Modeling and forecasting inflation in The Gambia: an ARMA approach

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6 May 2019

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ABSTRACT

This research uses annual time series data on inflation rates in The Gambia from 1962 to 2016, to model and forecast inflation using ARMA models. Diagnostic tests indicate that G is I(0). The study presents the ARMA (1, 0, 0) model [which is nothing but an AR (1) model]. The diagnostic tests further imply that the presented optimal ARMA (1, 0, 0) model is stable and indeed acceptable. The results of the study apparently show that G will be approximately 7.88% by 2020. Policy makers and the business community in The Gambia are expected to take advantage of the anticipated stable inflation rates over the next decade.

Key Words: Forecasting, Inflation, The Gambia

JEL Codes: C53, E31, E37, E47

INTRODUCTION

Inflation is the sustained increase in the general level of prices and services over time (Blanchard, 2000). The negative effects of inflation are widely recognized (Fenira, 2014). An increase in the general price level causes a reduction in the purchasing power of money. Inflation reflects a reduction in the purchasing power per unit of money – a loss o real value in the medium of exchange and unit of account within the economy (Walgenbach *et al*, 1973). Inflation exerts a constraining effect on the key drivers of growth. The price increase reduces consumption and therefore production and employment. It exerts an inhibitory effect on investment, due to the rise of the nominal wages and the prices of raw materials, both in local and foreign currency. Inflation also contributes to the deterioration of the trade balance when the prices of domestic goods and services rise more than those of foreign competitors. To this are added its negative effects on social activity because of the deterioration of the purchasing power (Fenira, 2014).

It is now generally accepted that keeping low and stable rates of inflation is the primary objective of central banks (Hector & Valle, 2002). Inflation forecasts and projections are also often at the heart of economic policy decision-making, as is the case for monetary policy, which in most industrialized economies is mandated to maintain price stability over the medium term (Buelens, 2012). Economic agents, private and public alike; monitor closely the evolution of prices in the economy, in order to make decisions that allow them to optimize the use of their resources (Hector & Valle, 2002). Decision-makers hence need to have a view of the likely future path of inflation when taking measures that are necessary to reach their objective (Buelens, 2012). The fundamental aim of monetary policy, both in The Gambia and elsewhere, continues to be the maintenance of a low and stable rate of inflation. This study seeks to model and forecast annual rates of inflation in The Gambia based on ARMA models.

LITERATURE REVIEW

Stovicek (2007) analyzed inflation in Slovenia using ARMA models with a data set ranging from January 1994 to June 2006 and revealed that in terms of forecast ability ARMA models outperform AR models, when allowing for the same degrees of freedom. Osarumwense & Waziri (2013) modeled and forecasted monthly inflation rate volatility using GARCH models with a data set ranging over the period January 1995 to December 2011 and found out that the GARCH (1, 0) + ARMA (1, 0) model is appropriate for forecasting inflation in Nigeria. Popoola *et al* (2017) forecasted inflation rate in Nigeria using Box-Jenkins ARIMA models with a data set ranging over the period January 2006 to December 2015 and established that the ARIMA (0, 1, 1) model was the best model for forecasting inflation rate in Nigeria. Nyoni (2018) investigated inflation in Zimbabwe using GARCH models with a data set ranging over the period July 2009 to July 2018 and established that there is evidence of volatility persistence for Zimbabwe's monthly inflation data. In another recent paper, Nyoni (2018) modeled inflation in Kenya using ARIMA and GARCH models and relied on annual time series data over the period 1960 – 2017 and found out that the ARIMA (2, 2, 1) model, the ARIMA (1, 2, 0) model and the AR (1) – GARCH (1, 1) model are good models that could be used to forecast inflation in Kenya. Nyoni & Nathaniel (2019), relying on ARMA, ARIMA and GARCH models; analyzed inflation in Nigeria using time series data on inflation rates from 1960 to 2016 and found out that the ARMA (1, 0, 2) model is the best model for forecasting inflation rates in Nigeria. In the case of The Gambia, Manjang (2014) analyzed inflation using SARIMA and GARMA models and revealed that k-factor GARMA outperforms the SARIMA in out-of-sample forecasting.

