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Empirical Modelling and Model Selection for Forecasting Monthly Inflation of Ghana

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Abstract

Inflation is the persistent increase in the level of consumer prices or a persistent decline in the purchasing power of money. Inflation is of global concerns because it can distort economic patterns and can result in the redistribution of wealth when not anticipated, thus there is a need to know the pattern of inflation in the country. In this study, we employed an empirical modeling and model selection for monthly inflation in Ghana from January 2009 to December 2013 using the Box-Jenkins approach. The results showed that ARIMA (1, 2, 1) model was appropriate for modelling the inflation rates with a maximum log likelihood value of -64.21, and least AIC value of 134,43, AICc value of 134.87 and BIC value of 140. 61. An ARCH-LM test and Ljung-Box test on the residuals of the models revealed that the residuals are free from heteroscedasticity and serial correlation respectively. Ghana is likely to experience a persistence increase in inflation rate with double digit hence the government should reconsider his monetary policies.

Keywords: Inflation, Box-Jenkins, Empirical, Ghana.

1. Introduction

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. High inflation distorts wealth redistribution in an economy, because it arbitrarily redistributes wealth among different groups of people in a society. Not only does inflation direct the link between effort and reward, it typically hits hardest those who least can afford it, Owusu (2010). 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. Inflation can also be expressed as a situation where the demand for goods and services exceeds their supply in the economy (Hall, 1982).

The most common measure of inflation is the consumer price index, which measures the inflation of a country over a time period (e.g. monthly, quarterly or annually). According to Ghana Statistical Service (2013), 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 the preceding year's price level (for example, 2012as reference for 2013).

Modeling inflation using the Box-Jenkins ARIMA approach is plausible to stakeholders because it generates reliable inflation forecast which follows closely with the actual data. Empirical researches have been carried out in the area of forecasting using Autoregressive Integrated Moving Average (ARIMA) models popularised by Box and Jenkins (1976). Meyer et al, (1998) considered the autoregressive integrated moving average (ARIMA) for forecasting Irish inflation and justified that ARIMA models are surprisingly robust with respect to alternative (multivariate) model. Candelaria et al., (2007), analyzed a set of countries which adopted inflation targeting as a policy tool and modelled the pre-IT period with ARMA and GARCH methods. They conducted the one-step ahead forecasting for the remainder of the times series data by comparing the actual and forecasted inflation levels for each country. Appiah and Adetunde (2011) used the Box and Jenkins (1976) approach to model and forecast the exchange rate between the Ghana cedi and the US dollar. In their study, they found that ARIMA (1, 1, 1) model was appropriate for forecasting, the exchange rate. Nasiru and Sarpong (2012) employed an empirical approach in modelling monthly data in Ghana using the Box-Jenkins approach. The result showed that ARIMA (3, 1, 3) (2, 1, 1)[12] model was appropriate for modelling the inflation rates.

In this study, our main objective was to model and forecast twelve (12) months inflation rate of Ghana outside the sample period. The post-sample forecasting is very important for 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 Ghana. 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.

2. Materials and Methods

This study was carried out in Ghana in January, 2014, using data on inflation rates from January, 2009 to December, 2013. The data was obtained from the website of the Bank of Ghana. The data was modeled using Autoregressive Integrated Moving Average (ARIMA) stochastic model. An autoregressive integrated moving average (ARIMA) model is a generalization of an autoregressive moving average (ARMA) model. These models are fitted to time series data either to better understand the data or to predict future points in the series.

Trends in time series can be removed by differencing the time series. This differencing is integrated into the ARMA models creating the ARIMA models. ARIMA (*p*, *d*, *q*) define models with an AutoRegressive part of order *p*, a Moving average part of order *q* and having applied *d* order differencing. 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.

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

$$\underbrace{(1-\Theta_1 B-\Theta_2 B^2-\ldots-\Theta_P B^P)}_{\mathrm{AR}(p)}\underbrace{(1-B)^d}_{\mathrm{I}(d)}y_t=\underbrace{(1-\alpha_1 B-\alpha_2 B^2-\ldots-\alpha_P B^P)}_{\mathrm{MA}(q)}\varepsilon_t$$

Where,
p is the Autoregressive order of the polynomial operator
q is the Moving Average order of the polynomial operator
Θ is the parameter estimate of the Autoregressive order
α is the parameter estimate of the Moving Average order
ε_t is purely a random process with mean zero and variance σ^2

The modelling of an ARIMA (*p*, *d*, *q*) model as delineated by Box–Jenkins consist of Model identification, Parameter Estimation and Diagnostic of selected model.

