Modelling the Ghanaian Inflation Rates Using Interrupted Time Series Analysis Approach

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Abstract

The article considers the application of interrupted time series analysis to model yearly inflation rates in Ghana from 1996 to 2006. This article, therefore, explored the effectiveness of the economic policy intervention in the year 2001 on the inflation rate time series for the period 2001 to 2006 using the interrupted time series experiment. We also sort to use this model to make forecasts of future values. To achieve this objective, yearly inflation rates for the period were obtained from Bank of Ghana (BoG). The Box-Jenkins Autoregressive Integrated Moving Average (ARIMA) method with interruption was employed in analyzing the data using Statistical Product for Service Solution (SPSS) version 20. It was found that the rate of inflation in Ghana can be fitted with an autoregressive model of order one, i.e. AR (1) model. From the results of the tests of the difference between the means before and after intervention, as well as the interrupted time series experiment, indicated that the intervention successfully reduced the rate of inflation in the Ghana's economy.

Keywords: Inflation, Interrupted Time Series, Box-Jenkins Method.

1. Introduction

In Ghana, the debate of achieving a single digit inflation value has been the major concern for both the government and the opposition parties. While the government boasts of a stable economy with consistent single digit inflation, the opposition parties' doubts these figures and believe that the figures had been cooked up and do not reflect the true situation in the economy. Webster (2000) defined inflation as the persistent increase in the level of consumer prices or a persistent decline in the purchasing power of money. Price stability (stable inflation) is one of the main objectives of every government as it is an important economic indicator that the government, politicians, economists and other stakeholders use as their basis of argument when debating on the state of the economy (Suleman and Sarpong, 2012). In recent years, rising inflation has become one of the major economic challenges facing most countries in the world especially developing countries like Ghana. David (2001) described inflation as a major focus of economic policy worldwide.

Inflation and its volatility entail large real costs to the economy (Moreno, 2004). Among the harmful effects of inflation volatility are the higher risk of permia for long term arrangement, unforeseen redistribution of wealth and higher costs for hedging against inflation risks (Rother, 2004). Thus inflation volatility canimpede growth even if inflation on the average remains restrained (Awogbemi and Oluwaseyi, 2011) and hence monetary policy makers are more interested in containing and reducing inflation through price stability (Amos, 2010). Policy makers will be content and satisfied if they are able to understand the underlying dynamics of inflation and how it evolves. Ngailo (2011) observes that inflation dynamics and evolution can be studied using a stochastic modelling approach that captures the time dependent structure embedded in the time series inflation data.

Inflation is a persistent rise in the general price levels of goods and services in an economy over a period of time. Inflation rate has been regarded as one of the main economic indicators in any country. According to Olatunji *et al*. (2010), inflation undoubtedly remains as one of the leading and most dynamic macro-economic issues confronting almost all economies of the world. Its dynamism has made it an imperative issue to be considered. Odusanya and Atanda (2010) determined the dynamic and simultaneous interrelationship between inflation and its determinants – growth rate of Gross Domestic Product (GDP), growth rate of money supply (M2), fiscal deficit, exchange rate (U.S dollar to Naira), importance and interest rates, using econometric time series model. Olatunji *et al*. (2010) examined the factors affecting inflation in Nigeria using cointegration and descriptive statistics. They observed that there were variations in the trend pattern of inflation rates and some variables considered were significant in determining inflation in Nigeria. These variables include annual total import, annual consumer price index for food, annual agricultural output, interest rate, annual government expenditure, exchange rate and annual crude oil export.

Some econometric models have been used to describe inflation rates, but they are restrictive in their theoretical formulations and often do not incorporate the dynamic structure of the data and have tendencies to inflict improper restrictions and specifications on the structural variables (Saz, 2011). Mordi *et al*. (2007), in their study of the best models to use in forecasting inflation rates in Nigeria identified areas of future research on inflation dynamics to include re-identifying ARIMA models, specifying and estimating VAR models and estimating a P-Star model, amongst others that can be used to forecast inflation with minimum mean square error.

