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Empirical Approach to Modelling and Forecasting Inflation using ARIMA Model: Evidence from Tanzania

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Abstract

This study investigates the dynamics of the inflation rate (INFL) in Tanzania spanning from 1990 to 2021 using advanced time series analysis techniques. The dataset sourced from the World Bank online database serves as the basis for analytical exploration. Initially, the Autoregressive Integrated Moving Average (ARIMA) model is applied to understand underlying patterns in the INFL data. Transitioning to Seasonal ARIMA (SARIMA) modeling encounters challenges due to the absence of pronounced seasonality or clear trends. Unit root tests, including the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests, assess the stationarity of the data. Following the identification of non-stationarity, differencing is employed to achieve stationarity. Estimation of ARIMA models (ARIMA (1,1,1) and ARIMA (2,1,1)) is conducted, with diagnostic checks confirming the suitability of the ARIMA (1,1,1) model. The study contributes to the understanding of inflation dynamics and facilitates evidence-based economic policymaking in Tanzania.

Keywords: forecasting, modelling, inflation, ARIMA, Tanzania

1. Introduction

1.1 Introduce the Problem

Inflation, as a fundamental macroeconomic indicator, holds significant implications for economic stability, investment decisions, and policymaking in any country. For emerging economies like Tanzania, understanding the dynamics of inflation and developing accurate forecasting models is of paramount importance to facilitate effective monetary policy implementation and support sustainable economic growth (Kimolo, 2012). In Tanzania, inflation has posed a significant macroeconomic challenge, peaking at 44.6 percent in April 1985 before gradually declining to 9.1 percent in January 1999. Factors contributing to high inflation rates included budget deficits, external shocks, excessive government borrowing, and structural rigidities. Despite fluctuations, inflation declined from 230.2 percent in January 1980 to a low of 3.4 percent in June 2004. However, it gained momentum, thereafter, reaching 12.2 percent in December 2009. On average, from January 1980 to December 2009, Tanzanian inflation averaged 20.2 percent (Kimolo, 2012). Forecasting inflation proves to be a daunting task in emerging markets due to the shifting trade and monetary regimes, as well as the high volatility of exchange rates, energy, and food prices (Aron, Muellbauer & Sebudde, 2015). Webster (2000) defines inflation as the persistent increase in the level of consumer prices or a persistent decline in the purchasing power of money. Hall (1982) describes inflation as a situation where the demand for goods and services exceeds their supply in the economy. To facilitate the economic development of Tanzania effectively, it is essential to gain a thorough understanding of the country's current inflation situation and anticipated future inflation. This understanding will enable policymakers to implement appropriate measures to mitigate price pressures and promote economic stability. The purpose of this study was to empirically develop ARIMA models for Tanzania's inflation and to forecast inflation rates using historical yearly data from 1990 to 2021.

1.2 Explore Importance of the Problem

Inflation plays a pivotal role in economic stability, investment decisions, and policymaking globally, particularly in emerging economies like Tanzania. Tanzanian inflation has fluctuated significantly over time, driven by factors such as budget deficits, external shocks, and structural rigidities. Forecasting inflation in emerging markets is challenging due to evolving trade and monetary regimes and volatile exchange rates, energy, and food prices. The empirical development of ARIMA models for Tanzania's inflation, as undertaken in this study, contributes to the existing literature on inflation modeling and forecasting. The findings and policy recommendations not only hold relevance for Tanzania but also offer insights applicable to other countries facing similar economic challenges. Through this empirical inquiry, we aim to enhance understanding of inflation dynamics and facilitate evidence-based economic policymaking in Tanzania.

