Forecasting inflation in Burkina Faso using ARMA models

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ABSTRACT

This research uses annual time series data on inflation rates in Burkina Faso from 1960 to 2017, to model and forecast inflation using ARMA models. Diagnostic tests indicate that B is I(0). The study presents the ARMA (2, 0, 0) model, which is nothing but an AR (2) model. The diagnostic tests further imply that the presented optimal ARMA (2, 0, 0) model is stable and acceptable. The results of the study apparently show that W will be approximately 4% by 2020. Policy makers and the business community in Burkina Faso are expected to take advantage of the anticipated stable inflation rates over the next decade.

Key Words: Burkina Faso, Forecasting, Inflation

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 Burkina Faso 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 Burkina Faso based on ARMA models.

LITERATURE REVIEW

Stovicek (2007) forecasted inflation in Slovenia using ARMA models with a data set ranging from 1994(1) to 2006(6) 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 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) modeled and forecasted inflation rate in Nigeria using Box-Jenkins ARIMA models with a data set ranging over the period 2006(1) - 2015(12) and established that the ARIMA (0, 1, 1) model was the best model for forecasting inflation rate in Nigeria. Nyoni (2018) analyzed inflation in Zimbabwe using GARCH models with a data set ranging over the period 2009(7) – 2018(7) and established that there is evidence of volatility persistence for Zimbabwe's monthly inflation data. Nyoni (2018) modeled and forecasted inflation in Kenya using ARIMA and GARCH models and relied on annual time series data over the period 1960 – 2017 and revealed 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 can be used to forecast inflation in Kenya. Nyoni & Nathaniel (2019), based on ARMA, ARIMA and GARCH models; analyzed inflation in Nigeria using time series data on inflation rates from 1960 to 2016 and showed that the ARMA (1, 0, 2) model is the best model for forecasting inflation rates in Nigeria.

MATERIALS & METHODS

ARMA Models

For the purpose of forecasting rates of inflation in Burkina Faso, ARMA models were specified and estimated. A generalized ARMA (p, q) model can be specified as follows:

$$B_t = c + \sum_{i=1}^{p} \emptyset_i B_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \qquad \varepsilon_t \sim N(0, \sigma^2) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots [1]$$

