual reveals that the residuals of the model have zero mean and constant variance. Also the ACF of the residuals depicts that the autocorrelation of the residuals are all zero, that is to say they are uncorrelated. Finally, the p-values for the Ljung-Box statistic in the third panel all clearly exceeds 5% for all lag orders, indicating that there is no significant departure from white noise for the residuals.

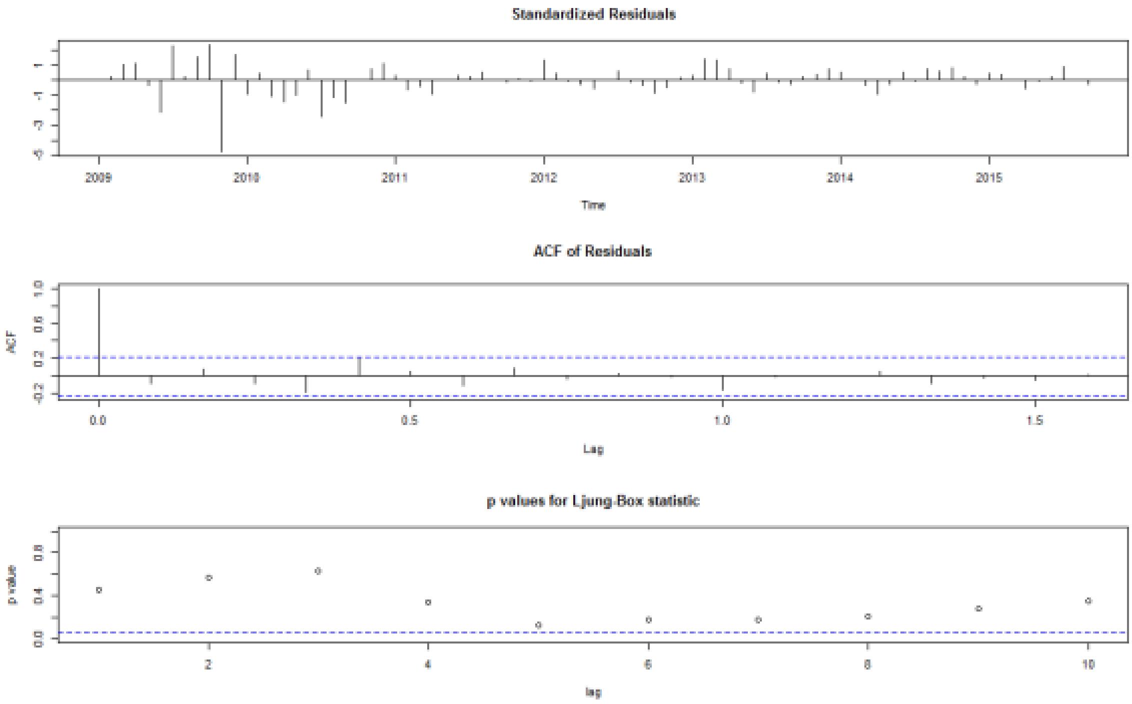

FIGURE 3: Diagnostic plot of Residuals of ARIMA(2,1,2)

TABLE 4: ARCH–LM Test for Homoscedasticity

Model	Chi-squared	p-value
ARIMA(2,1,2)	22.5947	0.5438

To support the information displayed by Fig. 3, we used the Autoregressive Conditional Heterocedasticity-Lagrange Multiplier (ARCH–LM) and t tests to test for constant variance and zero mean assumption respectively. From the ARCH–LM test results as shown in Table 4, we fail to reject the null hypothesis of no ARCH effect (homoscedasticity) in the residuals of the selected model. Also from t test results, since the p-value of 0.5438 is greater than 5% alpha level, we fail to reject the null hypothesis that, the mean of the residuals is approximately equal to zero. Hence, we conclude that there is a constant variance among residuals of the selected model and the true mean of the residuals is approximately equal to zero. Thus, the selected model satisfies all the model assumptions. Since our model ARIMA (2,1,2) satisfies all the necessary assumptions, now we can say that the model provide an adequate representation of the data.
In other form, ARIMA (2,1,2) can be written as,

$$Y_t = 1.4499Y_{t-1} - 0.8985Y_{t-2} - 0.4486Y_{t-3} - 1.1066e_{t-1} + e_{t-2} + e_t$$

The full details of the above derived equation can be seen at appendix for your consumption.