1.3 Describe Relevant Scholarship

Over the years, numerous empirical studies have been conducted in the field of inflation. Most of the research in inflation forecasting has focused on developed countries, particularly those that have adopted inflation-targeting strategies. Uwilingiyimana et al. (2015) evaluated the efficacy of combining ARIMA and GARCH models for forecasting monthly inflation rates. Utilizing the Box-Cox formula for variance transformation, they assessed 180 monthly data series. Their findings suggested that the ARIMA (1,1,12)-GARCH (1,2) model outperformed ten previous forecasting methods. This combination enhanced accuracy in estimating and forecasting inflation rates, showcasing the potential of ARIMA-GARCH in overcoming the limitations of linear models. Okeyo et al. (2016) explored different specifications of GARCH models, acknowledging that lower specifications effectively capture inflation rate characteristics while maintaining parsimony. Various GARCH, GJR-GARCH, and E-GARCH models were tested with variations in conditional distribution, including normal, Student's t, and generalized error distribution. Model selection criteria such as AIC, BIC, SIC, and LL were used to identify the best-fitting model. The resulting model was determined to be an E-GARCH (1,1) with a generalized error distribution. Nyoni and Nathaniel (2018) employed ARMA, ARIMA, and GARCH models to model and forecast inflation. Diagnostic tests, such as the ADF tests, suggested that the NINF time series data is essentially I(1), although it is generally I(0) at the 10% significance level. Based on the minimum Theil’s U forecast evaluation statistic, the study presented the ARMA (1, 0, 2) model, the ARIMA (1, 1, 1) model, and the AR (3) – GARCH (1, 1) model, with the ARMA (1, 0, 2) model identified as the optimal model. Diagnostic tests also indicated that the presented models are stable and reliable. The results suggested that inflation in Nigeria is projected to rise to about 17% per annum by the end of 2021 and is likely to exceed that level by 2027. Sammy (2018) found that the EGARCH model is the best fit for the Kenyan inflation data. The EGARCH (1,1) model exhibited the smallest AIC and BIC compared to various GARCH models. Kayisire (2014) evaluated Phillips curve forecasts of inflation for Rwanda. The study utilized various single-equation prototype Phillips curve models, following the approach outlined by Stock and Watson (2008). Pseudo-out-of-sample comparison tests were employed to assess the forecast performance of these Phillips curve forecasts relative to the AR (autoregression) benchmark forecasts. Results indicated that both the Phillips curve and augmented Phillips curve forecasts outperformed the AR benchmark forecasts at one- and two-quarter horizons. Chipili (2021) analyzed the drivers of inflation in Zambia from 1994.1 to 2019.4 using a single-error correction model. Results indicated that long-run inflation was influenced by the exchange rate and world non-food prices. Short-term inflation was affected by exchange rate fluctuations, energy price adjustments, imported inflation from South Africa, and changes in maize prices, representing supply constraints. Fannoh (2018) utilized the Box-Jenkins Methodology to model Liberia's inflation rates, determining ARIMA (0,1,0) (2,0,0)12 as the optimal model. Subsequent residual analysis found no evidence of ARCH effect or serial correlation, confirming the model's validity. Ngailo et al. (2014) conducted a study on time series modeling with a specific focus on modeling inflation data in Tanzania. The inflation data covered the period from January 1997 to December 2010. The study determined that the GARCH (1,1) model was the most suitable for the data. Utilizing this model, the twelve-month inflation rates for Tanzania were forecasted for the in-sample period from January 2010 to December 2010. The results indicated that the forecasted series closely approximated the actual data series. Nyoni (2019) employed the ARIMA model to investigate annual inflation rates in Tanzania over the study period. The primary objective of the study was to forecast inflation in Tanzania for the period spanning from 2018 to 2027, with the selection of the best-fitting model based on its ability to capture the stochastic variation in the data. The ARIMA (1, 1, 2) model was identified as not only stable but also the most suitable for forecasting inflation for the next ten years. In their study, Aron et al. (2015) developed 1-month and 3-month-ahead forecasting equations for domestic fuel, food, and non-food inflation in Uganda. They employed automatic model selection techniques to identify models with stable parameters aligned with economic priors. Their analysis accounted for major structural breaks and non-linearities, with a focus on relative price adjustments. Specifically, they included non-food and fuel prices in the food equation as well as food and fuel prices in the non-food equation to enhance accuracy. Kimolo (2012) utilized the Box-Jenkins (1970) methodology, involving stages of identification, estimation, diagnostic checking, and forecasting of a univariate time series. The study's findings suggest that during the sample period, the monthly inflation rate in Tanzania was non-stationary at the level but stationary after taking the first difference. Additionally, the results indicate that the model containing AR (1, 3, 8, and 15) and MA (1 and 12) components outperformed other models in both in-sample and out-sample forecasts. The study also provides six months of out-of-sample inflation forecasts.

1.4 State Hypotheses and Their Correspondence to Research Design

H_0**:** The inflation rate data possesses a unit root, indicating non-stationarity.

- Correspondence to Research Design**:** This hypothesis corresponds to the unit root test conducted using the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. The research design involves testing whether the inflation rate data exhibits stationary properties over time.

H_1**:** The inflation rate data does not possess a unit root, indicating stationarity.

- Correspondence to Research Design**:** This hypothesis also corresponds to the unit root test. The research design aims to determine if the inflation rate data is stationary or non-stationary based on the rejection or acceptance of the null hypothesis.

H_0**:** The ARIMA (1,1,1) model adequately represents the underlying time series data.

- Correspondence to Research Design**:** This hypothesis corresponds to the estimation and diagnostic checks conducted on the ARIMA model. The research design involves assessing whether the chosen ARIMA model accurately captures the patterns and trends in the inflation rate data.

