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Forecasting Inflation Rate Using the ARIMA Model: Zambia's Perspective from 2023 to 2043

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ABSTRACT

The study sought to forecast Zambia's inflation rate from 2023 to 2043 using the Autoregressive Integrated Moving Average Model (ARIMA). Using the Box–Jenkins modeling method, the study utilized 37 yearly time series data from 1986 to 2022 to forecast the next 20 years by using ARIMA Model. The ARIMA (4, 1, 2) model was used as being the one with the most significant parameters, the least log likelihood, Sigma, and the least Akaike and Bayesian information criteria. The ARIMA (4, 1, 2) model was also used due to its accuracy, mathematical soundness, and flexibility, thanks to the inclusion of AR and MA terms over a regression analysis. The results show that the value of the Zambia's inflation rate is predicted to rise by 47.27% in 20 years.

INTRODUCTION

Inflation is a rise in the average price of goods over time. The inflation is based on prices of goods that are commonly consumed by the public. These could be classified under different commodity baskets for example food and non-alcoholic beverages, alcoholic beverages and tobacco, clothing and footwear, housing and household services, health, transport, restaurants and hotels among others. The inflation rate is measured using the Consumer Price Index (CPI) which is the current price of a collection of goods and services in terms of the same period prices in the previous year (Fahruddin & dan Sumitro, 2020; Farida & As'ad, 2021).

Inflation affects economic decisions because of its volatility and therefore attracts the attention of economists for instance by doing forecasts of future inflation rates. Both business entities and consumers make economic decisions based on the forecasted inflation therefore affected by inflation uncertainty. Long term plans become hard to achieve so short-term investments are chosen over more profitable long-term investments because the aspect of profit in the long run is made to seem impossible and unclear; the will to invest and save could possibly decline and companies direct their resources in order to avoid the related risks (Devereux, 1989).

There is possible transfer of wealth between the debtors and the creditors when the inflation rate differs from its projection since repayment of the loans is done with money of different value. This calls for the need to adjust for inflation by both investors and governments when it comes to all future planning which can lead to reduced inflation uncertainty and a reduction in financial costs.

However, in Zambia, inflation was relatively stable prior to 1974 except for a spike in 1971 (Chipili, 2019). However, inflationary pressures intensified from 1975 and reached 9.1% by 1982. Inflation peaked at 183.3% in 1993. The acceleration in inflation over the 1982-1993 period was mostly because of the impact of large fiscal deficit financing through central bank borrowing and the pass-through from the significant depreciation of the Kwacha against the US dollar following the initial floatation of the Kwacha via an auction system between 1985 and 1987 (Bank of Zambia, 2019).

Arguably, Zambia's inflation fell sharply in 1994 to 61.9% but remained relatively high. This followed the implementation of economic reforms to restore macroeconomic stability, during which an aggressive disinflationary stance was prioritized after a prolonged period of stagflation. The reforms included trade and foreign exchange liberalization, price de-regulation, and tighter financial management. In addition, the Government implemented a cash budget system complimented by tight monetary policy measures to restrain excessive monetary expansion (Bank of Zambia, 1994; Bank of Zambia, 2015).

Inflation moderated after 1994, declining to below 20% in 2005 and later fell to single digits (8.2%) in 2006 after more than three decades. However, in October 2015, inflation rose sharply to 14.5% and peaked at 22.9% in February 2016. This followed a sharp depreciation of the Kwacha against the US dollar occasioned by lower copper prices attributed to the slowdown in China, uncertainty over the performance of the mining sector (with Glencore scaling down its operations at Mopani), stronger US dollar, deteriorating current account balance, widening fiscal deficit, sovereign rating downgrade and the impact of electricity shortages on economic activity (Bank of Zambia, 2019).

However, inflation decelerated to below 10% by the end of 2016 as base effects dissipated. However, inflationary pressures re-emerged towards the end of the second quarter of 2019 leading to inflation exceeding the target range of 6-8% by the end of the year (Bank of Zambia, 2020). The Government introduced a target range of 6-8% in 2018 as a precursor to inflation targeting. A notable observation about the dynamics in inflation over the sample period is that it broadly trended above the target. However, the annual inflation rate in Zambia rose to a three-month high of 9.9% in December from 9.8% in November. Inflation was mainly driven by non-food items (7.3% vs 6.7% in November), with prices accelerating most for transport, fuel, and lubricants. On the contrary, they slowed down for food items to 11.9% from 12.1% in the previous month. In this regard, a deeper understand of the underlying drivers of inflation will allow the authorities to design appropriate policy response to align and contain inflation within the set target (Bank of Zambia, 2022).

As a major macroeconomic variable, inflation is a measure of a country’s economic performance. Inflation presents challenges to policy makers especially in developing countries and Zambia is no exception. Mainly, a country facing inflation has a government with lots of uncertainty in prices of commodities and even in delivery of services. Inflation increases costs of investment and accordingly, many investors may turn away from investing in such a country. Most cases in which inflation has been experienced have to device tools of managing the inflation so as to have a stable economy. Zambia is a country within the African continent which from the recent past is moving towards double inflation. It is in this light that the study aims to come up with a model that will help in controlling inflation in Liberia.

Not only have many forecasting methods been developed in the past but equally many methods of measuring forecasting accuracy have been developed. Hyndman and Koehler (2006), for example studied and compared all measures accuracy and settled on mean Absolute Scaled Error (MASE) as the best measure of accuracy on forecasting. Time series researchers have also compared several models of forecasting with a view of determine which is a better model for forecasting depending on the nature of data and industry. For example, Gathingi (2014) modelled inflation in Kenya using ARIMA and VAR. Equally Ingabire and Mung’atu (2016) compared ARIMA and VAR models in forecasting inflation rate in Rwanda. In the IMF Working paper series, Tim and Dongkoo (1999) studied modelling and forecasting inflation in India using Bivariate VAR. They found out that broad money supply, exchange rate and import prices are relevant indicators that affect inflation especially in the manufacturing sector in India.

Other studies that concentrated on inflation include Otu et. al., (2014) who discussed the application of SARIMA Models in Modelling and Forecasting Nigeria’s Inflation Rates. While, Uwilingiyimana, Mungatu and Harerimana (2015) conducted a study on forecasting inflation in Kenya using two models, the ARIMA (1, 1, 12) and GARCH (1, 2) and a combination of the two model ARIMA (1, 1, 12)-GARCH (1, 2).