MATERIALS & METHODS

ARMA Models

For the purpose of forecasting rates of inflation in the Gambia, ARMA models were specified and estimated. A general ARMA (p, q) model is specified as follows:

$$G_t = \alpha_1 G_{t-1} + \alpha_2 G_{t-2} + \cdots + \alpha_p G_{t-p} + \varepsilon_t + \beta_1 \varepsilon_{t-1} + \beta_2 \varepsilon_{t-2} + \cdots + \beta_q \varepsilon_{t-q} \ldots\ldots\ldots\ldots\ldots [1]$$

Where:

G_t rates of inflation in the Gambia at time t;

ε_t is the error term at time t;

$\varepsilon_{t-1} \ldots \ldots \ldots \ldots . \varepsilon_{t-q}$ are past errors;

$G_{t-1} \ldots \ldots \ldots \ldots . G_{t-p}$ are past rates of inflation in the Gambia;

$\alpha_1 \ldots \ldots \ldots \ldots . \alpha_p$ and $\beta_1 \ldots \ldots \ldots \ldots . \beta_q$ are estimation parameters.

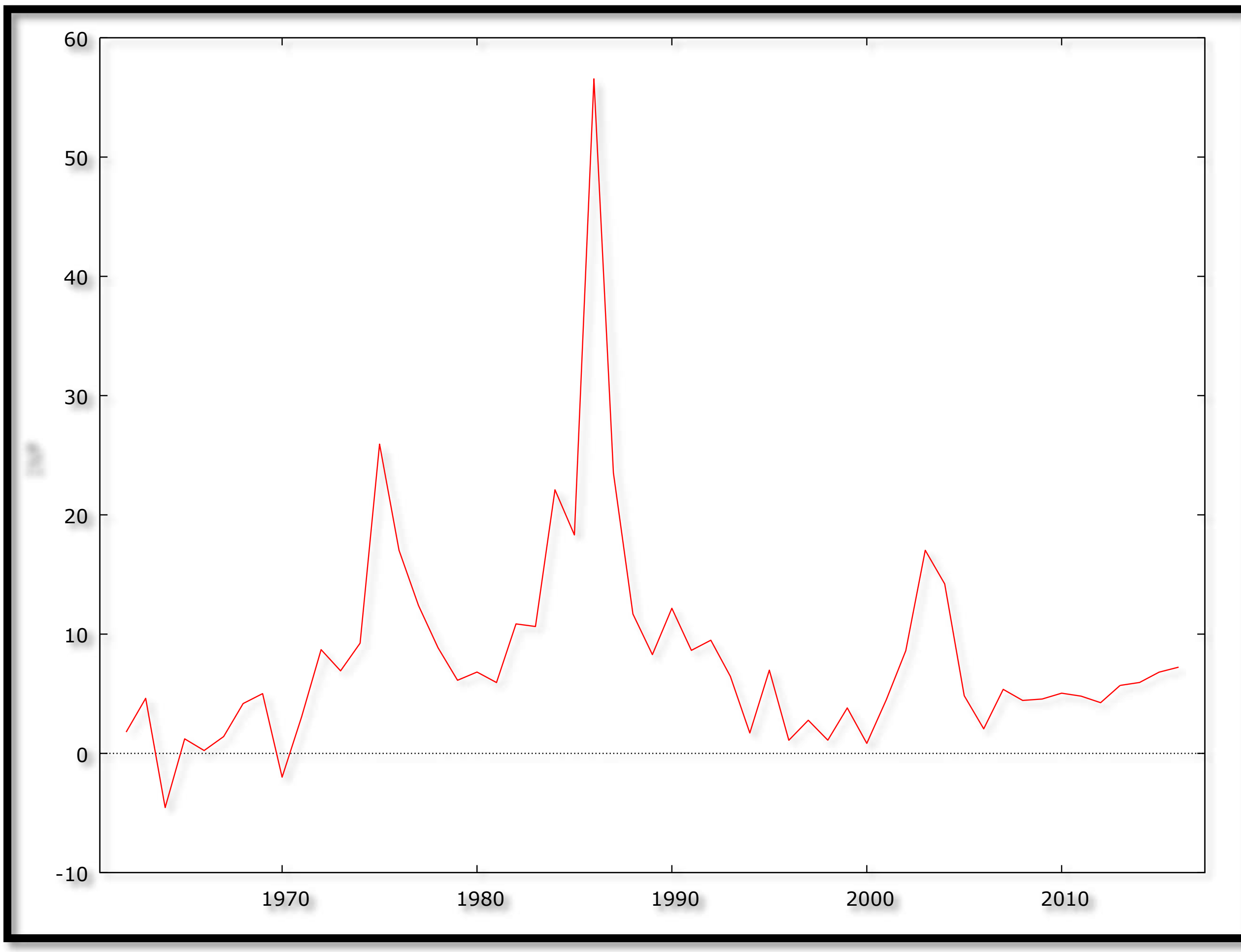
Data Collection

This study is based on a data set of annual rates of inflation in the Gambia (INF or simply G) ranging over the period 1962 – 2016. All the data was gathered from the World Bank.