H_1**:** The ARIMA (1,1,1) model does not adequately represent the underlying time series data.

- Correspondence to Research Design**:** This hypothesis also corresponds to the estimation and diagnostic checks on the ARIMA model. The research design aims to identify any shortcomings or inadequacies in the chosen ARIMA model and explore alternative models if necessary.

2. Method

2.1 Data and Source

The dataset utilized in this study was sourced from the World Bank online database, a reputable and comprehensive source of economic and financial data. Its data provided a rich historical record of the inflation Rate (INFL) spanning from 1990 to 2021, which served as the basis for analytical.

2.2 Modelling with ARIMA and SARIMA

The ARIMA model comprises two fundamental univariate time series models: The Autoregressive (AR) model and the Moving Average (MA) model. It leverages historical data within a time series to predict future values. The ARIMA model, denoted as ARIMA (p, d, q), consists of three parameters where p, d, and q are integers greater than or equal to zero, representing the autoregressive, integrated, and moving average components, respectively (Hurvich and Tsai, 1989; Kirchgässner and Wolters, 2012; Kleiber and Zeileis, 2008; Pankratz, 1983; Pfaff, 2008; Uwilingiyimana et al., 2015). The parameter p indicates the number of autoregressive lags (excluding unit roots), d denotes the order of integration necessary for stationarity, and q signifies the number of moving average lags. Initially, the study applied the Autoregressive Integrated Moving Average (ARIMA) model, a foundational method for time series analysis. ARIMA allowed us to explore and understand the underlying patterns, trends, and cyclic behavior inherent in the INFL data.

A process is ARIMA (p, d, q) if $\nabla_{y_t}^{d} = (1-L)_{y_t}^{d}$ is ARMA (p, q).

In general, we can write the model as

$$\theta(L)(1-L)_{y_t}^{d} = \emptyset\epsilon_t;\ \epsilon_t \sim WN(0,\sigma^2), \tag{1}$$

We then define the Lag operator as

$$L_{y_t}^{k} = y_{t-k},$$

while the autoregressive operator and the moving average operator are defined as

$$\theta(L) = 1 - \theta_1(L) - \theta_2(L^2) - \cdots - \theta_p(L^p) \tag{2}$$

$$\emptyset(L) = 1 + \emptyset_1(L) + \emptyset_2(L^2) + \cdots + \emptyset_p(L^p), \tag{3}$$

where

$\theta\ and\ \emptyset$ are standard autoregressive (AR) and moving average (MA) polynomials of order p and q in a variable $L, \theta(L) \neq 0$ for $|\theta| < 1$, and y_t is said to be stationary if and only if $d = 0$. In which it becomes ARMA (p, q) process.

The study transitioned into the Seasonal ARIMA (SARIMA) modelling and encountered a unique challenge. SARIMA models introduce the concept of seasonality, which is essential when data exhibits recurring patterns across specific time intervals. However, despite the efforts, it became apparent that the INFL data might not possess a pronounced seasonality or clear trends, making SARIMA modelling a more elaborate task.

2.3 Forecasting Using ARIMA Model

Forecasting using the ARIMA model constitutes the final step in the Box-Jenkins model building approach. Once a model has successfully undergone all diagnostic tests, it becomes suitable for forecasting, which involves making predictions about events whose actual outcomes are yet to be observed. ARIMA models, as demonstrated by various researchers, have exhibited robust performance in forecasting compared to other intricate models. Among the widely recognized univariate forecasting models is the ARMA (p, q) model introduced by Box and Jenkins (1970). Therefore, ARMA for the stationary and ARIMA for the 1st difference order when data are not stationary. Then, for a stationary time series, an ARMA (p, q) model is expressed as:

$$y_t = \theta_1 y_{t-1} + \theta_2 y_{t-2} + \cdots + \theta_p y_{t-p} + \varepsilon_t + \emptyset_1 \epsilon_{t-1} + \emptyset_2 \epsilon_{t-2} + \cdots + \emptyset_p \epsilon_{t-p}, \qquad (4)$$

where

ϵ_t is a white noise $\sim N(0, \sigma^2)$.

2.4 Unit Root Test

This study employed the unit root test method as a fundamental statistical to assess whether a given time series data is stationary or non-stationary. Testing for stationarity was a crucial concept in time series analysis because it implies that time series statistical properties remain consistent over time, making it more amenable for modelling and forecasting.

Two common approaches were used to conduct the unit root test that is the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test. These tests assumed that a time series variable, denoted as

$$y_t = y_{t-1} + e_{t,} \qquad (5)$$

where

$y_t =$ the value of the time series variable at time t.