The absence of restriction in the ARIMA model gives it the necessary flexibility to capture dynamic properties and thus significant advantage in short-run forecasting (Saz, 2011). Encouraged by these empirical results on the superiority of ARIMA models, Saz (2011) applied Seasonal Autoregressive Integrated Moving Average (SARIMA) model to forecast the Turkish inflation. Longinus (2004) examined the influence of the major determinants of inflation with a particular focus on the role of exchange rate policy of Tanzania from 1986 to 2002. He discovered that the parallel exchange rate had a stronger influence on inflation. Other works on modeling inflation rates are seen in the works of Fatukasi (2003), Eugen *et al.* (2007) and Tidiane (2011).

This paper explores the effectiveness of the economic policy intervention in the year 2001 on the inflation rate time series for the period 2001 to 2006 using the interrupted time series experiment. We also seek to use this model to make forecasts of future values.

2.0 Materials and Method

2.1 Model Specification

2.1.1 ARMA or "Mixed" Process

Consider the process given by;

$$Y_t = \alpha_1 Y_{t-1} + \theta_1 e_{t-1} + e_1$$

This can be rewritten as

$Y_t - \alpha_1 Y_{t-1} = e_t + \theta_1 e_{t-1}$ Or

$(1 - \alpha B)Y_t = (1 + \theta B)e_t$…………………………….. (1)

$AR(B)Y_t = MA(B)e_t$

This is called a mixed or autoregressive moving average (ARMA) process of order (1,1).

Since equation (1) is ARMA(1,1) if $|\theta| < 1$ it can be rewritten as

$$(1 - \alpha B)\left(\frac{1}{1 + \theta B}\right)Y_t = e_t$$

$$(1 - \alpha B)(1 - \theta B + \theta^2 B^2 - \theta^3 B^3 + \cdots)Y_t = e_t$$

$$[(1 - \alpha + \theta)B + (\alpha\theta + \theta^2)B^2 + \cdots]Y_t = e_t$$

This is an infinite order AR process. This is true if $|\alpha| < 1$ and $|\theta| < 1$ i.e. if the AR is stationary and MA is invertible. If we have two polynomial in B, MA(B) and AR(B), and an ARMA model,

$AR(B)Y_t = MA(B)e_t$

It is possible to write the model as an infinite AR process:

$$\left(\frac{AR(B)}{MA(B)}\right) Y_t = e_t$$

Or an infinite MA process

$$Y_t = \left(\frac{MA(B)}{AR(B)}\right) e_t$$

And approximate either by finite processes

ARMA processes are parsimonious however identifying those using ACF and PACF may be difficult. The condition necessary for dividing by AR(B) is that the AR process be stationary and by MA(B) is that the MA process be invertible.

2.1.2 Autoregressive Moving Average Model (ARMA)

A more general model is a mixture of the AR(p) and MA(q) models and is called an autoregressive moving average model (ARMA) of order (p,q).

The ARMA(p,q) is given by

$$Y_t = \sum_{i=1}^{p} \alpha_i Y_{i-1} + \sum_{i=1}^{q} \theta_i e_{i-1} + \mu + e_t$$

An example of an ARMA(1,1)

$$Y_t = \alpha_1 Y_{t-1} + \theta_1 e_{t-1} + \mu + e_t$$

An important characteristic of ARMA models is that both the ACF and PACF do not cut off as in AR and MA models.

(Box and Jenkins, 1971)

2.1.3 The Autoregressive Integrated Moving Average Model (ARIMA)

If a non-stationary time series which has variation in the mean is differenced to remove the variation the resulting time series is called an integrated time series. It is called an integrated model because the stationary model which is fitted to the differenced data has to be summed or integrated to provide a model for the non-stationary data. Notationally, all AR(p) and MA(q) models can be represented as ARIMA(1,0,0) that is no differencing and no MA part.

The general model is ARIMA(p,d,q) where p is the order of the AR part, d is the degree of differencing and q is the order of the MA part.