Diagnostic Tests & Model Evaluation

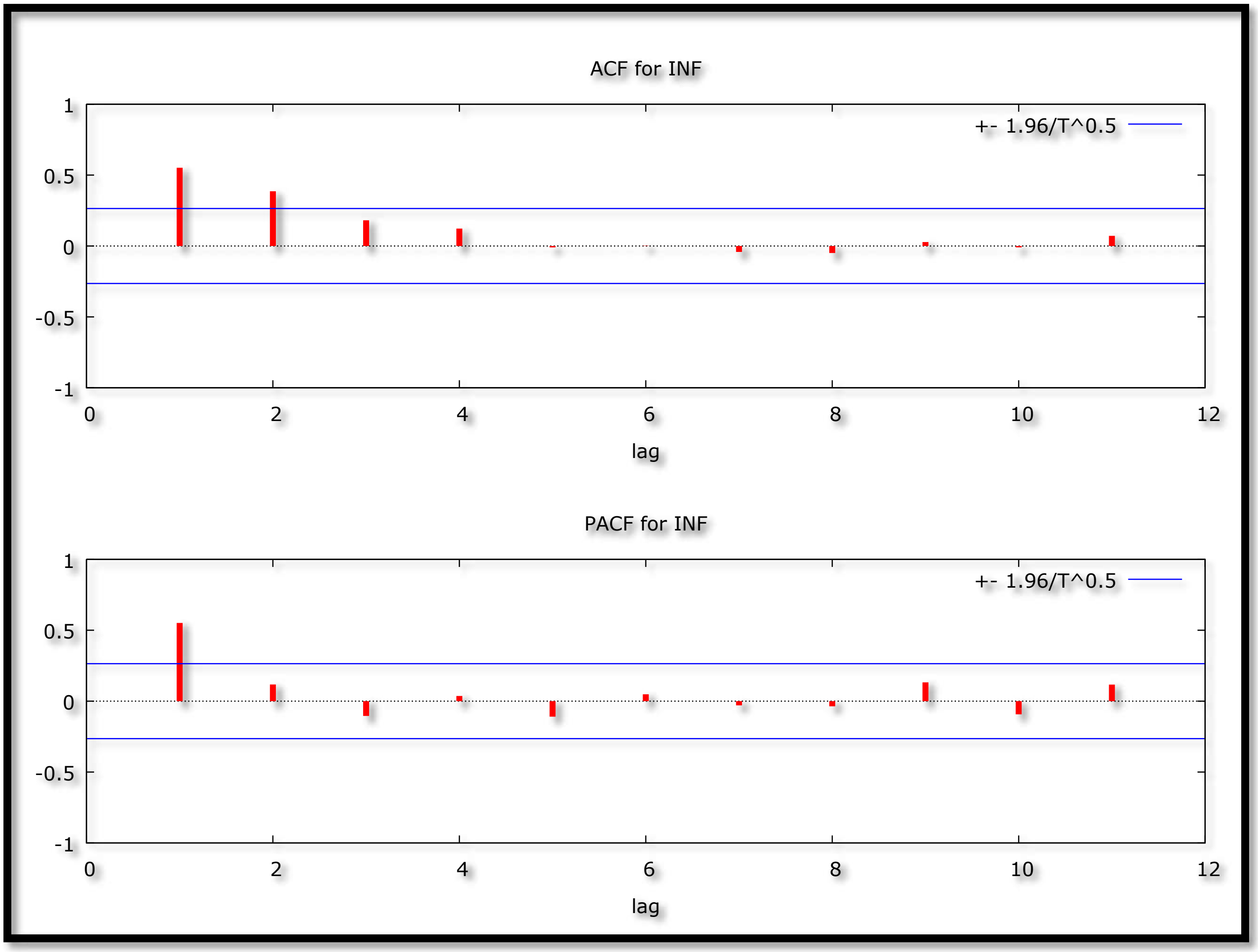
Stationarity Tests: Graphical Analysis

Figure 1



The Correlogram in Levels

Figure 2



The ADF Test

Table 1: Levels-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
G	-3.903006	0.0038	-3.557472	@1%	Stationary
			-2.916566	@5%	Stationary
			-2.596116	@10%	Stationary

Table 2: Levels-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
G	-3.869722	0.0202	-4.137279	@1%	Not stationary
			-3.495295	@5%	Stationary
			-3.176618	@10%	Stationary

Table 3: without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
G	-2.681754	0.0082	-2.608490	@1%	Stationary
			-1.946996	@5%	Stationary
			-1.612934	@10%	Stationary

Figures 1 and 2 and tables 1 – 3 show that G is an I (0) variable.

Evaluation of ARMA models (with a constant)

Table 4

Model	AIC	ME	MAE	RMSE	MAPE
ARMA (1, 0, 1)	384.4906	0.081067	3.8959	7.4055	103.68
ARMA (2, 0, 2)	387.4388	0.053527	3.8977	7.334	99.422
ARMA (1, 0, 0)	**383.057**	0.061209	3.862	7.4446	110.99
ARMA (2, 0, 0)	384.2986	0.080162	3.9158	7.3921	101.47
ARMA (0, 0, 1)	390.0844	0.028697	4.3572	7.9413	153.97

A model with a lower AIC value is better than the one with a higher AIC value (Nyoni, 2018). The study will consider the AIC in order to choose the best model for modeling and forecasting inflation rates in Gambia. Therefore, the ARMA (1, 0, 0) model is carefully selected.

Residual & Stability Tests

ADF Tests of the Residuals of the ARMA (1, 0, 0) Model

Table 5: Levels-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	-7.629690	0.0000	-3.560019	@1%	Stationary
			-2.917650	@5%	Stationary
			-2.596689	@10%	Stationary

Table 6: Levels-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	-7.565727	0.0000	-4.140858	@1%	Stationary
			-3.496960	@5%	Stationary
			-3.177579	@10%	Stationary