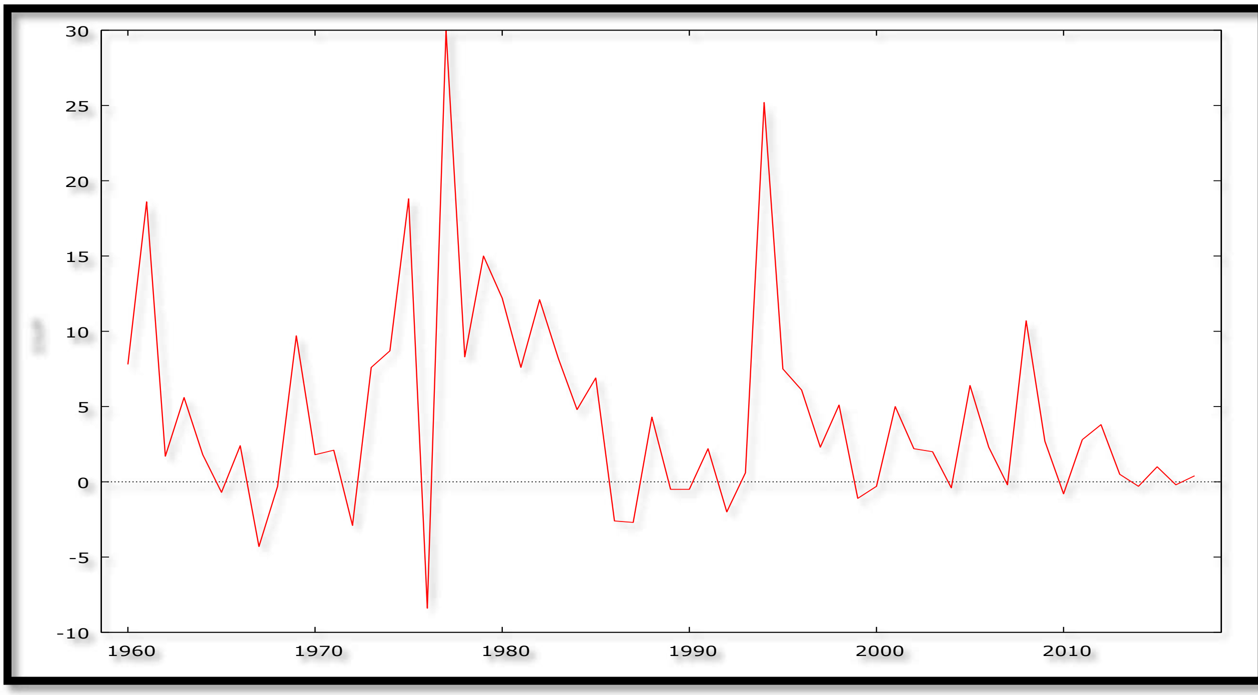
Data Collection

This study is based on a data set of annual rates of inflation in Burkina Faso (INF or simply B) ranging over the period 1960 – 2017. All the data was gathered from the World Bank.

Diagnostic Tests & Model Evaluation

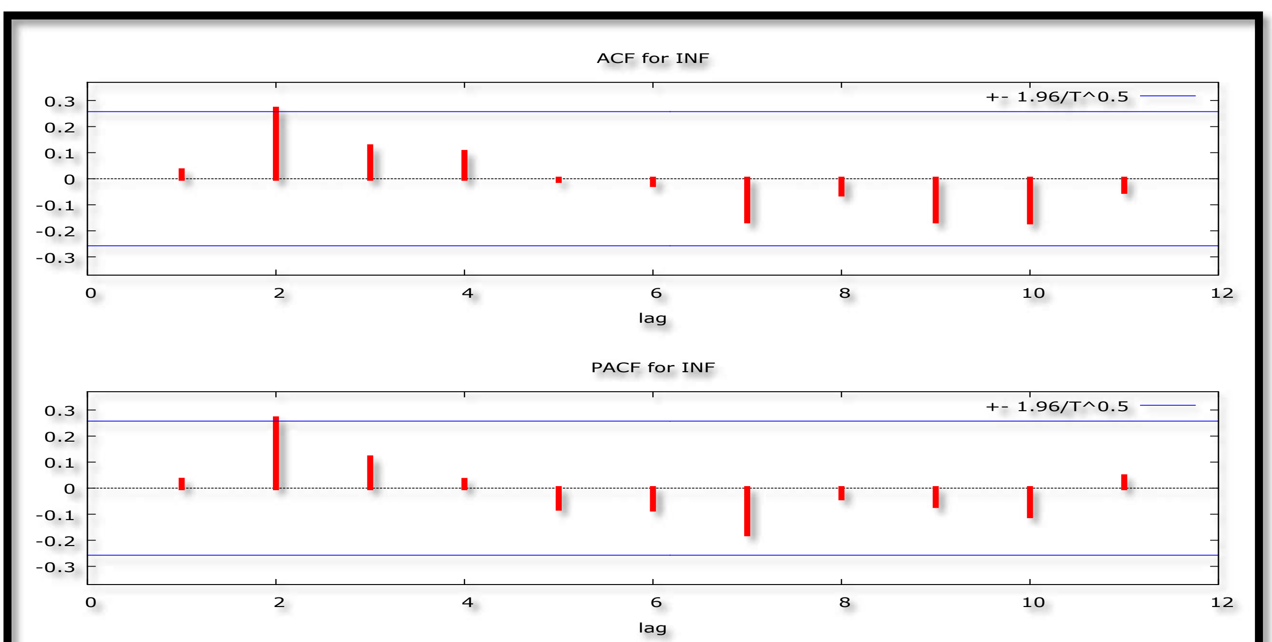
Stationarity Tests: Graphical Analysis

Figure 1



The Correlogram in Levels

Figure 2



The ADF Test

Table 1: Levels-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
B	-4.050725	0.0024	-3.552666	@1%	Stationary
			-2.914517	@5%	Stationary
			-2.595033	@10%	Stationary