Writing $$W_t = \nabla^d Y_t = (1 - B)^d Y_t$$

The general ARIMA process is of the form

$$W_t = \sum_{t=1}^{p} \alpha_i W_{t-i} + \sum_{t=1}^{q} \theta_i e_{t-i} + \mu + e_t$$

(Hamilton J.D, 1994)

2.1.4 Extension of the Procedure to AR(p) Models

Assume that n_1 data points before intervention consist of a stationary stochastic component, which is fitted with an autoregressive model, plus a linear trend. Thus before intervention $(t = p + 1, p + 2, \dots n_1)$ the data can be represented as

$$Y_t = m_1 t + b_1 + \sum_{t=1}^{p} \alpha_i Y_{i-1} + e_t$$

ISSN 2224-5804 (Paper) ISSN 2225-0522 (Online)
Vol.6, No.2, 2016

After intervention $(t = n_{t+1}, \dots, N)$ and assume $n_2 = N - n$ data points move to a new asymptotic trend line. It is further assumed that the autoregressive parameters have not changed as a result of the intervention. Thus after the intervention the data can be represented as

$$Y_t = m_2 t + b_2 + \sum_{t=1}^{p} \alpha_i Y_{t-i} + e_t$$

The next stage is to estimate the parameters m_1, b_1, α_1, m_2 and b_2. one proceeds to find whether there has been significant changes in the values of m_1 and b_1 as reflected in the values of m_2 and b_2 which will be used to test whether the intervention was successful.

$$\beta = \begin{pmatrix} b_1 \\ m_1 \\ b_2 \\ m_2 \\ \alpha_1 \\ \alpha_2 \\ . \\ . \\ . \\ \alpha_p \end{pmatrix} = \begin{pmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \\ \beta_4 \\ \beta_5 \\ \beta_6 \\ . \\ . \\ . \\ \beta_{p+4} \end{pmatrix} \qquad E = \begin{pmatrix} e_{p+1} \\ e_{p+2} \\ . \\ . \\ . \\ . \\ e_N \end{pmatrix}$$

As usual the least squares estimates are

$$\beta = (X^T X)^{-1} X^T Y$$

If the estimate of σ_e^2 is denoted by S_e^2 which $\left(\frac{1}{v}\right)(Y - X\beta)^T(Y - X\beta)$,

Where v, the degrees of freedom for errors is $N - 2p - 4$ and denote the C as the diagonal of $(X^T X)^{-1}$, then each of the parameters in $\beta_i = (b_1, m_1, b_2, m_2, \alpha_1, \dots, \alpha_p)$ can be referred to a

t-distribution with v degrees of freedom, where

$$T = \frac{\beta_1}{S_e\sqrt{C_i}}$$

The data points do not actually lie on the lines $m_1 t + b_1$ before and $m_2 t + b_2$ after intervention. Rather, before intervention the data follow a steady-state trend line of the form $B_1 + M_1 t$ and approach $B_2 + M_2 t$ after intervention.

2.3 Estimation of Parameters

2.3.1 Estimating the Parameters of an ARMA Model

The procedure for estimating the parameters of the ARMA model is like the one for the MA model it is an iterative method. Like the MA the residual sum of squares is calculated at every point on a suitable grid of the parameter values, and the values, and the values give the minimum sum of squares are the estimates.

For an ARMA (1, 1) the model is given by

$$Y_t - \mu = \alpha_1(Y_{t-1} - \mu)e_t + \theta_1 e_{t-1}$$

Given N observation $Y_1, Y_2, \dots, Y_N$, we guess values for μ, α_1, θ_1, set $e_0 = 0$ and $Y_0 = 0$ and then calculate the residuals recursively by

$$e_1 = Y_1 - \mu$$

$$e_2 = Y_2 - \mu - \alpha_1(Y_1 - \mu) - \theta_1 e_1$$

$$\dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots$$

$$\dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots$$

$$e_N = Y_N - \mu - \alpha_1(Y_1 - \mu) - \theta_1 e_{N-1}$$

The residual sum of squares $\sum_{t=1}^{N} e_t^2$ is calculated. Then other values ofμ, α_1, θ_1, are tried until the minimum residual of squares is found.