3.1 Forecasting

Forecasting plays an important role in decision making process. It is a planning tool which helps decision makers to foresee the future uncertainty based on the behavior of past and current observations. Forecasting as described by Box and Jenkins [12], provides basis for economic and business planning, inventory and production control and control and optimization of industrial processes. From Table 2, the forecast accuracy of ARIMA (2,1,2) was better because its Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) are smaller as compared to the other tentative models. Table 5, shows a forecast of Volta region inflation rates for six (6) months.

TABLE 5: ARIMA(2,1,2) Forecasting Results for Volta Region Inflation Rates of Ghana

Year	Month	Forecast	Lower Bound	Upper Bound
2015	October	18.66	14.48	22.84
2015	November	18.59	14.15	23.02
2015	December	17.94	12.86	23.03
2016	January	17.68	11.13	24.24
2016	February	17.85	9.94	25.78
2016	March	18.05	9.26	26.85

IV. Conclusion

This study used time series analysis to model monthly inflation rates of Volta region of Ghana using data from the Ghana Statistical Service (GSS) from the year 2009 to 2015. The modeling of the inflation rate was done mainly by ARIMA model. The Study revealed that, inflation rate was best modeled with $Y_t = 1.4499Y_{t-1} - 0.8985Y_{t-2} - 0.4486Y_{t-3} - 1.1066e_{t-1} + e_{t-2} + e_t$ or ARIMA (2, 1, 2). The diagnostics of this model showed that the model adequately fits the series hence is adequate for the forecasting Volta region inflation rates of Ghana. Six (6) month's forecast with the model for the year 2015/2016 showed fluctuation in the inflation pattern but the values were within 17% and 18%. From the out-sample forecast, we surmise that Volta region is likely to experience continuous double digit inflation rates from October 2015 to March 2016. Hence, policy makers should re-evaluate their policies in order to determine other factors that contribute to the high inflation rates because it has effect on national rates.

Appendix

A predictive model, ARIMA(2,1,2) for Volta region inflation rates of Ghana

ARIMA(2,1,2) process

Suppose $\{e_t\}$ is zero mean white noise process with $\operatorname{var}(e_t) = \sigma_e^2$. An $ARIMA(p,d,q)$ process with $p = 2,\ d = 1$ and $q = 2$ is called an $ARIMA(2,1,2)$ process and can be expressed as;

$$\left(1-\phi_1 B-\phi_2 B^2\right)\left(1-B\right)^1 Y_t = \left(1-\theta_1 B-\theta_2 B^2\right)e_t \tag{1}$$

$$\left(1-\phi_1 B-\phi_2 B^2\right)\left(Y_t - BY_t\right) = \left(1-\theta_1 B-\theta_2 B^2\right)e_t \tag{2}$$

$$Y_t - \phi_1 BY_t - \phi_2 B^2 Y_t - BY_t + \phi_1 B^2 Y_t + \phi_2 B^3 Y_t = e_t - \theta_1 Be_t - \theta_2 B^2 e_t \tag{3}$$

$$Y_t - \phi_1 Y_{t-1} - \phi_2 Y_{t-2} - Y_{t-1} + \phi_1 Y_{t-2} + \phi_2 Y_{t-3} = e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} \tag{4}$$

$$By\ \text{Re}-arrangement\ of\ (4), we\ have$$

$$Y_t - Y_{t-1} - \phi_1 Y_{t-1} + \phi_1 Y_{t-2} - \phi_2 Y_{t-2} + \phi_2 Y_{t-3} = -\theta_1 e_{t-1} - \theta_2 e_{t-2} + e_t \tag{5}$$