Table 2: Levels-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
B	-7.419110	0.0000	-4.127338	@1%	Stationary
			-3.490662	@5%	Stationary
			-3.173943	@10%	Stationary

Table 3: without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
B	-3.180576	0.0020	-2.606911	@1%	Stationary
			-1.946764	@5%	Stationary
			-1.613062	@10%	Stationary

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

Evaluation of ARMA models (with a constant)

Table 4

Model	AIC	U	ME	MAE	RMSE	MAPE
ARMA (1, 0, 1)	393.9225	0.75283	-0.06779	4.6576	6.7399	311.54
ARMA (2, 0, 2)	393.1371	0.76048	-0.14083	4.6123	6.4801	282.78
ARMA (1, 0, 0)	393.6365	0.72405	-0.0018472	4.9907	6.8397	354.92
ARMA (2, 0, 0)	**391.0182**	0.7816	-0.087881	4.8219	6.5851	330.52
ARMA (0, 0, 1)	393.6569	0.72303	-0.0010808	5.0068	6.841	357.57
ARMA (0, 0, 2)	391.7154	0.75231	-0.14093	4.9795	6.6213	352.15
ARMA (1, 0, 2)	391.5114	0.75391	-0.14093	4.7118	6.5045	295.58
ARMA (2, 0, 1)	392.2824	0.77403	-0.12761	4.7537	6.5453	315.06
ARMA (3, 0, 3)	394.1396	0.72977	-0.071564	4.7254	6.3159	300.65
ARMA (3, 0, 0)	392.1187	0.76153	-0.12816	4.728	6.5363	310.06
ARMA (0, 0, 3)	392.7064	0.72345	-0.078821	4.8096	6.5647	318.52
ARMA (1, 0, 3)	393.4038	0.75088	-0.14061	4.6822	6.4977	288.65

A model with a lower AIC value is better than the one with a higher AIC value (Nyoni, 2018). Theil's U must lie between 0 and 1, of which the closer it is to 0, the better the forecast method (Nyoni, 2018). The study will consider the AIC and the Theil's U in order to choose the best model for forecasting inflation rates in Burkina Faso. Therefore, the ARMA (2, 0, 0) model is carefully selected.

Residual & Stability Tests

ADF Tests of the Residuals of the ARMA (2, 0, 0) Model

Table 5: Levels-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	-7.411435	0.0000	-3.555023	@1%	Stationary
			-2.915522	@5%	Stationary
			-2.595565	@10%	Stationary

Table 6: Levels-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	-7.449932	0.0000	-4.133838	@1%	Stationary
			-3.493692	@5%	Stationary
			-3.175693	@10%	Stationary

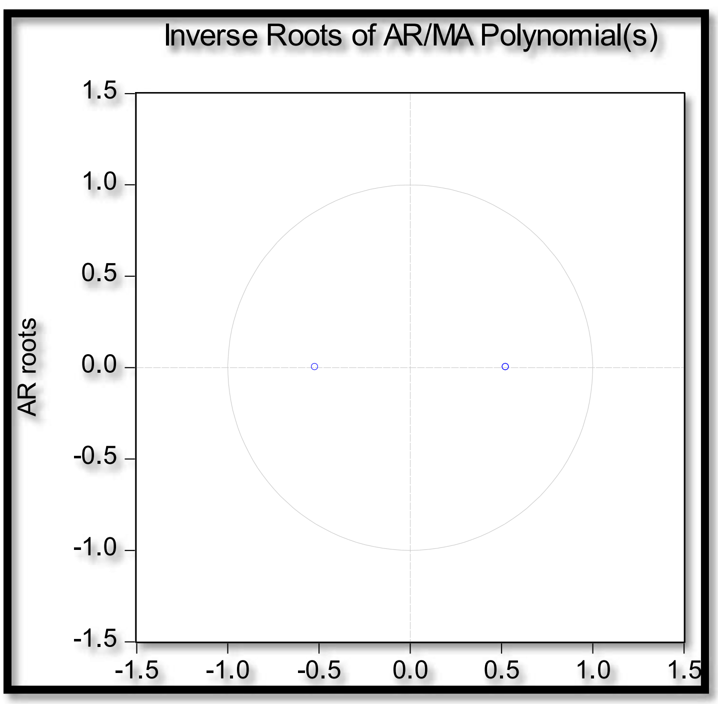
Table 7: without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	-7.480348	0.0000	-2.607686	@1%	Stationary
			-1.946878	@5%	Stationary
			-1.612999	@10%	Stationary