Note: It has been found that most of the stationary time series occurring in practices can be fitted by AR(1), AR(2), MA(1), MA(2), ARMA(1,1) or white noise models that are customarily needed in practice.

(Hamilton J.D, 1994)

2.3.2 Estimating the parameters of an ARIMA Model

In practice most time series are non-stationary and the series is differenced until the series becomes stationary. An AR, MA or ARMA model is fitted to the differenced series and estimation procedures are as described for the AR, MA, ARMA above.

2.4 Tests

2.4.1 The Box-Jenkins Method of Modeling time Series

The Box-Jenkins methodology is a statistical sophisticated way of analyzing and building a forecasting model which best represents a time series. The first stage is the identification of the appropriate ARIMA models through the study of the autocorrelation and partial autocorrelation functions. For example if the partial autocorrelation cuts off after lag one and the autocorrelation function decays then ARIMA(1,0,0) is identified. The next stage is to estimates the parameters of the ARIMA model chosen.

The third stage is the diagnostic checking of the model. The Q-statistic is used for the model adequacy check.

If the model is not adequate then the forecaster goes to stage one to identify an alternative model and it is tested for adequacy and if adequacy then the forecaster goes to the final stage of the process.

The fourth stage is where the analysis uses the model chosen to forecast and the process ends.

2.4.2 Measurement of the intervention Effect

The procedure used in this work is to fit an AR(p) an autoregressive model of order p to the interrupted time series data using the Box-Jenkins methods of fitting a model to a time series data. The next step is to use the least squares method to estimate the parameters and statistical methods to assess the effectiveness of the intervention. (McDowall, et al)

Let us consider an imaginary interrupted time series data which can be fitted with a stationary AR(1) model which has a zero mean.

$Y_t = \alpha_1 Y_{t-1} + e_t$ where α_1 is the AR(1) parameter and e_t is the white noise. Let us assume further that we have n_1 data points before intervention and n_2 points after intervention and $n_1 + n_2 = N$. Suppose we assume that the effect is to add γ to the mean level.

The data can be expressed as follows

$$Y_2 = \alpha_1 Y_1 + e_2$$

$$Y_3 = \alpha_1 Y_2 + e_t$$

$$\vdots$$

$$Y_n = \alpha_1 Y_{n-1} + e_{n-1}$$

$$Y_{n+1} = \alpha_1 Y_n + e_n + \gamma$$

$$\vdots$$

$$Y_N = \alpha_1 Y_{N-1} + e_{N-1} + \gamma$$

This model can be written in matrix notation as

$$Y = X\beta + E$$

Where

$$X = \begin{bmatrix} 0 & Y_1 \\ 0 & Y_2 \\ . & Y_{n-1} \\ . & Y_n \\ 1 & . \\ 1 & . \\ 1 & Y_{N-1} \end{bmatrix} \quad Y = \begin{bmatrix} Y_2 \\ Y_3 \\ . \\ . \\ . \\ Y_n \end{bmatrix} \quad \beta = \begin{bmatrix} \gamma \\ \alpha \end{bmatrix} \quad \text{and} \quad E = \begin{bmatrix} e_2 \\ e_3 \\ . \\ . \\ . \\ . \\ e_N \end{bmatrix}$$

This has the least squares solution as

$\beta = \begin{bmatrix} \gamma \\ \alpha_1 \end{bmatrix} = (X^T X)^{-1} X^T X$. Where X^T is the transpose of$X$.