In Zambia, Jere and Sianga (2016) researched on inflation prediction and consumer price index using the ARIMA model and Holt's double exponential smoothing (DES) model. In another study, Jere, Banda, Chilyabanyama, and Moyo, (2019) took a Multicointegration and Arima Approach to model Consumer Price Index in Zambia. Again, in Zambia, Phiri (2013) conducted a study which examines threshold effects of inflation on economic growth for the Zambian economy using quarterly data collected between 1998 and 2011. This objective is tackled through the use of a threshold autoregressive (TAR) model and the conditional least squares

(CLS) estimation technique.

Despite having many researchers that used different models in forecasting inflation, most researches have concentrated on using SARIMA, TAR, and GARCH, little is known about forecasting inflation rates using ARIMA in Zambia. ARIMA models can explore data in more detail and can improve forecasting accuracy. In this study, the ARIMA model is used to predict yearly inflation in Zambia from 2023 to 2043. The study actually intended to model long term behavior of yearly inflation rate data of Zambia from 2023 to 2033 and predict future values using the ARIMA model. This research study actually attempted to provide information to policy makers to enable them make better decisions about the future and increase to the existing human stock of knowledge from which will be able to generate new insights and ideas about inflation.

MATERIALS AND METHODS

The study aims at establishing a representative yet parsimonious ARIMA model that can effectively estimate and accurately forecast Zambia's inflation rate. This section contains the methodological framework of the model, and the steps followed to achieve the study objective. The study utilizes yearly time series data of Zambia's inflation rates from the website https://www.worlddata.info/africa/zambia/inflation-rates.php of the WorldData.Info for the period of 36 years between 1986 and 2022 of the statistics section, and there are no missing values. The following sections provide theoretical foundations of ARIMA modelling, also called the Box–Jenkins forecasting technique.

Theoretical Foundation of ARIMA Modelling

The Autoregressive Integrated Moving Average (ARIMA) modeling, popularly known as Box–Jenkins methodology, was initially contributed by George Box and Gwilym Jenkins in a 1970 seminal book which was later summarized into a paper published in 1976 (Zulu, Mwansa, & Wakumelo, 2022). Mathematicians and Economist, since then, have widely used ARIMA models in estimating and forecasting univariate time series economic variables to provide evidence-based economic policy advice. The model assumes that the series at hand is both stationary and invertible. Stationarity entails that both the mean and variance of the series are time-invariant, while invariability requires the uniqueness of the autocorrelation function of the moving average (MA) component of the model. A classic challenge in time series analysis is that the values of the series at time t tend to correlate with its lagged values and both current and past errors. To deal with this, the paper accommodated autoregressive (AR) and moving average (MA) components. The AR component with "p" lags represents the relationship between the dependent variable and its previous period, as shown in Equation (1) below:

$$Y_t = \propto + \sum_{i=1}^{p} \beta Y_{t-i} + E_t \qquad \text{Equation (1)}$$

For any series to be weekly dependent, the $AR\ (p)$ process presented in Equation (1) assumes that $|b| < 1$ and the Et is independently and identically distributed (Zulu, Mwansa, & Wakumelo, 2022). Similarly, the study controlled the moving average (MA) component with "q" lags to take care of the potential dependence of the model residual to its past values, as shown in Equation (2) below:

$$Y_t = \propto + \beta E_t + \sum_{i=1}^{q} \gamma E_{t-i} \qquad \text{Equation (2)}$$

Finally, to incorporate both lag effects of (AR) and moving average (MA) components in a single model, the study specifies ARMA modeling for estimation and forecasting, as shown in Equation (3) below:

$$Y_t = \propto + \sum_{i=1}^{p} \beta Y_{t-i} + \sum_{i=1}^{q} \gamma E_{t-i} + E_t \qquad \text{Equation (2)}$$

where Yt is the series at hand, p is the order or the number of lags in the (AR) component, q is the order or the number of lags in the (MA) component, and Et is the error term. Two potential possibilities of using the $ARMA\ or\ ARIMA$ model emerge depending on the result of the stationary test. Given that most of the time series variables are not stationary at level, the generic form of the model is $ARIMA\ (p, d, q)$, where "I" corresponding to "d" is the number of times the series is integrated or differenced before it becomes stationary.

Estimation Techniques

To correctly estimate the in-sample values of the series and forecast the future out-of-sample of the series, the researchers followed the Box Jenkins four steps namely model identification, model estimation, diagnostic checking and forecasting.

Model Identification

The study conducted an identification process of testing stationarity and inerrability assumptions to identify the appropriate lags of $AR(p)$ and $MA(q)$ components of the model. Hence, the study displayed graphical and statistical stationary tests using Augmented Dickey–Fuller (ADF) and Philips Parron (PP) tests to check if the series was white noise, as shown below:

$$Y_t = \rho Y_{t-1} + \varepsilon_t$$

$$Y_t - Y_{t-1} = \rho Y_{t-1} + Y_t i1 + \varepsilon_t$$

$$\Delta Y_t = (\rho - 1)Y_{t-1} + \varepsilon_t$$

$$\Delta Y_t = \delta Y_{t-1} + \varepsilon_t$$

whereby d equals to $(\rho - 1)$, assuming that if $|r| = 1$ then the series is not stationary.

Model Estimation

The parameters are estimated by the maximum likelihood estimation method. For the estimated models, we select the one with the minimum values of Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC).

Model Diagnostics

After estimating the parameters of the chosen model based on the information criteria, the last step is model diagnostics. This step is aimed at certifying the adequacy of the chosen model. The commonly used test is the examination of the ACF and PACF plots of the residuals to satisfy the assumption of ARIMA model that the residuals of the model should be white noise. The ACF of the white noise residuals is approximately zero. Other tests such as the Ljung-Box Q statistic and ARCH-LM test compliments the residual diagnostics.

Forecasting

In this stage we test the forecasting ability of the chosen model. In the case, the study will use in-sample forecast.

RESULTS AND DISCUSSIONS

This section presents the analysis and discussions of the study. Typically, effective fitting of Box-Jenkins models requires at least a moderately long series. Zulu, Mwansa, Wakumelo (2022) recommends at least 30 observations. Many others would recommend at least 100 observations. For the current study, secondary data from the the website https://www.worlddata.info/africa/zambia/inflation-rates.php of the WorldData.Info has been selected for analysis. The data covers the period 1986 to 2022, thereby giving a total of 37 observations. The data collected was called into STATA version 14.2 to perform the necessary analysis. The first data set is used for model estimation and the second set for forecasting and model validation. To present the findings, we followed the Box-Jenkins (B-J) four steps namely model identification, model estimation, diagnostic checking and forecasting.

Model Identification

The first stage involves checking the stationarity of the series through visual examination and formal statistical tools. A point to be noted at this point is that stationarity is a prerequisite for applying Box-Jenkins method. For the current study stationarity will be checked through time series plot of Zambia's foreign debt along with scatter plot, time series plot, series Corelogram-Autocorrelation Function (ACF) plot, and Partial Autocorrelation Function (PACF) plot.