$$Y_t - \left(1+\phi_1\right)Y_{t-1} + \left(\phi_1 - \phi_2\right)Y_{t-2} + \phi_2 Y_{t-3} = -\theta_1 e_{t-1} - \theta_2 e_{t-2} + e_t \tag{6}$$

$$Y_t = \left(1+\phi_1\right)Y_{t-1} - \left(\phi_1 - \phi_2\right)Y_{t-2} - \phi_2 Y_{t-3} - \theta_1 e_{t-1} - \theta_2 e_{t-2} + e_t \tag{7}$$

$$From\ Table\ 3,$$

$$\phi_1 = 0.4499$$

$$\phi_2 = 0.4486$$

$$\theta_1 = 1.1066 \quad [Note, R\ software\ negates\ MA\ parameters / estimates]$$

$$\theta_2 = -1.0000 \quad [Note, R\ software\ negates\ MA\ parameters / estimates]$$

$$By\ substitutions\ \text{in}\ (7),$$

$$Y_t = \left(1+0.4499\right)Y_{t-1} - \left(0.4499-(-0.4486)\right)Y_{t-2} - (-0.4486)Y_{t-3} - (1.1066)e_{t-1} - (-1.0000)e_{t-2} + e_t$$

$$Y_t = 1.4499Y_{t-1} - 0.8985Y_{t-2} - 0.4486Y_{t-3} - 1.1066e_{t-1} + e_{t-2} + e_t$$

Source: Author's calculations

References

[1]. A. S. Sarpong, Modeling and Forecasting Maternal Mortality; an Application of ARIMA Models, *International Journal of Applied Science and Technology*, *3(1)*, 2013, 19-28.

[2]. B. Chaves, Stochastic modelling of monthly sun bright in coffee growing areas, Revista *Colombiana de Estad´ıstica*, *25(1)*, 2012, 59-71.

[3]. C. J. Andreeski and P. M. Vasant, Comparative Analysis of Bifurcation Time Series, *Biomedical Soft Computing and Human Sciences*, *13(1)*, 2008, 45-52.

[4]. Census, 2010 census *population by region, distribution, age groupings and sex*, http://www.statsghana.gov.gh/docfiles/pop_by_region_district_age_groups_and_sex_2010.pdf, accessed on September 21, 2015.

[5]. D. M. K. N. Seneviratna and M. Mao Shuhua, Forecasting the Twelve Month Treasury Bill Rates in Sri Lanka: Box Jenkins Approach, *Journal of Economics and Finance (IOSR-JEF) 1(1)*, 2013, 44 – 47.

[6]. E. Aidoo, *Modelling and Forecasting Inflation Rates in Ghana: An Application of SARIMA Models [Master's Thesis],* Högskolan Dalarna School of Technology and Business Studies. Sweden, 2010.

[7]. F. K. Oduro-Gyimah, K. Harris and K. F. Darkwah, Sarima Time Series Model Application to Microwave Transmission of Yeji-Salaga (Ghana) Line-Of-Sight Link, *International Journal of Applied Science and Technology*, *2(9)*, 2012, 40-51.

[8]. F. K. Owusu, *Time series ARIMA modelling of inflation in Ghana: (1990-2009), [Unpublished Master's Thesis],* Kwame Nkrumah University of Science and Technology, Kumasi, Ghana, 2010.

[9]. F. Okyere and C. Mensah, Empirical Modelling and Model Selection for Forecasting Monthly Inflation of Ghana, *Mathematical Theory and Modeling*, *4(3)*, 2014, 99-106.

[10]. F. Okyere and L. Kyei, Temporal Modelling of Producer Price Inflation Rates of Ghana, *Journal of Mathematics (IOSR-JM)*, *10(3)*, 2014, 70-77.

[11]. F. Okyere and S. Nanga, Forecasting Weekly Auction of the 91-Day Treasury Bill Rates of Ghana, *Journal of Economics and Finance (IOSR-JEF)*, *3(5)*, 2014, 46-53.