$y_{t-1} =$ lagged value at time $t-1$.

$e_{t=}$ an error term at time t or random walk.

For stationarity, the unit root test considered whether the parameter e_t has a unit root, which means that it equals 1 ($e_{t=1}$).

However, a study performed 1st difference for the stationarity test.

$y_{t=y_{t-1}+e_t}$ and subtract $y_{t-1}$from both sides of the equation, resulting in:

$\nabla y_t = e_t$,

where

Δ= The differencing operator, such that

∇y_t= the differenced time series variable at time t.

$e_{t=}$error term at time t.

The null hypothesis (H_0) of the unit root test assumes that the parameter e_t has a unit root, indicating non-stationarity ($e_1 = 1$). The alternative hypothesis (H_1) suggests that a unit root does not exist, signifying stationarity ($e_{t=0}$). Therefore, in testing for stationarity, the objective is to determine whether the data are stationary by rejecting H_0 or to conclude non-stationarity by not rejecting H_0.

2.5 Identification

In modeling and forecasting the INFL Rate, the study ensured the reliability of predictive models. The exploration commenced with an investigation into the stationarity of the time series data, as a critical foundation for modeling. This was initiated with a visual assessment, represented by a time series graph. The initial inspection suggested non-stationarity, as the data displayed discernible trends.

To further validate observations, proceeded to examine the autocorrelation of the data, which confirmed the presence of serial correlation. These results collectively underlined the non-stationary nature of the dataset.

With the understanding that most economic variables tend to be non-stationary, the study recognized the need for differencing to achieve stationarity. Then formal unit root tests, specifically the ADF and PP tests applied. These tests evaluated the null hypothesis that the data had a unit root, indicative of non-stationarity.

2.6 Estimation

After achieving stationarity through differencing, the next step was to determine the optimal order of correlation for the ARIMA model. This determination considered an accurate analysis of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF). This ACF exhibited a pronounced correlation at the first lag, exceeding the confidence interval, while the PACF revealed two lags exceeding the same threshold.

With this critical information in hand, we proceeded to estimate two distinct ARIMA models: ARIMA (1,1,1) and ARIMA (2,1,1). During estimation, essential parameters were computed and scrutinized, including the variance of error (Sigma SQ), log-likelihood, Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC). These metrics allowed to assess the goodness of fit and make informed decisions regarding the most suitable model for forecasting.

2.7 Diagnostic

Following the estimation, ARIMA (1,1,1) emerged as a promising candidate due to its favorable fit criteria. However, it is essential to ensure the model's validity and its ability to adequately represent the underlying time series data. To achieve this, a comprehensive diagnostic check study was conducted on the residuals to ascertain whether they exhibit characteristics of white noise, which is a crucial assumption in time series modeling. The stationarity of the estimated ARIMA (1,1,1) process was confirmed by ensuring that its roots lie inside the unit circle, rendering its covariance stationary.

The examination of residual behavior commenced with a visual inspection of the ACF plot. Here, purposely to observe if the residuals exhibited random fluctuations around the mean, indicative of white noise. Positively, the ACF plot revealed white noise in the case for the model validity. To identify the white noise assumption, statistical tests were applied as the Portmanteau (Q) test was employed to rigorously assess the whiteness of residuals. Additionally, Ljung-Box Q statistics were leveraged to evaluate the adequacy of the fitted model. These tests served a double purpose not only to confirm the presence of white noise in the residuals but also to test the overall goodness of fit of the model.

Moreover, the diagnostic process encompassed checks for homoscedasticity, employing the ARCH LM-test, and inspecting autocorrelation through the Durbin test. These tests are essential in forecasting, as they ensure that the residuals exhibit consistent variance over time and remain free from undesirable autocorrelation patterns.

3. Results and Discussion

The findings of this study shed valuable light on the dynamics of inflation (INFL) within the Tanzanian economy. These findings offer essential insights for Tanzanian policymakers, businesses, and investors in navigating the complex landscape of economic dynamics and inflation management. The time series analysis in Figure 1 on inflation data revealed a pattern characterized by periods of both increase and decrease in the overall price levels of goods and services over the years. These fluctuations, often referred to as ups and downs, indicate the economic forces at play within the nation. The upward movements in inflation signify periods of demand relative to supply, often driven by various factors, including increased consumer spending, economic growth, and external shocks.

In contrast, the downward trends represent moments of relative price stability or even deflation, reflecting demand or effective fiscal and monetary policies aimed at controlling inflation. This cyclical nature of inflation in Tanzania underscores the importance of adaptable economic policies that can respond to changing economic conditions. Policymakers may consider utilizing contractionary measures during inflationary periods to safeguard price stability, while expansionary policies can stimulate growth during deflationary phases.