In this case, it is easy to show that

$$.X^T X = \begin{bmatrix} n_2 & \sum_{n_1}^{N-1} Y_t \\ \sum_{n_1}^{N} Y_t & \sum_1^{N-1} Y_t^2 \end{bmatrix} \qquad X^T Y = \begin{bmatrix} \sum_1^N Y_t \\ \sum_2^N Y_t Y_{t-1} \end{bmatrix}$$

If the first element (first row, first column) of $(X^T X)^{-1}$ is denoted by C, it can also be shown that an asymptotic standard normal $[N(0,1)]$ tests can be derived for δ under the null hypothesis that $\delta = 0$ for small samples.

The following is a statistic with an approximate t distribution

$t_{N-3} = \frac{\gamma}{(Se)\sqrt{c}}$ where Se is the square root of the residual variance, computed as

$$S_e^2 = \frac{1}{N-3}(Y - X\beta)^T (Y - X\beta).$$

2.4.3 Steady-state solutions

Suppose that $Y_t = \sum \alpha Y_{t-1} + mt + b + e_t$

Then the expected value of Y_t is $E(Y_t) = \sum \alpha_i E(Y_{t-1}) + m_t + b$

Mathematical Theory and Modeling
ISSN 2224-5804 (Paper) ISSN 2225-0522 (Online)
Vol.6, No.2, 2016

To find the steady-state solution of this difference equation in $E(Y_t)$, we assume

$$M_t + B = \sum \alpha_i \left(M(t-1) + B\right) + m_t + b$$

Equating coefficients of t and constant terms we have

$$Mt = \left(\sum \alpha_i\right) Mt + mt$$

$$B = \sum \alpha_i(-i)M + (\sum \alpha_i) + mt + b$$

So that $M = \frac{m}{1-\sum \alpha_i}$ and $B = \frac{b-M(\sum \alpha_i)}{1-\sum \alpha_i}$

For example for an AR(p) model with n_1 data points before intervention and n_2 data points after intervention where $n_1 + n_2 = N$, the model becomes

$$Y_t = m_1 t + b_1 + \sum_{i=1}^{p} \alpha_i Y_{t-1} + e_t$$

Before intervention and

$$Y_t = m_2 t + b_2 + \sum_{t=1}^{p} \alpha_i Y_{t-1} + e_t$$

After intervention.

The matrix notation is follows

$$Y = \begin{pmatrix} Y_3 \\ Y_4 \\ Y_{N1-2} \\ . \\ . \\ Y_N \end{pmatrix} \qquad X = \begin{pmatrix} 1 & 1 & 0 & 0 & Y_2 & Y_1 \\ 1 & 2 & 0 & 0 & Y_3 & Y_2 \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ 0 & N1 & 0 & 0 & Y_{N1-1} & Y_{n1-2} \\ 0 & 0 & 1 & 1 & Y_{N1} & Y_{N1-1} \\ 0 & 0 & 2 & 2 & . & Y_{n1} \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ 0 & 0 & 1 & n_2 & Y_{N-1} & Y_{N-2} \end{pmatrix}$$

$$\beta = \begin{bmatrix} M_1 \\ B_1 \\ M_2 \\ B_2 \\ \alpha_1 \\ \alpha \end{bmatrix} = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \\ \beta_4 \\ \beta_5 \\ \beta_6 \end{bmatrix} \qquad E = \begin{bmatrix} e_3 \\ e_4 \\ . \\ . \\ . \\ e_N \end{bmatrix}$$

And $\beta = (X^T X)^{-1} \quad X^T X$ and $\quad T = \frac{\beta_1}{S_e\sqrt{C_i}} \qquad i = 1, 2, 3, 4$

2.4.4 Testing for the significance of the Intervention

Here we test:

$$H_0 : m_1 = m_2, \qquad b_1 = b_2 \ (intervention\ ineffective\ )$$

Against:

$$H_1 : m_1 \neq m_2, \qquad b_1 \neq b_2 \ (intervention\ efffective)$$

Let SS_0 denote the residual error sum of squares in the reduced model.