2.1 Model Identification

Identification step involves the use of the techniques to determine the values of *p*, *q* 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.

2.1.1 Unit root test:

This test was performed to check whether the data was stationary. In view of this, the Augmented Dickey-Fuller (ADF) test. The test is based on the assumption that a time series data y_t follows a random walk:

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

And Hypothesis

H_0: $\rho = 1$ (non-stationary)

H_0: $\rho < 1$ (stationary)

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

2.2 Estimation Parameters

The second step is the estimation of the model parameters for the tentative models that have been selected. Here, the model with the maximum log-likelihood and minimum values of Akaike Information Criterion (AIC), modified Akaike Information Criterion (AICc), and Normalized Bayesian Information Criterion (BIC) was considered as the best model.

2.3 Model Diagnostics

The estimated model must be check 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 plot of the ACF of the residuals was examined to see if the residuals are white noise. An overall check of the model adequacy was made using the Ljung-Box Q statistics.

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

$$Q_m = n(n+2)\sum_{k=1}^{n}(n-k)^{-1}r_k^2 \approx \chi^2_{m-r}$$

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, a plot of the ACF squared residual and PACF squared residuals was performed on the residuals of the fitted model to check for heteroscedasticity and again an ARCH LM-test for conformity of the presence of, or otherwise ARCH effect was performed.

3. Results and Discussion

Figure 1 shows the monthly inflation rate of Ghana. It is revealed from that Figure that inflation rate for the period of 2009 to 2013 is non-stationary due to an unstable mean which increase and decrease at certain points. 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 Figure 2, which shows a slow decline also from Figure 3 of the PACF plot which has a very significant spike at lag 1. The Augmented Dickey-fuller test further confirms this affirmation. The series was therefore first differenced and tested for stationary with the Augmented Dickey-fuller test: The first difference was not sufficient to make the series stationary as shown by the test but rather the second difference achieved stationarity as shown in Table 1. Table 2 shows the different models fitted to the series, ARIMA (1, 2, 1) appears to be the best model as it has the least AIC, AICc, BIC values. The estimates of the parameters of the model, shown in table 4.3, indicates that MA(1) model was significant at 0.05 significant level. Our diagnostic checking of the ARIMA (1, 2, 1), model revealed that the model was adequate for the series. The ACF plot of Squared of Residuals, PACF plot of Squared of Residuals and an ARCH-LM test showed that there were no ARCH effects; hence the residuals have a constant variance. The Ljung-Box p–values (> 0.05) showed that there is no serial correlation in the residuals of the model. The ACF plot of the residuals also shows that the residuals are white noise series.

4. Conclusion

This study used time series to model monthly inflation rate in Ghana using data from the Bank of Ghana (BoG) from the year 2009 to 2013. The modeling of the inflation rate was done mainly by ARIMA model. The Study revealed that, inflation rate is best modeled with ARIMA (1, 2, 1). The diagnostics of this model showed that the model adequately fits the series hence is adequate for the forecasting of inflation rate in Ghana. A twelve (12) month’s forecast with our model for the year 2014 showed continues increase in the inflation pattern. From the out-sample forecast, we surmise that the country is likely to experience double digit inflation for the year 2014. Hence, policy makers should re-evaluate their policies in other to determine other factors that contribute to the high inflation rates in Ghana.