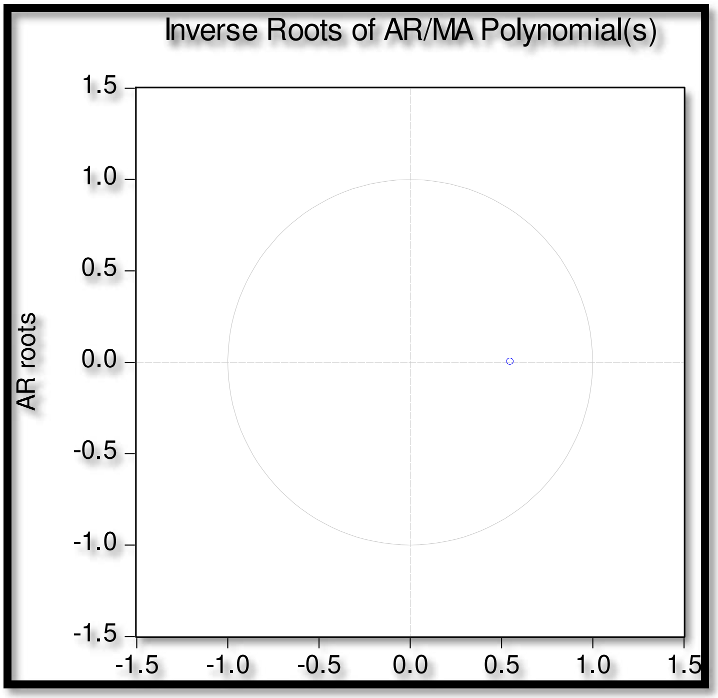
Table 7: without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	-7.704128	0.0000	-2.609324	@1%	Stationary
			-1.947119	@5%	Stationary
			-1.612867	@10%	Stationary

Tables 5, 6 and 7 demonstrate that the residuals of the ARMA (1, 0, 0) model are stationary.

Stability Test of the ARMA (1, 0, 0) model

Figure 3



Since the corresponding inverse roots of the characteristic polynomial lie in the unit circle, it illustrates that the chosen ARMA (1, 0, 0) model is indeed stable.

FINDINGS

Descriptive Statistics