$$Y_t = m_1 + b + \sum_{i=1}^{p} \alpha_i Y_{i-1} + e_t \qquad for\ all\ t$$

And let SS_0 denote the residual sum of squares in the full model

$$Y_t = m_1 t + b_1 + \sum_{i=1}^{p} \alpha_i Y_{i-1} + e_t \qquad t = p + 1, \ldots, n_1$$

And

$$Y_t = m_2 t + b_2 + \sum_{i=1}^{p} \alpha_i Y_{i-1} + e_t \qquad t = n_1, \ldots, N$$

Then under the null hypothesis,

$$F = \frac{(SS_0 - SS_1)/_2}{SS_1/_v}$$

Has an F(1,v) distribution. Here v, the error degrees of freedom is equal to the number of observations minus the number of “start up” observations (2 in AR(2) model or 3 in AR(3) minus the number of parameters fit, that is 6 in AR(2) and 4 in AR(1).

3.0 Results

3.1 Identification of the Model

The autocorrelation function dies down and the partial autocorrelation function cuts off after lag one. This identifies an AR (1) process which has the form

$$Y_t = \alpha Y_{t-1} + e_t$$

Fig. 1 and Fig. 2 shows the graph of the autocorrelation and partial autocorrelation functions respectively.

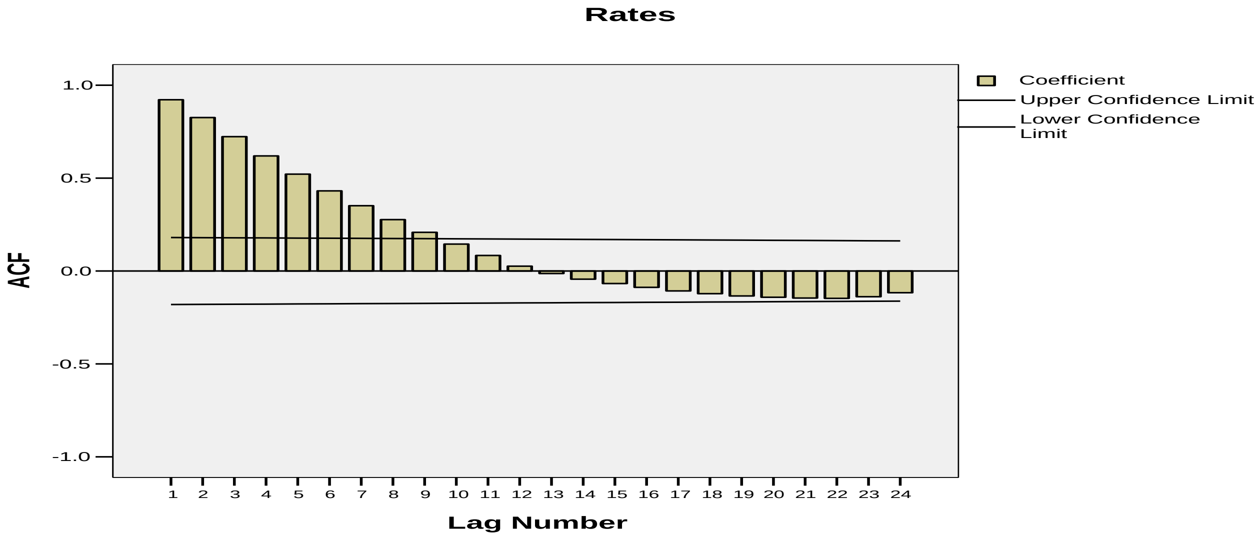

Fig 1 ACF of monthly inflation rate in Ghana from Jan. 96 to Dec. 06

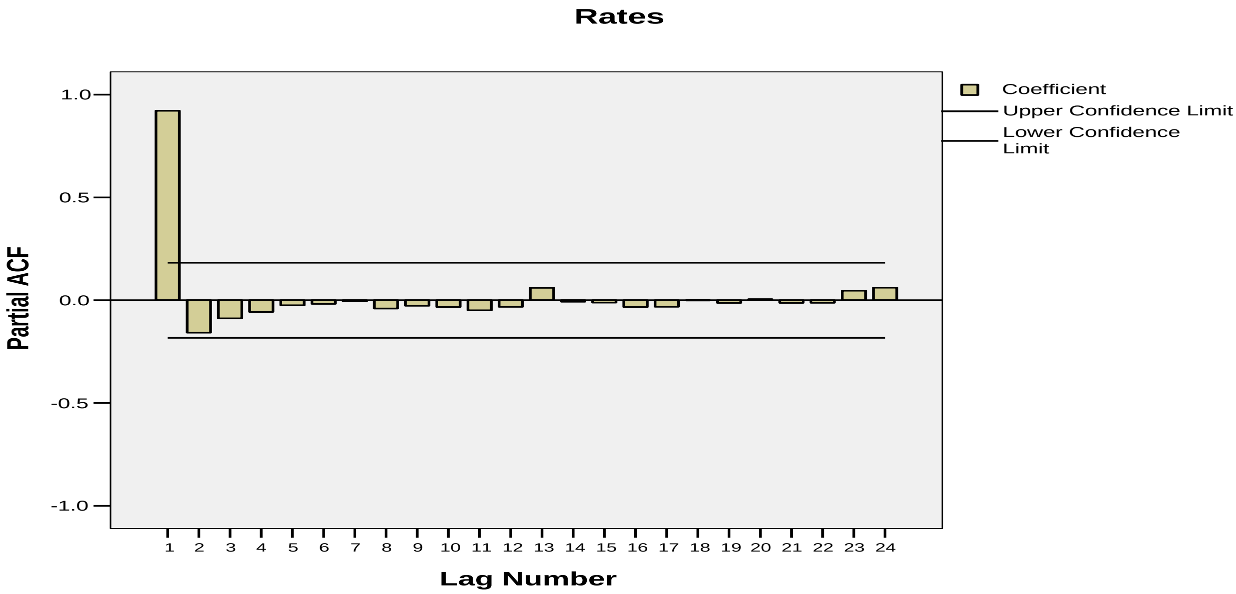

Fig 2 PACF of monthly inflation rate in Ghana from Jan. 96 to Dec. 06

Table 1 Analysis of the time series data

ARIMA MODEL	RESIDUAL VARIANCE	AIC	Q-VALUE
(1,0,0)	6.197	566.019	16.780

Since the interrupted time series analysis look out for an ARIMA (p.0.0), the ARIMA (1,0,0) is the best model for the time series data and it is also adequate since the Q- value is less than the critical value. It has the form