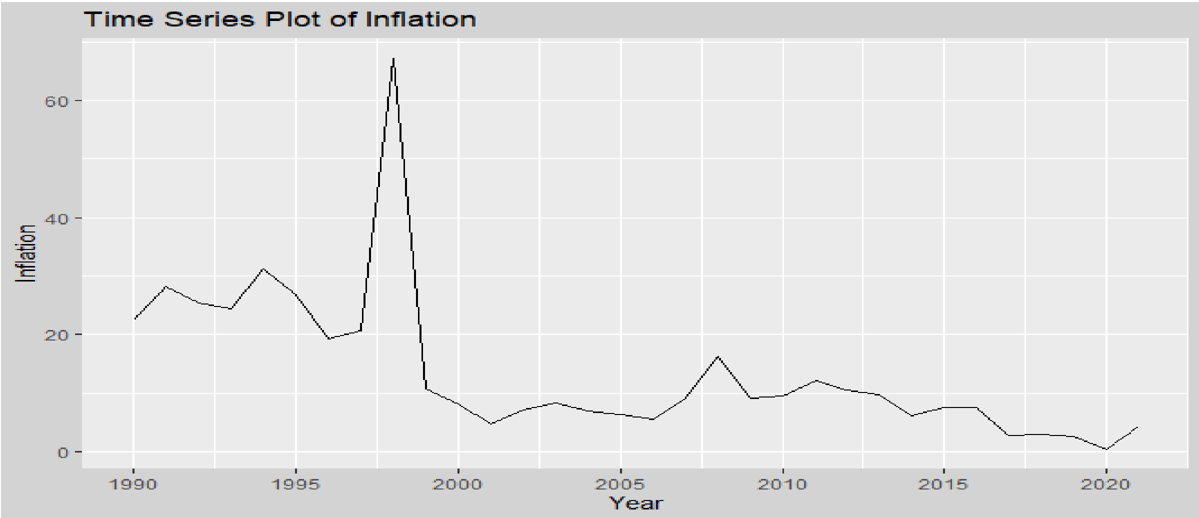

Figure 1. Time series plot of the INFL

Source: Researchers own, (2023)

Also, in Table 1, the ADF test statistic of -0.9384, and the p-value is less than 0.001 ($p < 0.001$). The Phillips-Perron (PP) test statistic is 0.0616, and the p-value is 0.746 ($p = 0.746$). The PP test, in this case, suggests that the data before differencing is non-stationary, as the p-value is above the common significance level of 0.05. This indicates strong evidence against the null hypothesis of the series having a unit root for PP though ADF were sig but since the graphical showed nonstationary, it is concluded that the data before differencing was found to be non-stationary.

Table 2, After the first ADF test statistic is -1.4411, and the p-value is less than 0.001 ($p < 0.001$). The PP test statistic is -0.4411, and the p-value is 0.015 ($p = 0.015$). Like the ADF test, the PP test suggests that the data is now stationary after the first difference ($p<0.05$).

These results are essential for economic study as they allow us to work with a stationary time series, which forms the basis for constructing and estimating various time series models, including ARIMA and SARIMA that are crucial for obtaining reliable forecasts and insights into the behavior of INFL in an economic context.

Table 1. The unit root of the INFL rate

Test	Test statistic	ρ - value
Augmented Dickey-Fuller (ADF)	-0.9384	<0.001
Phillips-Perron test (PP)	0.0616	0.746

Source: Researchers own, (2023)

Table 2. The unit root of INFL rate 1st diff

Test	Test statistic	ρ - value
Augmented Dickey-Fuller (ADF)	-1.4411	<0.001
Phillips-Perron test (PP)	-0-.4411	0.015

Source: Researchers own, (2023)

Furthermore, in the Auto-Correlation Function (ACF) plot, it is observed that the autocorrelation coefficients for lags gradually decrease, but they do not drop to zero quickly. This suggests that the data before differencing retains some memory of past values. From an economic perspective, this pattern could imply that past inflation (INFL) rates influence current rates, possibly due to inactivity in price movements.

Partial Auto-Correlation Function (PACF) plot, coefficients exhibit significant spikes at the first and second lags (p=1,2), indicating a strong relationship between the current observation and values one or two time periods ago. This suggests that past INFL rates strongly influence the current rate, which could be due to various economic factors and policy decisions.

In the case of non-stationary data, the persistence of autocorrelation in INFL rates suggests that past INFL levels have a persistent effect on current rates. This persistence could be due to factors like INFL expectations, pricing behavior, or government policies that influence price stability.