In order to forecast Zambia's foreign debt from 2022 to 2035, a time series analysis was carried out for the given data shown in Table 1 above. However, the scatter plot of the time series data against time periods from 1998 to 2022 is given in Figure 1 below.

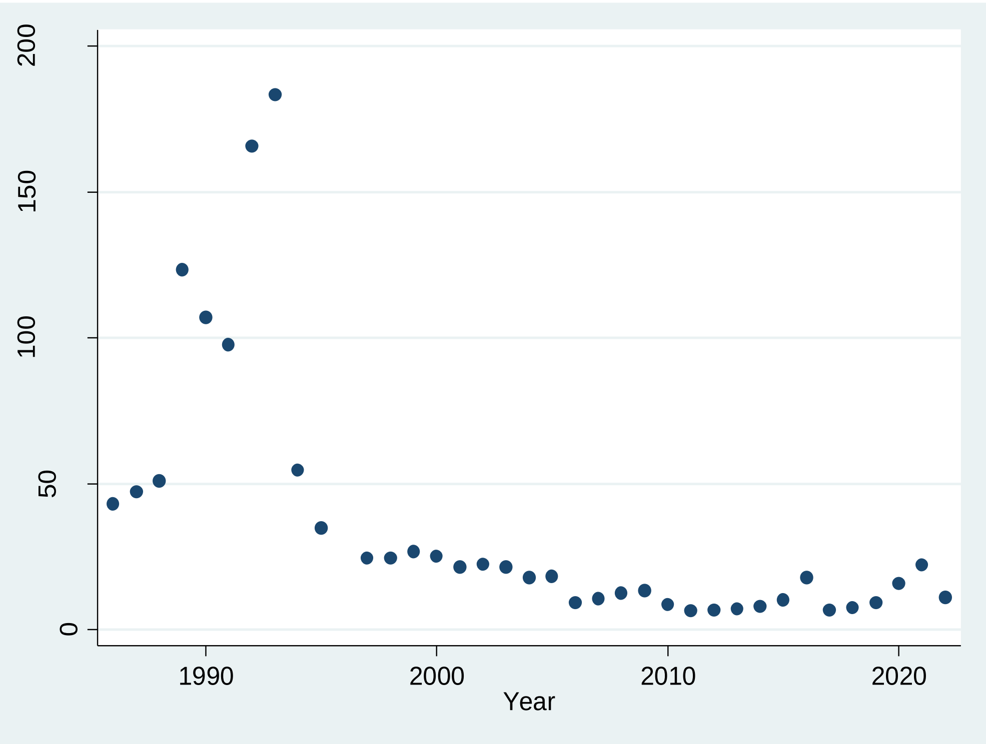
Table 1: Zambia's Inflation Rate from 1986 to 2022

Year	Inflation Rate (%)
1986	55.83
1987	47.05
1988	51
1989	123.4
1990	107.02
1991	97.64
1992	165.71
1993	183.31
1994	54.6
1995	34.93
1996	43.07
1997	24.42
1998	24.46
1999	26.79
2000	25.03
2001	21.39
2002	22.23
2003	21.4
2004	17.79
2005	18.32
2006	9.02
2007	10.66
2008	12.45
2009	13.4
2010	8.5
2011	6.43

2012	6.58
2013	6.98
2014	7.81
2015	10.11
2016	17.87
2017	6.59
2018	7.49
2019	9.15
2020	15.73
2021	22.02
2022	10.99

Source: Field work, 2023

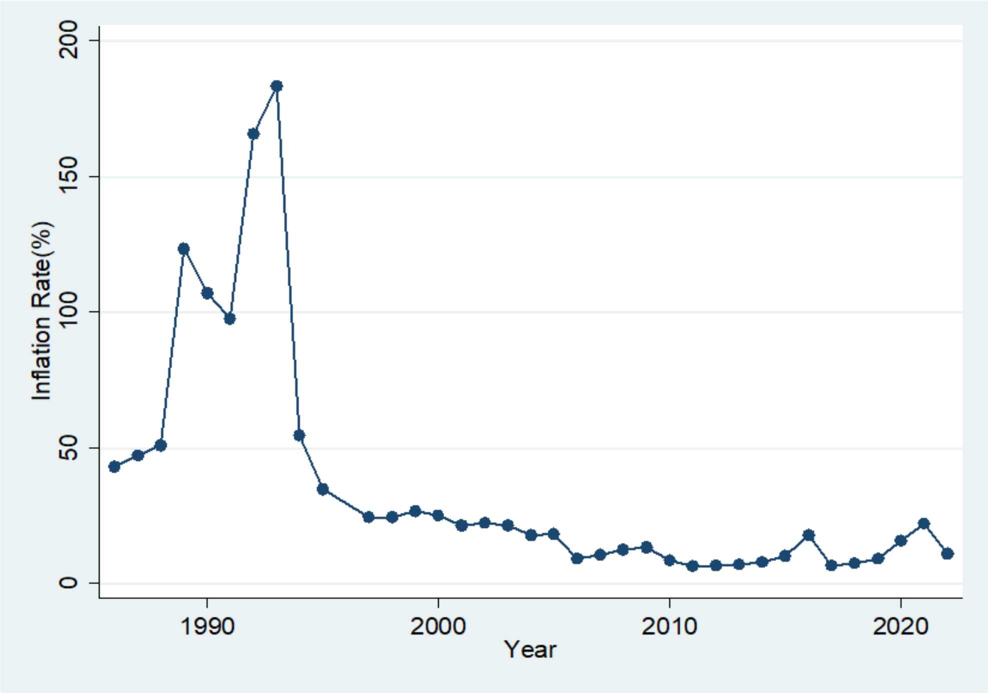
Figure 1: The scatter plot of the time series data against time periods