Table 8

Description	Statistic
Mean	8.0987
Median	5.95
Minimum	-4.54
Maximum	56.56
Standard deviation	9.0072
Skewness	3.1213
Excess kurtosis	13.612

As shown above, the mean is positive, i.e. 8.0987%. The minimum is -4.54% and the maximum is 56.56%. The skewness is 3.1213 and the most striking characteristic is that it is positive, indicating that the inflation series is positively skewed and non-symmetric. Excess kurtosis is 13.612; showing that the inflation series is not, normally distributed.

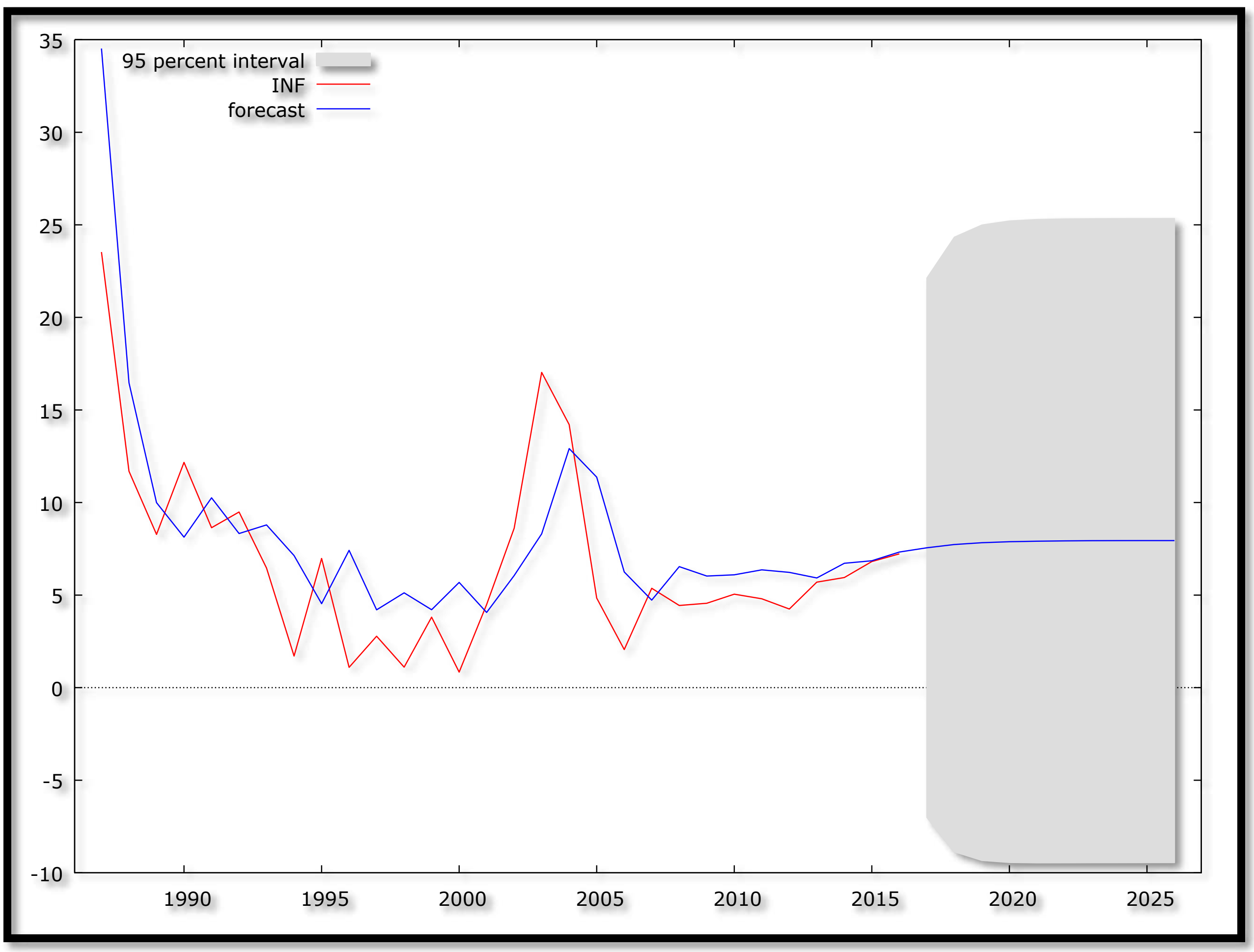
Results Presentation[1]