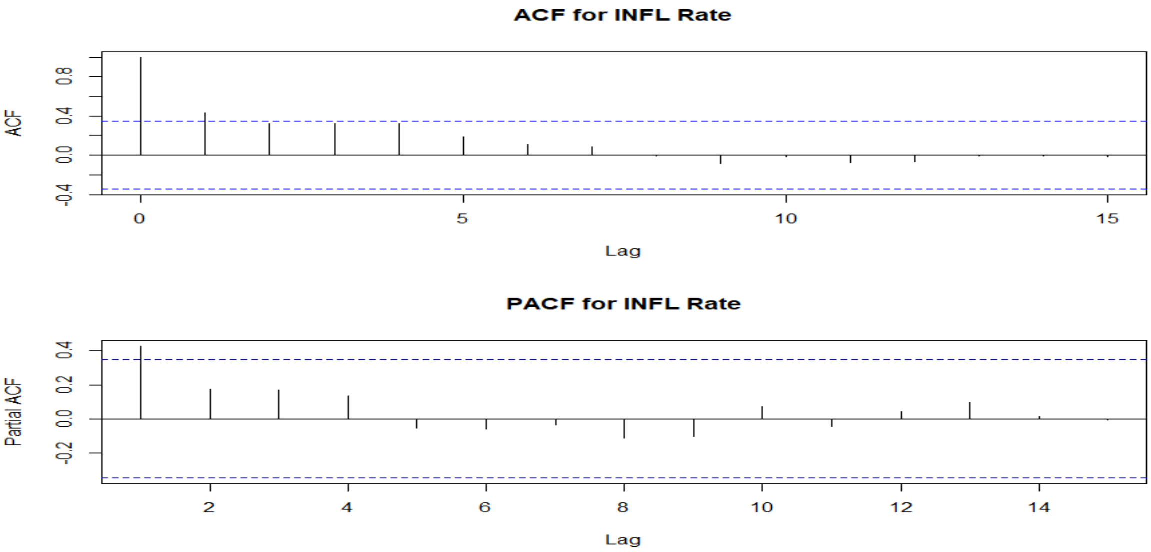

Figure 2. ACF and PACF for INFL rate

Source: Researchers own, (2023)

In the ACF plot for stationary data, the autocorrelation coefficients drop to near zero quickly after the first lag (q=1). This rapid decrease in autocorrelation suggests that the data no longer exhibits significant memory of past values. From an economic viewpoint, this implies that the current inflation (INFL) rate is not significantly influenced by past rates, indicating a more responsive and dynamic economic environment.

In the PACF plot for stationary data, the partial autocorrelation coefficients drop to near zero after the first and second lags (p=1,2). This suggests that after differencing, the current INFL rate is not significantly dependent on values from one or two periods ago. From an economic perspective, this can be seen as a positive sign, indicating that INFL rates respond quickly to changing economic conditions and external factors.

Therefore, for stationary data, the rapid decay in autocorrelation indicates that INFL in Tanzania responds quickly to changes in economic conditions. This responsiveness can be beneficial for policymakers as it suggests that INFL can be controlled more effectively, and the economy can adapt swiftly to external shocks.

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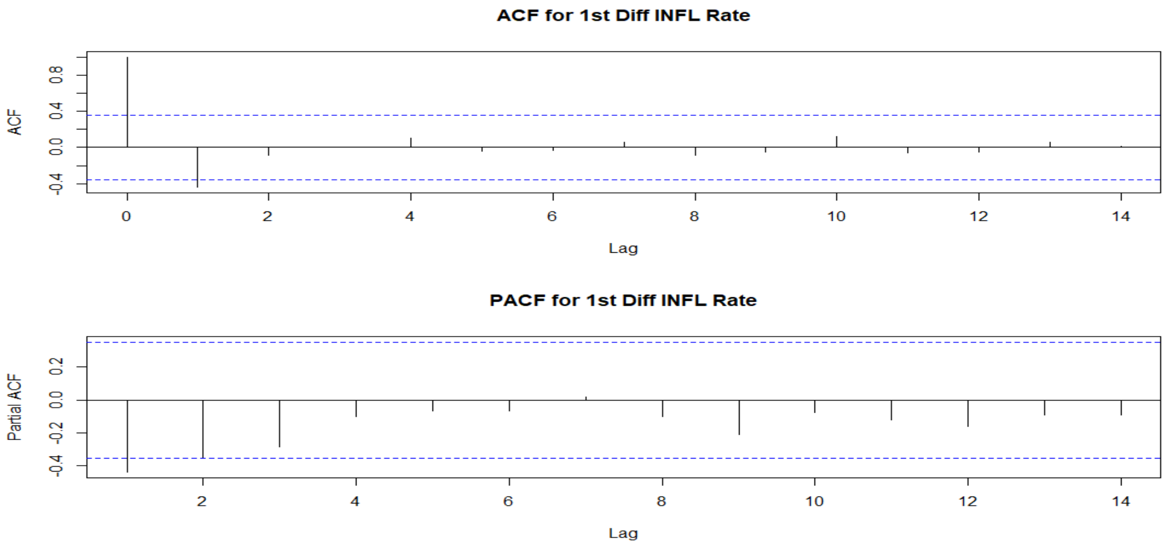