Source: Output from STATA version 14.2

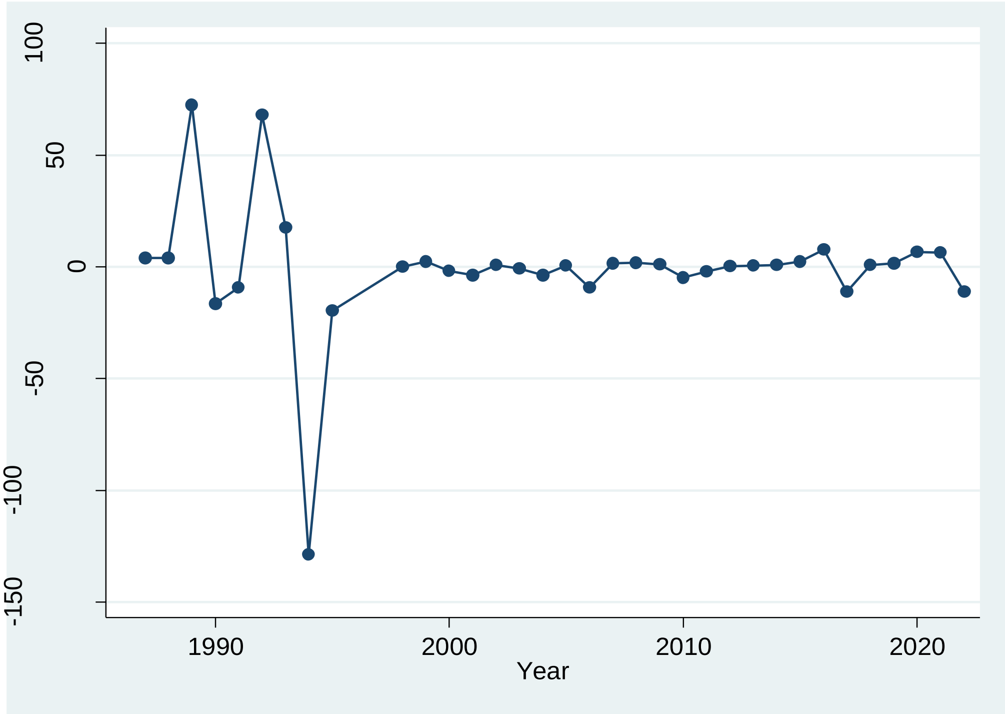
Figure 1 shows that during 1986–1993, 1985 to 1999, and 2000 to 2004, there was a slight increase in inflation rate, with a minimal growth rate for this period. Figure 1 shows that since 2006, there has been a rapid aggravation of the debt stability of Zambia. The period from January 2006 can be called the extensive growth phase, with a peak value in 2021. This, however, suggests that the foreign debt has been on an upward trend over a long period of time i.e., from 1973 to 1985, 1985 to 1999, 2000 to 2004, and 2006 to 2021. In addition, the graph in Figure 1 is at constant variance because the graph is getting bigger and bigger over time i.e., from 1973 to 1985, 1985 to 1999, 2000 to 2004, and 2006 to 2021 over some time and fluctuating i.e., from 2004 to 2006 over some time. In order to verify whether the data is stationary time series plot has been plotted, and it is shown in Figure 2 and Figure 3.

Figure 2: Stationary test using graphical method



Source: Output from STATA version 14.2

Figure 2: Stationary test using graphical method of the first difference



Source: Output from STATA version 14.2

Figure 1 exhibited an upward trend since 1986 over a long period of time but time series data values do not have a constant mean and variances and hence no trend difference but transformed the data by taking log and first difference and re-evaluated the trend and Figure 2 clearly indicates that the trend is not significant.

In addition to the pictorial stationarity check, the study also conducted a formal unit root test using both Augmented Dickey–Fuller (ADF) and Philips Parron (PP) tests with 1% and 5% MacKinnon p-value statistics

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as shown in Table 2. The hypothesis of the Augmented Dickey–Fuller (ADF) and Philips Parron (PP) tests is:

HO: The data needs to be differenced to make it stationary

H1: The data is stationary and does not need to be differenced Test regression trend

$$Call: lm\ (formula\ =\ z.diff\ z.lag.1\ +\ 1\ +\ tt)$$

Table 2: Formal stationary tests using both ADF and PP tests

Augmented Dickey–Fuller (ADF) Test			
	Coef.	$P > \lvert t \rvert$	*Std. Err*
LI. Inflation Rate	*-.49823*	*.004*	*.1579054*
LD. Inflation Rate	*.2287786*	*.002*	*.1792776*
Trend	*-1.609778*	*.024*	*.6723959*
Constant	*49.26815*	*.013*	*18.52484*
T-statistics	*-4.316*	*MacKinnon p-Value*	*.00937*
1% Critical Value	*-3.155*	*5% Critical Value*	*-3.572*
Philips Parron (PP) Test			
	Coef.	$P > \lvert t \rvert$	*Std. Err*
LI. Inflation Rate	*.6167808*	*.0000*	*.1360322*
Trend		*.0052*	*.5795268*
Constant		*.0280*	*35.66838*
T-Statistics	*-4.297*	*MacKinnon p-Value*	*.001594*
1% Critical Value	-2.909	5% Critical Value	*-3.564*

Note: *critical value α 1%, **critical value α 5%, *** critical value α 10%

Table 2 shows that the series is stationary since the calculated value of the t-statistic for both Augmented Dickey–Fuller (ADF) Test (-4.316) and Philips Parron (PP) Test (-4.297) is greater than the than the critical values at the 1% *and* 5% significance levels. This has also been confirmed by MacKinnon p-value statistics. The MacKinnon p-value statistics for both Augmented Dickey–Fuller (ADF) Test (*.00937*) and Philips Parron (PP) Test (*.001594*) is less than 1% *and* 5% significance levels. Therefore, the null hypothesis is rejected. Zulu, Mwansa, Wakumelo (2022), the series is stationary if the null hypothesis of a unit root is rejected against the one-sided alternative hypothesis if the test statistics exceeds the MacKinnon critical values at $1\%, 5\%,$ *and* 10%. Additionally, Febriyanti, Pradana, Saputra, and Widodo, (2021) contended that the series is stationary if MacKinnon p-Value computed is less the level of significance.

Furthermore, the study ran autocorrelation (ACF) and partial autocorrelation functions (PACF) at both levels and first differences as shown in Figure 4, 5, 6, and 7 below. The visual analysis of the correlogram (ACF/PACF functions) makes it possible to determine whether the selected data set is a pure AR or MA process or a mixed ARMA process (Zulu, Mwansa, Wakumelo, 2022).