Table 9

ARMA (1, 0, 0) Model: $G_t = 7.94795 + 0.546701G_{t-1}$ ……………………………………………….[2] P: (0.0002) (0.0000) S. E: (2.13688) (0.112274)				
Variable	Coefficient	Standard Error	z	p-value
Constant	7.94795	2.13688	3.719	0.0002***
AR (1)	0.546701	0.112274	4.869	0.0000***

Forecast Graph

Figure 4



[1] *The *, ** and *** means significant at 10%, 5% and 1% levels of significance; respectively.*

Predicted Annual Inflation

Table 10

Year	Actual	Prediction	Std. Error	95% Confidence Interval	
2013	5.70	5.93			
2014	5.95	6.72			
2015	6.81	6.86			
2016	7.23	7.33			
2017		7.56	7.431	-7.01 -	22.12
2018		7.73	8.469	-8.86 -	24.33
2019		7.83	8.755	-9.33 -	24.99
2020		7.88	8.839	-9.44 -	25.21
2021		7.91	8.864	-9.46 -	25.29
2022		7.93	8.871	-9.46 -	25.32
2023		7.94	8.873	-9.45 -	25.33
2024		7.94	8.874	-9.45 -	25.34
2025		7.94	8.874	-9.45 -	25.34
2026		7.95	8.874	-9.45 -	25.34

Figure 4 and table 10, both with a forecast range of 10 years clearly show that inflation rates in The Gambia may hover around 8% within the next 10 years, ceteris paribus. With a 95% confidence interval of -9.44% to 25.21% and a predicted annual inflation rate of 7.88% by 2020, the chosen ARMA (1, 0, 0) model indicates that there will be price stability in The Gambia in 2020 and beyond.

CONCLUSION

Accurate forecasting is useful for effective policy planning (Jesmy, 2010). The main purpose of this study was to select the optimal ARMA model for modeling and forecasting inflation in The Gambia and the optimal model was selected based model identification statistics shown in table 4 above. As already shown, the optimal model is the ARMA (1, 0, 0) model and this model is envisaged to serve as an early warning signal to The Gambian policy makers, business leaders, investors and employers to prepare themselves and to take the right actions to calculate the strength of the anticipated new environment and to make feasible necessary decisions in their business activities.

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