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Appendix

Tables and figures of inflation rate of Ghana

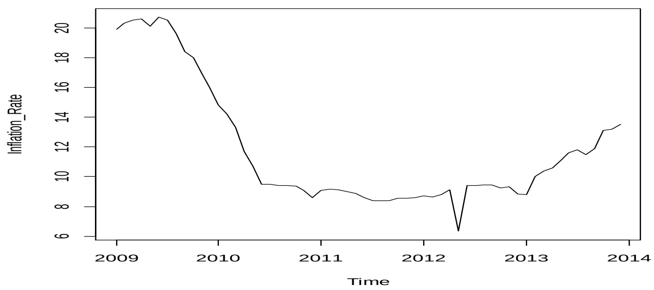


Figure 1: General trend of Ghana's monthly inflation rate

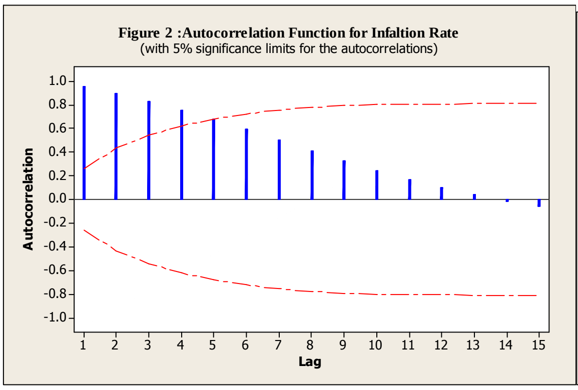


Figure 2 :Autocorrelation Function for Infaltion Rate
(with 5% significance limits for the autocorrelations)

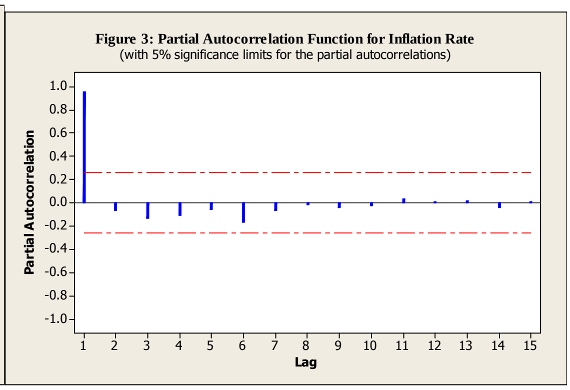
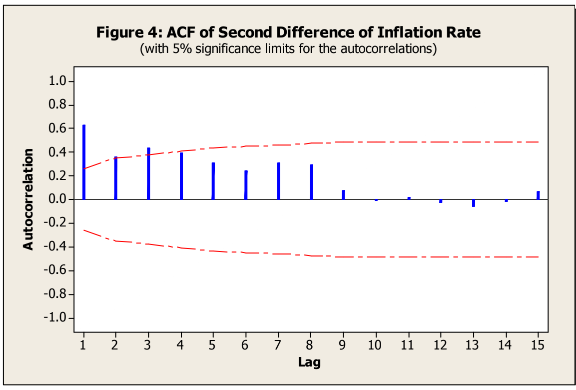


Figure 3: Partial Autocorrelation Function for Inflation Rate
(with 5% significance limits for the partial autocorrelations)

Table 1 Augmented Dickey Fuller Test for Inflation Rate

Oder of Differencing	ADF Test Statistic	P-Value
0	-1.0035	0.93
1	-3.3808	0.07
2	-6.2167	0.01



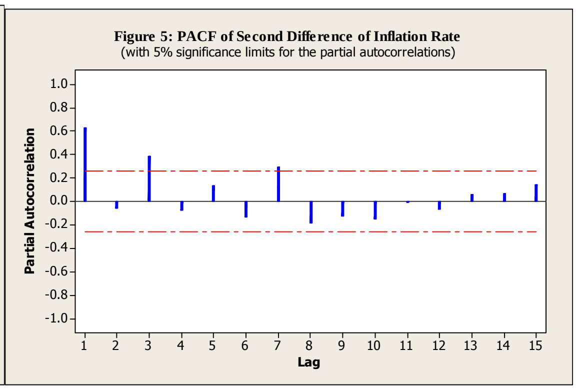


Table 2: Different ARIMA (p, 2, q) Models fitted

Model	AIC	AICC	BIC	Log-Likelihood
ARIMA(1,2,1)	134.43*	134.87*	140.61*	-64.21
ARIMA(1,2,3)	136.89	138.04	147.19	-63.45
ARIMA(2,2,1)	135.85	136.61	144.09	-63.93
ARIMA(2,2,3)	135.14	136.79	147.51	-61.57
ARIMA(2,2,7)	142.35	147.03	162.95	-61.17*
ARIMA(3,2,1)	137.80	138.95	148.10	-63.90
ARMA(3,2,3)	141.66	143.90	156.08	-63.83
ARIMA(3,2,7)	145.75	151.49	168.42	-61.88

*****Best model based on the selection criterion

Table 3: Estimate of ARIMA (1,2,1) model

Type	Coefficient	SE	T statistic	P-Value
Constant	0.012	0.021	0.590	0.560
AR(1)	-0.279	0.147	-1.900	0.063
MA(1)	0.789	0.094	8.390	0.000