[12]. G. E. P. Box and G. M. Jenkins, *Time Series Analysis, Forecasting and Control*, San Francisco, Holden-Day, California, USA, 1976.

[13]. Ghana Statistical Service, Newsletter Consumer Price Index September 2015 New series, http://www.statsghana.gov.gh/docfiles/new_CPI_pdfs/CPI_2015/CPI_Newsletter%20Sept_2015.pdf, accessed on September 15, 2015.

[14]. Government of Ghana, *Volta Region*, http://www.ghana.gov.gh/index.php/about-ghana/regions/volta, accessed on September 21, 2015.

[15]. H. A. S. Valle, Inflation forecasts with ARIMA and vector autoregressive models in Guatemala. *Economic Research Department,* Guatemala, Banco de Guatemala, 2002.

[16]. H. Javedani, M. H. Lee and Suhartono, An Evaluation of some Classical Methods for Forecasting Electricity Usage on Specific Problem. *Journal of Statistical Modeling and Analytics*, *2(1)*, 2011, 1-10.

[17]. I. A. Adetunde and F. K. Datsomor, Time Series Behaviour of Non-traditional Exports of Ghana, *International Journal of Modern Mathematical Sciences*, *7(1)*, 2013, 102-120.

[18]. I. Kaushik and M. S. Singh, Seasonal ARIMA model for forecasting of monthly rainfall and temperature, *Journal of Environmental Research and Development*, vol. 3, no. 2, pp. 506-514, 2008.

[19]. J. Contreras, R. Espínola, F. N. Nogales and A. J. Conejo, ARIMA Models to Predict Next-Day Electricity Prices, *IEEE Transactions on Power Systems*, *18(3)*, 2003, 1014-1020.

[20]. J. D. Cryer and K. S. Chan, *Time series analysis with application in R*, New York, USA, Springer, 2008.

[21]. K. Assis, A. Amran and Y. Remali, Forecasting cocoa bean prices using univariate time series models, *International Refereed Research Journal*, *1(1)*, 2010, 71-80.

[22]. O. K. Onasanya and O. E. Adeniji, O. E, Forecasting of exchange rate between naira and us dollar using time domain model, *International Journal of Development and Economic Sustainability*, *1(1)*, 2013, 45-55.

[23]. P. C. Etebong, Using Normalized Bayesian Information Criterion (BIC) to Improve Box - Jenkins Model Building, *American Journal of Mathematics and Statistics*, *4(5)*, 2014, 214-221.

[24]. P. Chujai, N. Kerdprasop and K. Kerdprasop, Time Series Analysis of Household Electric Consumption with ARIMA and ARMA Models, *Proceedings of the International MultiConference of Engineers and Computer Scientists*, *1*, 2013, 295-300.

[25]. Q. A. Samad, M. Z. Ali and M. Z. Hossain, The forecasting performance of the Box-Jenkins Model: the case of wheat and wheat flour prices in Bangladesh. *The Indian Journal of Economics*, *vol. LXXXII(327)*, 2002, 509-518.

[26]. R. Hall, *Inflation, Causes and Effects*, University of Chicago Press, Chicago, 1982

[27]. S. E. Alnaa and F. Ahiakpor, ARIMA approach to predicting inflation Ghana, *Journal of Economics and International Finance*, *3(5)*, 2011, 328-336.

[28]. S. Nasiru and S. Sarpong, Empirical Approach to Modelling and Forecasting Inflation in Ghana, *Current Research Journal of Economic Theory*, *4(3)*, 2012, 83-87.

[29]. S. T. Appiah and L. A. Adetunde (2011), Forecasting Exchange rate between the Ghana Cedi and the US dollar using time series analysis. *Current research journal of economic theory*, *3(2)*, 2011, 76 -83.

[30]. Zakai, M (2014), A Time Series Modeling On GDP of Pakistan, *Journal of Contemporary Issues in Business Research*, *4(3)*, 2014, 200 – 210.