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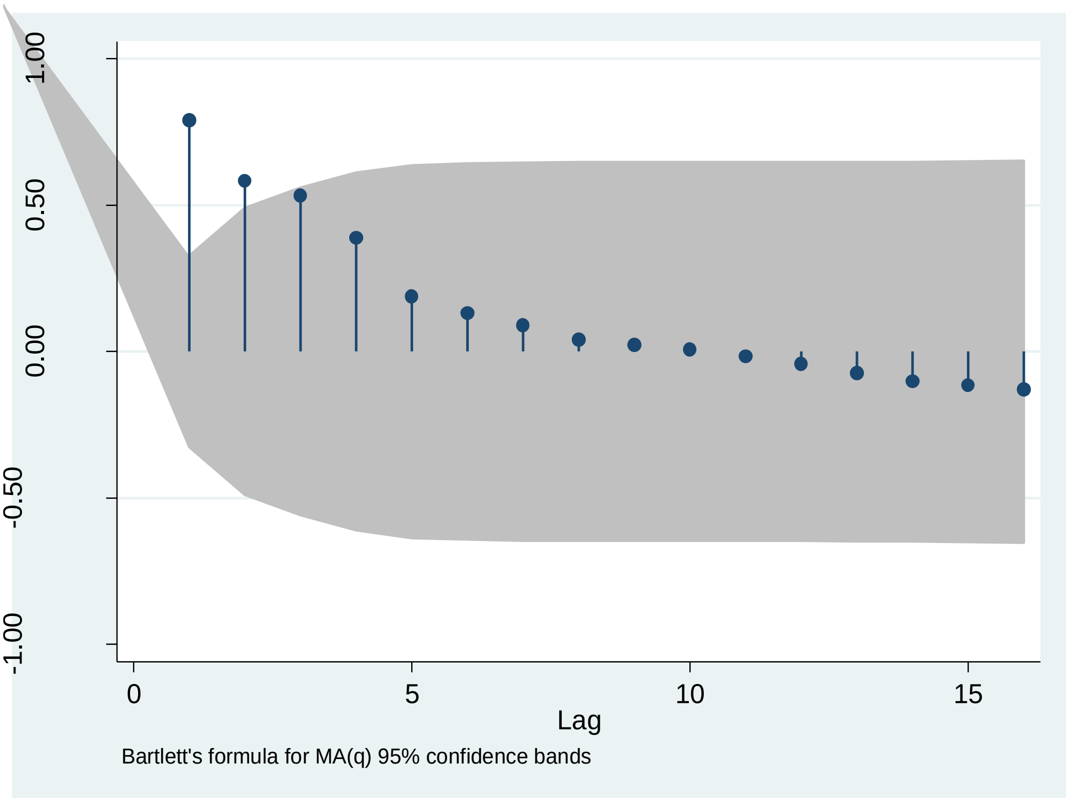
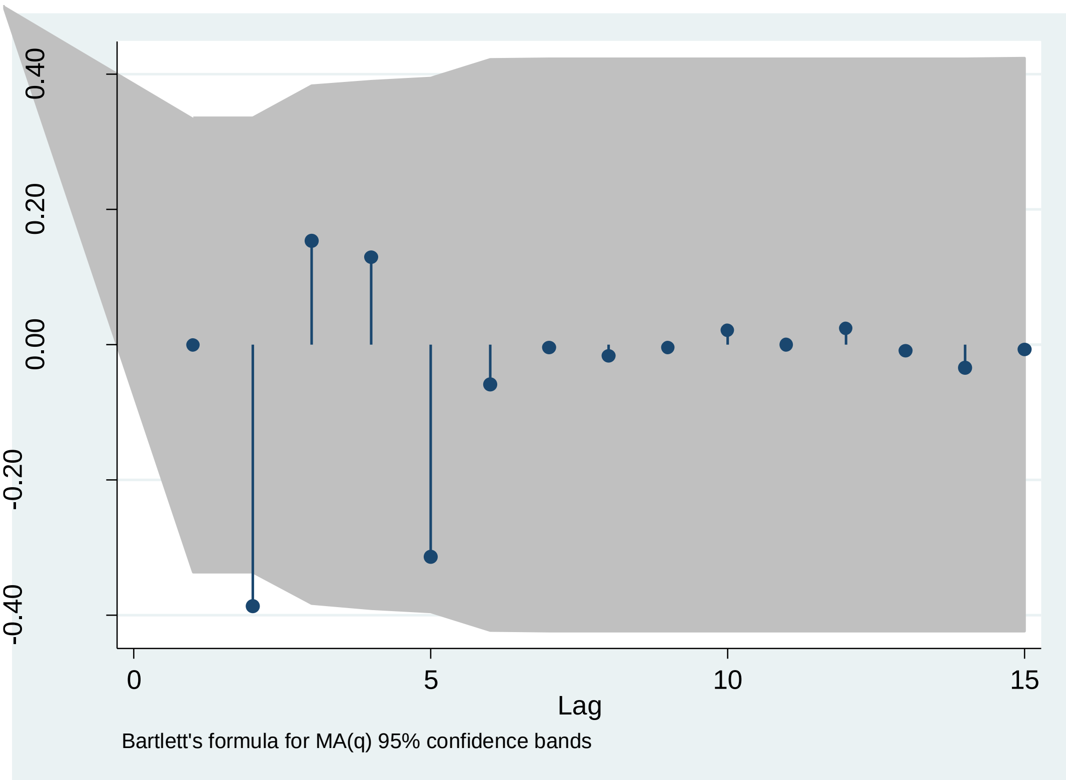
Figure 4: Plot of ACF of the level data



Source: Output from STATA version 14.2

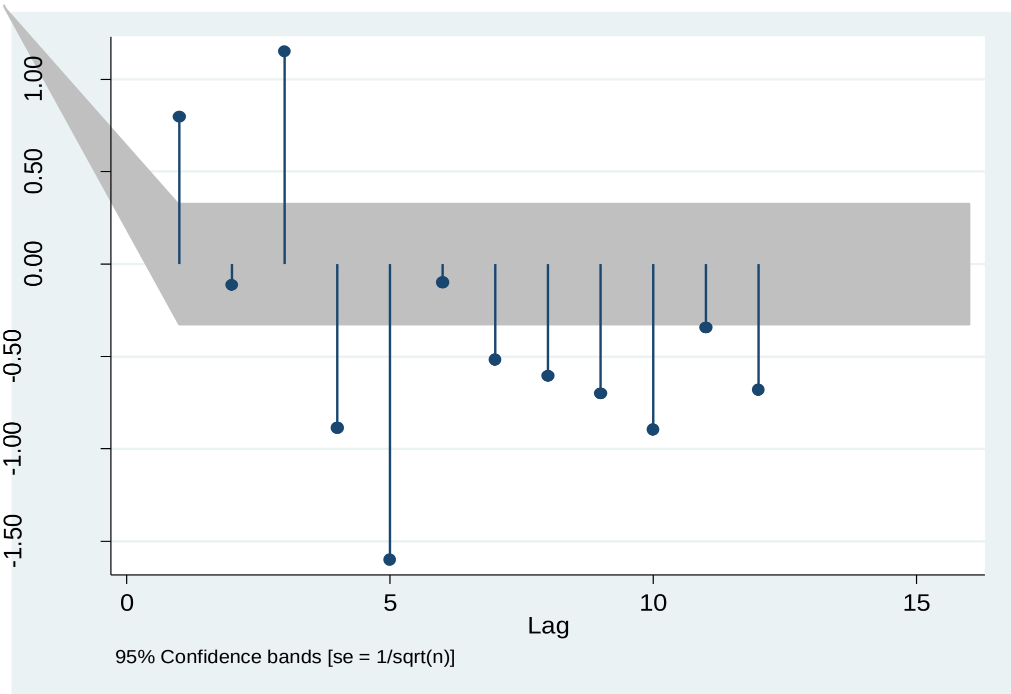
Figure 5: Plot of ACF of the first difference data