Figure 3. ACF and PACF for INFL rate

Source: Researchers own, (2023)

3.1 Model Criterion

The results in Table 3 indicate that after confirming the data's stationarity following differencing and observing significant lags in the ACF (q=1) and PACF (p=1,2), the study selected ARIMA (1,1,1) and ARIMA (2,1,1) models. These models capture the dynamics of inflation (INFL), considering both short-term and longer-term influences, making them suitable for forecasting INFL in Tanzania.

The analysis of ACF and PACF plots provides insights into the temporal dependencies of INFL data in Tanzania. The transition from non-stationary to stationary data is essential for accurate modeling and forecasting, and the selected ARIMA models account for the observed lagged effects in the data, contributing to more reliable INFL predictions within the economic context of Tanzania.

Table 3. Model selection between ARIMA (p,1, d) and (p,1, d)

	Criteria	Model A (1,1,1)	Model B (2,1,1)	Model choice
1	C, AR, MA	3/3	4/4	Equal (both sig)
2	Sigma SQ; variance of error	9.9539	9.9481	B
3	Log-likelihood	-116.8653	-116.8621	A
4	AIC	239.7307	241.7241	A
5	BIC	244.0326	247.4601	A

Source: Researchers own, (2023)

3.2 Estimation

The findings in Table 4 from the model selection process for forecasting INFL in Tanzania suggest that the moving average (MA) components play a significant role in explaining the behavior of INFL. Both MA (1) and MA (2) coefficients are highly significant, with coefficients close to -1.000. This implies that the current INFL is strongly influenced by the lagged moving average values of INFL. In other words, fluctuations in INFL are mostly driven by recent past values.

Conversely, the autoregressive (AR) components, AR (1) and AR (2) do not appear to be statistically significant in explaining INFL. These coefficients are not significantly different from zero, and their p-values are relatively high. This suggests that the relationship between the current INFL and its past values (autoregressive relationship) is weak and may not be crucial for forecasting INFL in Tanzania.

In practical terms, these findings imply that when forecasting INFL in Tanzania, it is essential to consider recent past moving average values as they have a substantial impact on the current INFL levels. On the other hand, the historical INFL values themselves do not contribute significantly to the forecasting accuracy. This insight can be valuable for policymakers, economists, and businesses in understanding the drivers of INFL and making more accurate forecasts and decisions related to economic planning and financial stability in Tanzania.

Table 4. The estimation of ARIMA (1,1,1) and (2,1,1)

Model Type	Coefficient	Std.Err	Test statistic	ρ - value	95% CI
AR (1)	0.0944	0.1238	0.76	0.446	-0.1484 to 0.3371
AR (2)	-0.0144	0.1711	-0.08	0.933	-0.3497 to 0.3209
MA (1)	-1.000	0.1301	-7.69	0.000	-1.2550 to -0.7450
MA (2)	-0.9999	0.1352	-7.40	0.000	-1.2649 to -0.7351

Source: Researchers own, (2023)

3.3 The ACF for Residual

The diagnostic checks on the residuals of the ARIMA (1,1,1) and ARIMA (2,1,1) models reveal promising results for adequacy in representing INFL data in Tanzania. The ACF plot of the residuals shows that, for the most part, it resembles white noise. White noise in residuals implies that there are no systematic patterns or correlations left in the model errors. This is a positive sign, suggesting that the model has effectively captured the underlying structure in the data, leaving little room for further improvement.

However, worth noting that there is a significant spike at lag 0 in the ACF plot. But this spike is often considered acceptable in time series analysis, especially when it occurs at lag 0. It could be attributed to random fluctuations or minor noise that is difficult to model precisely but does not significantly impact the overall model performance.

Moreover, the Ljung-Box test p-values confirm the adequacy of the model. The p-values are consistently above the threshold of 0.05, as indicated by the blue line. This suggests that there is no significant autocorrelation remaining in the residuals beyond what would be expected by chance. In simpler terms, the residuals do not exhibit any systematic patterns or trends that the model has failed to capture.