Tables 5, 6 and 7 demonstrate that the residuals of the ARMA (2, 0, 0) model are stationary.

Stability Test of the ARMA (2, 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 (2, 0, 0) model is indeed stable.

FINDINGS

Descriptive Statistics

Table 8

Description	Statistic
Mean	4.4241
Median	2.3
Minimum	-8.4
Maximum	30
Standard deviation	6.903
Skewness	1.5362
Excess kurtosis	3.0583

As shown above, the mean is positive, i.e. 4.4241%. The minimum is -8.4% and the maximum is 30%. The skewness is 1.5362 and the most striking characteristic is that it is positive, indicating that the inflation series is positively skewed and non-symmetric. Excess kurtosis, as reiterated by Nyoni & Bonga (2017) should be around 3 for normally distributed variables and in this study kurtosis has been found to be 3.0583; implying that the inflation series is normally distributed.

Results Presentation[1]

Table 9

ARMA (2, 0, 0) Model:

$$B_t = 4.48551 + 0.0292092B_{t-1} + 0.284681B_{t-2} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.\ldots.[2]$$

P: (0.0003) (0.8168) (0.0249)
S. E: (1.23429) (0.126117) (0.126884)

Variable	Coefficient	Standard Error	z	p-value
Constant	4.48551	1.23429	3.634	0.0003***
AR (1)	0.0292092	0.126117	0.2316	0.8168
AR (2)	0.284681	0.126884	2.244	0.0249**

Predicted Annual Inflation

Table 10

Year	Prediction	Std. Error	95% Confidence Interval
2018	3.0	6.56	-9.8 - 15.9
2019	3.3	6.57	-9.6 - 16.1
2020	4.0	6.83	-9.3 - 17.4
2021	4.1	6.83	-9.3 - 17.5

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

2022	4.3	6.85	-9.1 -	17.8
2023	4.4	6.85	-9.0 -	17.8
2024	4.4	6.85	-9.0 -	17.9
2025	4.5	6.85	-9.0 -	17.9
2026	4.5	6.85	-9.0 -	17.9
2027	4.5	6.85	-9.0 -	17.9

Table 10, with a forecast range of 10 years clearly shows that inflation rates in Burkina Faso will not exceed 5% within the next 10 years, ceteris paribus. With a 95% confidence interval of -9.3% to 17.4% and a predicted annual inflation rate of 4% by 2020, the chosen ARMA (2, 0, 0) model indicates that there will be price stability in Burkina Faso in 2020.

CONCLUSION

Accurate forecasting is useful for effective policy planning (Jesmy, 2010). The main aim of this study was to select the optimal ARMA model for modeling and forecasting inflation in Rwanda and the optimal model was selected based model identification statistics shown in table 4 above. As already shown, the optimal model is the ARMA (3, 0, 0) model and this model is envisaged to serve as an early warning signal to Rwandan policy makers, business leaders, investors and employers to prepare themselves and to make the right move to calculate the strength of the anticipated new environment and to take feasible necessary action in their business activities.

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