Source: Output from STATA version 14.2

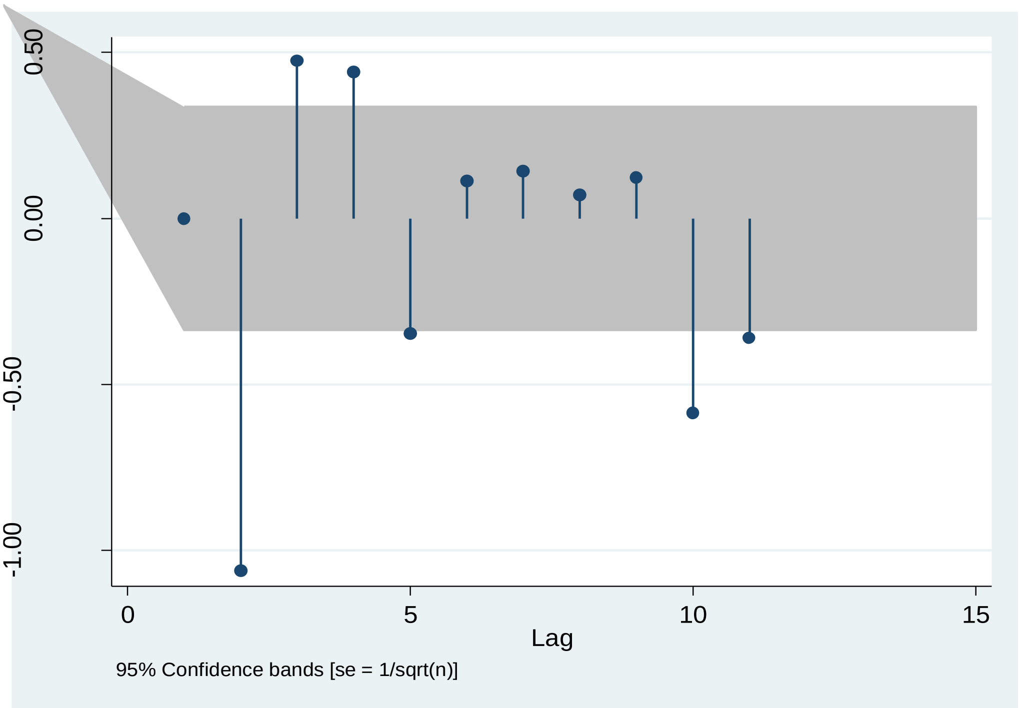
Figure 4 and 5 indicates a slow decay of lags at level series compared to sharp cut-off results in the first difference figure, justifying the first difference or order one integration I (1) of the series. However, the first difference data indicates that the auto-correlations has one statistically significant spike, indicating that MA (2) behaviour is appropriate because only the second lag is significant for the time-series data.

Figure 6: Plot of PACF of the level data



Source: Output from STATA version 14.2

Figure 7: Plot of PACF of the first difference data



Source: Output from STATA version 14.2

In Figure 6 and 7 above reveals that the partial autocorrelations for the first difference data have six statistically significant spike namely: AR (2), AR (3), AR (4), AR (5), AR (6), and AR (7). Consequently, given parsimony priority, the first difference of PACF suggests six AR(p) lags while the ACF suggests one MA(q) lag. Hence, the potential ARIMA models of the study include: ARIMA (2,1,2), ARIMA (3,1,2), ARIMA (4,1,1), ARIMA

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(5,1,2), ARIMA (6,1,2), ARIMA and (7,1,2).

Model Estimation

In this section, the study estimates those models to identify the most suitable one for Inflation Rate-forecasting conditional on a set of criteria proposed by (Box et. al., 2008): paramour significance, loglikelihoods, sigma error variance, and Akaike and Bayesian information criteria. Table 3 below presents the results of candidate models.

Table 3: ARIMA results

Variables	ARIMA (2,1,2)	ARIMA (3,1,2)	ARIMA (4,1,2)	ARIMA (5,1,2)	ARIMA (6,1,2)	ARIMA (7,1,2)
L1.ar	-.3529901	.7692589	-.9475247	-.0125541	1.135616	.0496698
L2.ar	-.5860876	-.5191609	-1.213807	-.0605144	-.9709799	-.6213648
L3.ar		3323359	-.3521528	-.2682867	.3751105	-.2887991
L4.ar			-.2835079	.1211611	-.2462762	-.2095995
L5.ar				-.483533	-.2029421	-.7181652
L6.ar					.0083867	-.0335113
L7.ar						-.5704947
L1.ma	4.556576	-222.7306	1.325443	.2641321	-1.988465	.9659521
L2.ma	.9966413	221.7096	.9998909	-1.264098	1.000003	-1.965982
Constants	1.198389	.108497	2.024171	-.3838672	-.6100228	-.5192731
Obs.	34	34	34	34	34	34

Table 3 above presents the results of all candidate models for forecasting purposes. Following the ARIMA theoretical framework, we selected the most suitable model by comparing model results based on four criteria (model fitness, sigma volatility, log-likelihood, and Akaike and Bayesian information criteria) outlined in (Box, et. al., 2008). Table 4 below shows the model selection criteria.