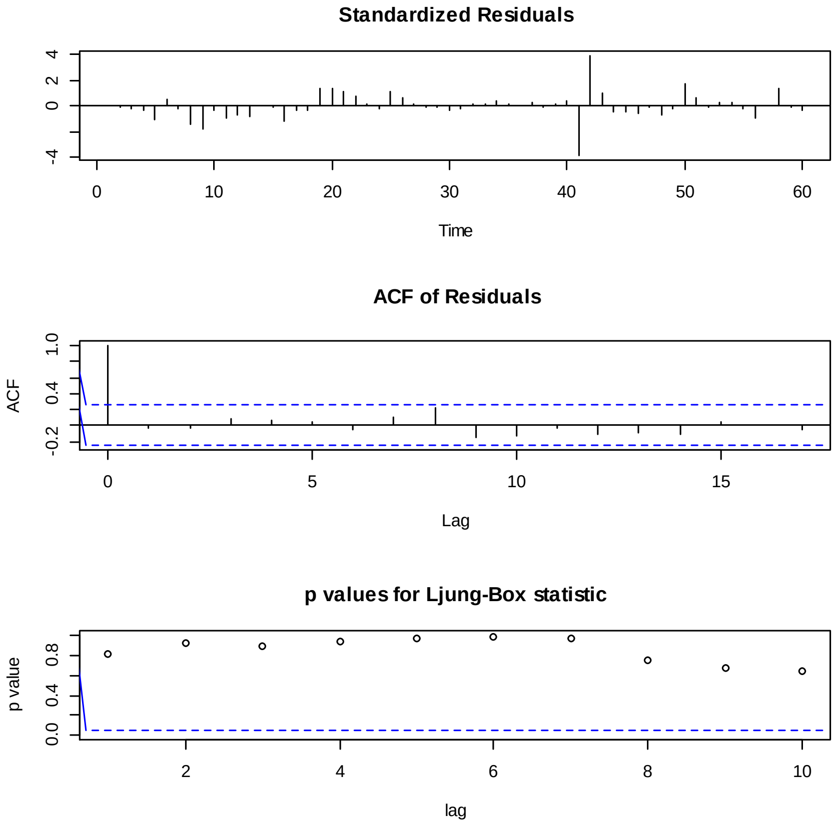
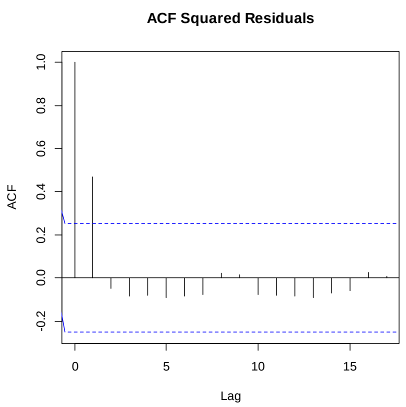


Figure 4.6 Diagnostic Plot of Residuals of ARIMA (1, 2, 1)



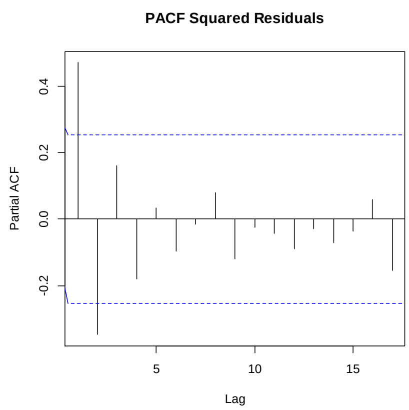


Figure 7 Plot of ACF Squared Residuals Figure 8 Plot of PACF Squared Residuals

Table 4 ARCH LM Test for ARIMA (1,2,1) Residuals

Lag	Chi-squared	P-Value
12	18.829	0.093
24	19.722	0.712
36	24.000	0.937
48	12.000	1.000

Table 5: 12 Months Out Sample Forecast For the Year 2014

Month	Forecast	LCL	UCL
January	13.885	12.465	15.304
February	14.244	12.271	16.217
March	14.611	11.969	17.253
April	14.976	11.653	18.299
May	15.341	11.293	19.389
June	15.706	10.897	20.516
July	16.072	10.897	21.68
August	16.437	10.463	22.88
September	16.802	9.994	24.115
October	17.167	9.489	25.385
November	17.533	8.95	26.687
December	17.898	8.378	28.021