$$Y_t = 0.995Y_{t-1} + 37.657$$

3.2 Adequacy Test for an ARIMA (p, d, q) Model

For any ARIMA (p,d,q) model, the χ^2-distribution can be used to test for the adequacy of the model. The Q-statistics is distributed as χ^2_{k-p-q} where k=24 (maximum lag) used for Q, p is the order of the AR process and q is the order of the MA process. For example, ARIMA (1,0,0) is distributed as $\chi^2_{24-1-0} = \chi^2_{23}$.

In Table 2 below, we display the critical values for some ARIMA models.

Table 2 Chi Square Distribution

DISTRIBUTION	SIGNIFICANCE LEVEL	CRITICAL VALUE
χ^2_{23}	0.05	35.172
χ^2_{22}	0.05	33.924
χ^2_{21}	0.05	32.671
χ^2_{20}	0.05	31.410

3.3 Interrupted Time Series

3.3.1 Test For Significance of Difference Between The Means of The Pre-Intervention Data and The Post-Intervention Data

Let μ_1 *be the sample mean of the pre − intervention data*

μ_2 *be the sample mean of the post − intervention data*

${\sigma_1}^2$ *be the sample variance of the pre − intervention data*

${\sigma_2}^2$ *be the sample variance of the post − intervention data*

$$\mu_1 = 27.1063 \qquad \mu_2 = 21.3250$$

$$n_1 = 48 \qquad n_2 = 72$$

$${\sigma_1}^2 = 239.482 \qquad {\sigma_2}^2 = 87.086$$

$${\sigma_p}^2 = 147.786 \qquad \sigma_p = 12.158$$

Where σ_p^2 is the pooled variance of the population which is given by

$$\sigma_p^2 = \frac{(n_1-1)\sigma_1^2 + (n_2-1)\sigma_2^2}{n_1+n_2-2}$$

Hypothesis

$H_0 : \mu_1 = \mu_2$ (Intervention not effective)