Table 4: Model Section Process

Model Selection Process						
Models	Significance	Sigma	Loglikelihood	AIC	BIC	Best Model
ARIMA (2,1,2)	1/4	10.52249	-150.7446	313.4892	322.2836	
	2/5	3.844551	-150.7435	315.4871	325.0012	
ARIMA (4,1,2)	4/6	.4415824	-136.6978	310.3955	314.1214	
ARIMA (5,1,2)	3/7	.1816368	-149.4421	316.8843	330.0759	
ARIMA (6,1,2)	3/8	-10.59809	-148.5395	317.079	331.7364	

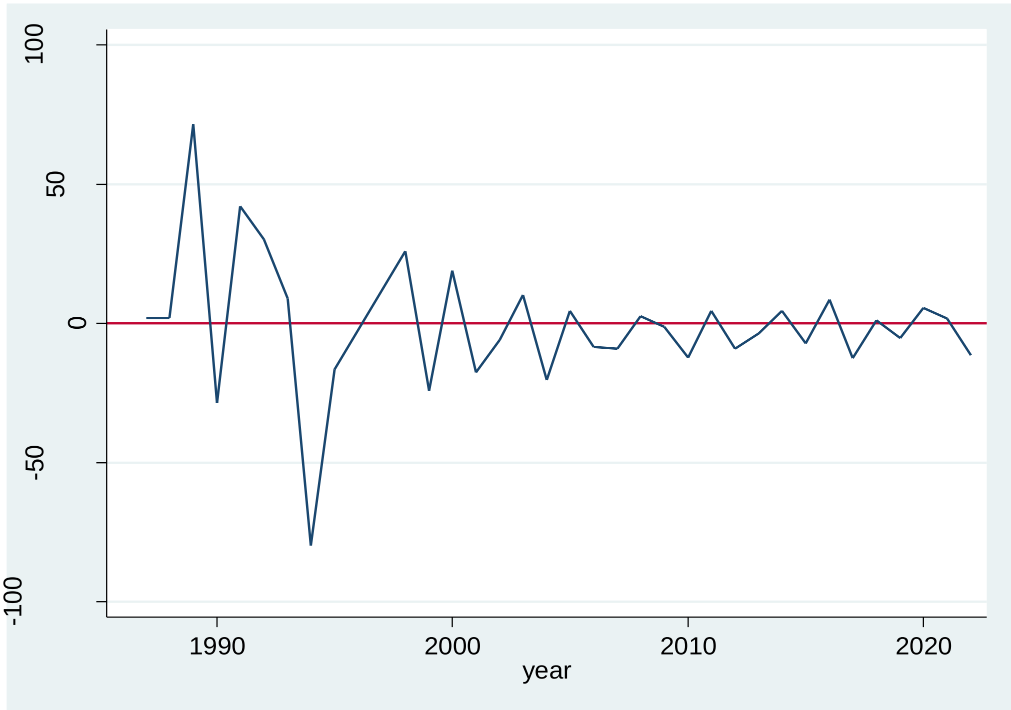
ARIMA (7,1,2)	1/9	9.290199	-148.5029	319.0058	335.1289	
Model Choice	ARIMA (4,1,2)	ARIMA (4,1,2)	ARIMA (4,1,2)	ARIMA (4,1,2)	ARIMA (4,1,2)	ARIMA (4,1,2)

The results in Table 4 above suggest that ARIMA (4,1,2) is the most suitable model for Zambia's Inflation Rate-forecasting. The choice of model is justified as being the one with the most significant parameters, the least log likelihood, Sigma, and the least Akaike and Bayesian information criteria (Zulu & Mwansa, 2022). Before ARIMA (4,1,2) was eligible for forecasting purposes, the study ran some diagnostics.

Model Diagnostics

In Section 3.3, the study proposed ARIMA (4,1,2) as the most appropriate model for Inflation Rate-forecasting. To objectively justify the model selection process, the study ran a test to check if model residuals are white noise and both AR and MA processes are covariance stationary, as shown in Figure 8 below.

Figure 8: White noise test for time series residuals



Source: Output from STATA version 14.2

Wiggling consistently around the mean, the results in Figure 8 above show that the residuals are white noise and that the series follows a stable univariate process. In addition to the pictorial residual check, the study also conducted a formal Portmanteau Test for white noise as shown in Table 5 below:

Table 5: Portmanteau Test for white noise

Portmanteau (Q)	statistic	=	6.3156
Prob > chi2(15)	=	0.9739	

Results in Table 5 above indicate the residuals are white noise since the $p = .9739 > .05$. Therefore, null hypothesis cannot be cannot be rejected. Zulu and Mwansa (2022) argued that if the p-value calculated from Portmanteau Test for white noise is greater than the level of significance set, reject the alternative hypothesis

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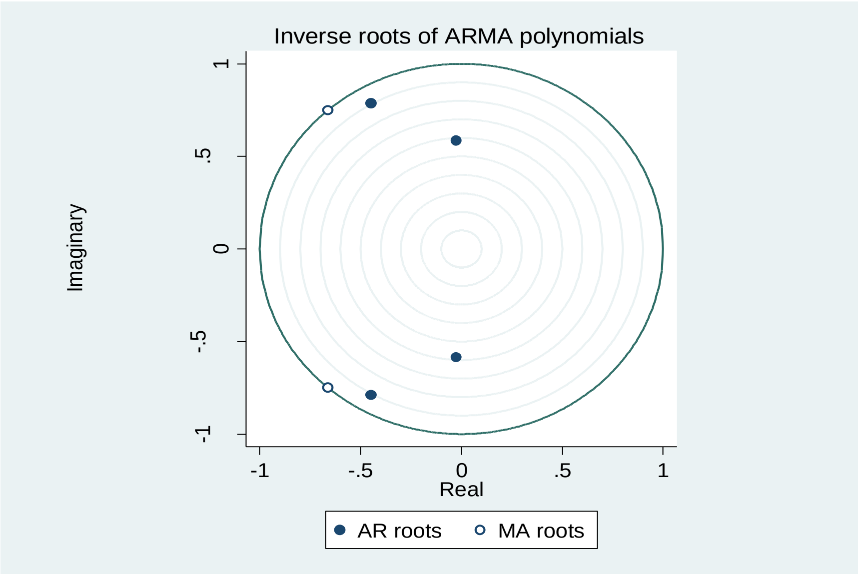
and accept the null hypothesis.

Moreover, checking that AR and MA processes are covariance stationery, the study ran stationarity and invariability tests as shown in Figure 9 below:

Figure 9: Covariance stationery test for both AR and MA components



Source: Output from STATA version 14.2

Figure 9 shows that both AR and MA roots lie inside and along the unit circle, verifying that the series follows a stable univariate process. According to Zulu, Mwansa, and Wakumelo, (2022), to verify that the time series follows a stable univariate process, both AR and MA roots lie inside and along the unit circle and not outside the unit circle. Thus, the results shown in Figure 5, Table 4, and Figure 7 indicate that the ARIMA (4,1,2) model performs better than the other models for this given time series. It was rightfully concluded that ARIMA (4, 1, 2) is the best model fit for the Zambia's inflation rate.

Model Forecasting

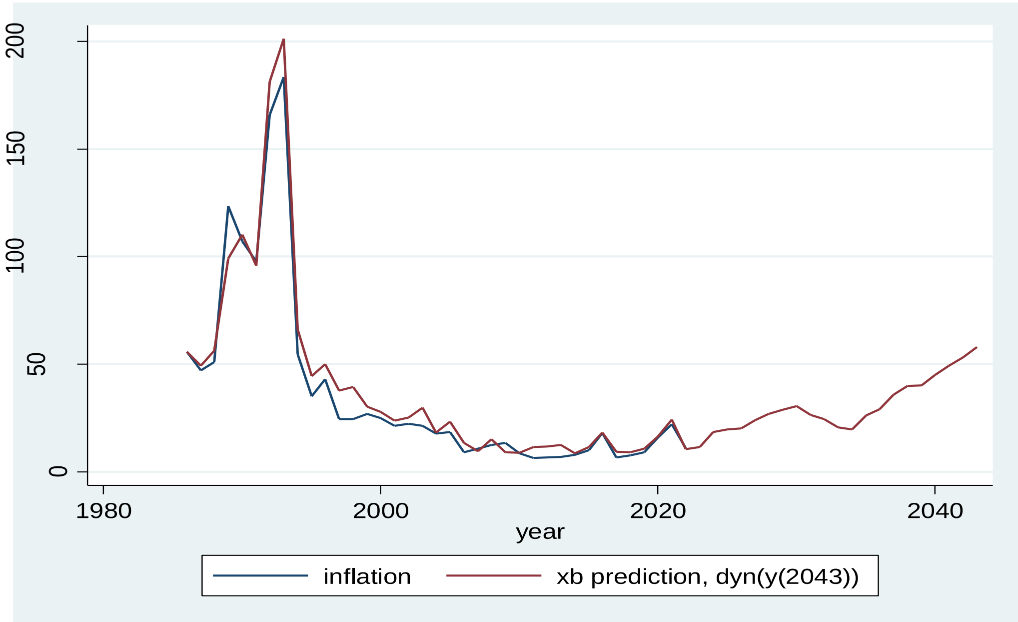
Finally, as the final step of the ARIMA modeling process, this section uses the ARIMA (4,1,2) model selected in Section 3.1 and tested in Section 3.2 to forecast Zambia's inflation rate for fifteen years. Table 6 and Figure 10 below presents the out-of-the-sample forecasting results between 2023 and 2043.

Table 6: Forecasted time series data for Zambia's Inflation Rate

Year	Forecasted Inflation Rates
2023	11.45
2024	18.34
2025	19.56
2026	20.03
2027	23.93
2028	26.77
2029	28.89
2030	30.45

2031	26.39
2032	24.54
2033	20.61
2034	19.56
2035	26.27
2036	29.11
2037	35.71
2038	39.83
2039	40.08
2040	44.99
2041	49.16
2042	53.17
2043	57.82

Figure 9: Plot of forecasted Zambia's Inflation Rate



Source: Output from STATA version 14.2

Results from Table 6 and Figure 10 shows that in 2023, inflation rate is estimated to be 11.45% an increase of 0.9% from 2022 compared to 2024 at 18.34% an increase of 6.89% from 2023. In 2025, inflation rate is estimated to be at 19.56% an increase of 1.22% from 2024 compared to 2026 at 20.03% an increase of 0.47% from 2025.

Besides, in 2027, inflation rate is estimated to be 23.93% an increase of 3.9% from 2026 compared to 2028 at 26.77% an increase of 2.84% from 2027. In 2029, inflation rate is estimated to be 28.89% an increase of 2.12% from 2028 compared to 2030 at 30.45% an increase of 1.56% from 2029.

However, in 2031, inflation rate is estimated to be 26.39% a drop of 4.06% from 2030 compared to 2032 at 24.54% a drop of 1.85% from 2031. In 2033, inflation rate is estimated to be 20.61% a drop of 3.93% from 2032 compared to 2034 at 19.56% a drop of 1.05% from 2033.

However, in 2035, inflation rate is estimated to be 26.27% an increase of 6.71% from 2034 compared to 2036 at 29.11% an increase of 2.84% from 2035. In 2037, inflation rate is estimated to be at 35.71% an increase of 6.6% from 2036 compared to 2038 at 39.83% an increase of 4.12% from 2037.

Additionally, in 2039, inflation rate is estimated to be at 40.09% an increase of 0.25% from 2038 compared to 2040 at 44.99% an increase of 4.9% from 2039. In 2041, inflation rate is estimated to be at 49.16% an increase of 4.17% from 2040 compared to 2042 at 53.17% an increase of 4.01% from 2041. Furthermore, in 2043, inflation rate is estimated to be 57.82% an increase of 4.65% from 2042.

Results of the study from Figure 6 show that from 2023 to 2029, inflation rate is expected to grow by 19.9%; from 2030 to 2034, inflation rate is expected to drop by 10.89%' and from 3035 to 2043, inflation rate is expected to grow by 38.25%. However, in 20 years Zambia's inflation rate is forecasted to rise by 47.27%.

Policy Implication

The estimation of Zambia's inflation rate growth is large and will be very critical if it is not properly controlled and managed to stimulate the economy. The increase in inflation during this period could be mainly due to the significant depreciation of the Kwacha against the US dollar, upward adjustment in fuel pump prices, load shedding, and reduced supply of some food items, mostly maize the staple food.

Also, high inflation rate poses significant problems to Zambia, i.e. to investors (both foreign and local Investors), policy makers, and even to a community at large. Among the problems include, small notes of money losing power to operate in circulation, critical shortage of goods especially domestic products.

Additionally, in an economy where there are high rates of inflation, investors lose confidence in such an economy, as a result the country loses out in terms of foreign direct investment. Policy makers face difficulties in implementing their policies and perpetuate poor living conditions among the low and middle classes of the country.

Further, high inflation rate can cause business costs to rise faster than productivity gains and lead entrepreneurs to become risk-averse, less willing to invest in the future, thereby reducing competitiveness. This has a negative impact on economic growth and employment in Zambia.

CONCLUSION

After applying the Box-Jenkins technique, the ARIMA framework was engaged to investigate yearly inflation rates in Zambia over the study period. The study mostly planned to forecast inflation in Zambia for the upcoming period from 2023 to 2043 and the best fitting model was selected based on how well the model captures the stochastic variation in the data. The ARIMA (4, 1, 2) model is not only stable but also the most suitable model to forecast inflation for the next 20 years. Additionally, the choice of the ARIMA (4, 1, 2) model is justified as being the one with the most significant parameters, the least log likelihood, Sigma, and the least Akaike and Bayesian information criteria. In general, Zambia's inflation rate is forecasted to rise by 47.27% in 20 years.

RECOMMENDATIONS

Based on the results, policy makers in Zambia should continue to engage proper economic and monetary policies in order to fight such increase in inflation as reflected in the forecasts. In this regard, the Bank of Zambia is encouraged to rely more on contractionary monetary policy, which should be complimented by a tight fiscal policy.

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