$H_1 : \mu_1 \neq \mu_2$ (Intervention effective)

Test Statistic

$$Z = \frac{(\mu_1-\mu_2)}{\sigma_P\sqrt{\frac{1}{n_1}+\frac{1}{n_2}}} \sim N(0,1$$

Decision Rule

$$If\ Z \geq 1.65,\ reject\ H_0\ \ and\ accept\ H_1$$

$$If\ Z < 1.65, accept\ H_0\ and\ reject\ H_1$$

Calculation

$$Z = \frac{(27.1063 - 21.3250)}{12.158\sqrt{\frac{1}{48} + \frac{1}{72}}} = 2.552$$

Since Z=2.552 > 1.65 we reject H_0 and accept H_1 and conclude that there is enough evidence at the 5% level of significance of a decrease in the mean level of the inflation in Ghana after the intervention policy in 2000.

3.3.2 USE OF REGRESSION ANALYSIS TO MODEL TREND AND AUTOREGRESSIVE COMPONENTS

We attempt to apply the interrupted time series analysis described in section 2.0 to estimates b_1, b_2, m_1, m_2, α. Here b_1 and b_2 are the intercepts and m_1 and m_2 are the slopes before and after intervention while α is the AR parameters. This is done by use of SPSS for the regression analysis.

The results for the full and reduced models are displayed in the tables below.

Table 3 Variables in the equation of full model

VARIABLE	ESTIMATES	STD. ERROR	95% CI LOWER	95%CI UPPER	T-VALUE	SIG.
B_1	1.230	1.529	-1.800	4.260	0.804	0.423
M_1	-.004	0.035	-0.074	0.066	-0.117	0.907
B_2	3.097	0.961	1.193	5.001	3.222	0.002
M_2	-.036	0.014	-0.064	-0.008	-2.532	0.013
α	.916	0.027	0.000	0.970	34.002	0.000

Table 4 Model efficiency of full model

R	R-SQUARE	ADJUSTED R	STD. ERROR
0.997	0.993	0.993	2.19774

From the Table 4 it indicates that about 99.3% of the variability in the inflation was explained by the predictor variables with standard error of about 2.19774.

Table 5 ANOVA of full model

MODEL	DF	SSS	MSE	F	SIG. F
REGRESSION	5	80110.663	16022.133	3317.167	0.000
RESIDUAL	114	550.627	4.830		

From Table 5 above, the value of the p-value is less than the significance level (0.05). This means that there is sufficient evidence to reject the null hypothesis and conclude that the intervention effect was effective at 95% confidence level.

The autocorrelation function dies down and the partial autocorrelation function cuts off after lag one indicating an autoregressive process of order one i.e. AR (1) process**.** The model is;

$Y_t = 0.995Y_{t-1} + 37.657$

The significance test of the difference between the means of the pre and post intervention data was significant. There was enough evidence at the 5% level of significance that the mean before the intervention was greater than the mean after the intervention.

4. Conclusion

It was found that the rate of inflation in Ghana can be fitted with an autoregressive model of order one, i.e. AR (1) model. From the results of the tests of the difference between the means before and after intervention, as well as the interrupted time series experiment, it means/imply that the intervention has successfully reduced the rate of inflation in the nation.

It is recommended that the Government continues with the tight monetary policy, Open Market Operations (OMO), Repurchase Agreements (Repos) and prime rate (interest Rate) policies that has been used since Jan 2000 to Dec 2006 in trying to reduce the rate of inflation since it was effective.

Also further study that relates interest rate to inflation could be carried researched into.

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