From an economic perspective, these findings are encouraging, indicating that the selected ARIMA models, ARIMA (1,1,1) and ARIMA (2,1,1), provide a reasonable representation of inflation (INFL) dynamics in Tanzania. The absence of significant autocorrelation in the residuals implies that the models have effectively accounted for the historical patterns and relationships in the data. Policymakers and economists can have confidence in using these models for forecasting and policy analysis related to inflation in Tanzania, as they seem to capture the essential aspects of inflation behavior without leaving significant unexplained variations.

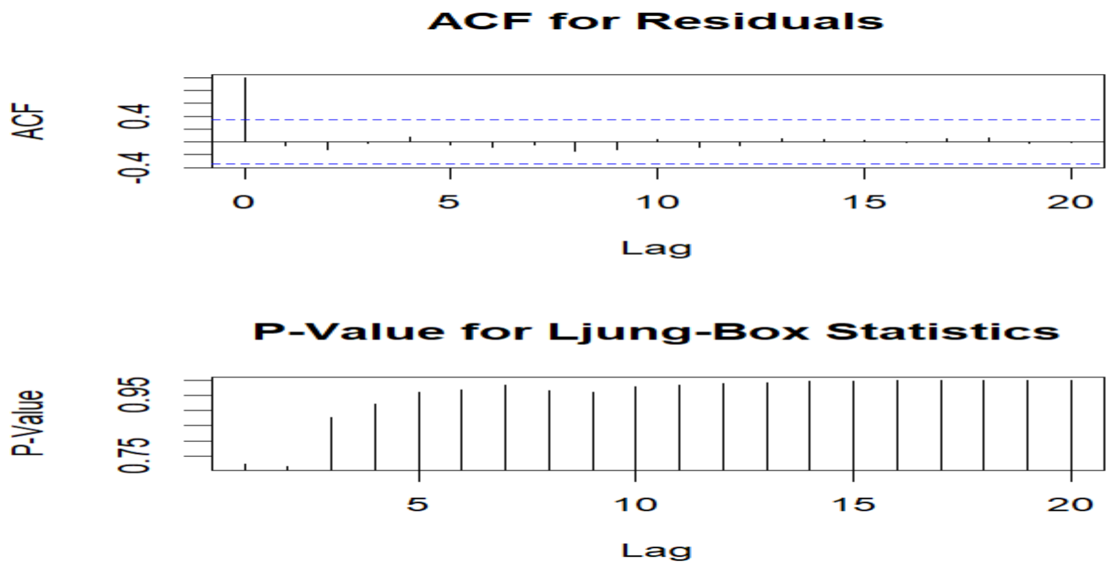

Figure 4. Diagnostic plots of residuals of ARIMA (1, 1, 1) (2, 1,1)

Source: Researchers own, (2023)

3.4 Test Statistics Diagnostics

Table 5, the diagnostic tests reveal certain hints in the performance of model. While there is evidence of conditional heteroskedasticity in the residuals and a slight indication of positive autocorrelation. The Portmanteau (Q) test indicated whether the residuals resemble white noise, and that there are no remaining patterns or correlations. The high p-value (0.9910) in the Q test suggests strong evidence in favor of the residuals being white noise. This means that the models have successfully captured the systematic components of INFL in Tanzania.

While there may be minor fluctuations or patterns that are challenging to model precisely, policymakers and economists can still rely on these models with confidence for most practical purposes, understanding limitations in capturing certain hints of INFL dynamics.

Table 5. Test statistics diagnostics.

Test	Test statistic	ρ - value
ARCH LM	2.4017	0.000
Durbin-Watson	1.339	0.0594
Portmanteau (Q) test for white noise	4.0149	0.9910

Source: Researchers own, (2023)

4. Discussion

One important economic indicator that shows how prices for goods and services have changed overall over time in an economy is inflation. To develop successful plans for financial stability, economic planning, and forecasting, policymakers, companies, and investors must have a thorough understanding of the dynamics of inflation. Tanzania's inflation dynamics and its consequences for the country's economy are thoroughly examined in the debate that follows.

With an emphasis on inflation data from Tanzania, the study used an empirical methodology to model and forecast inflation using the ARIMA model. The study provides insight into several areas related to inflation dynamics, such as time series patterns, residual diagnostic tests, autocorrelation functions, model criteria, and unit root tests.

The time series analysis of the study showed variations in inflation throughout time, which were marked by times when the general prices of goods and services in the Tanzanian economy increased and decreased. These oscillations, which are impacted by economic factors including supply and demand, economic expansion, and external shocks, highlight the significance of flexible economic policies in navigating the challenging landscape of inflation control.

The time series analysis conducted for the study showed variations in inflation over time, which pointed to the economic factors at work in Tanzania. Times of higher demand than supply are indicated by upward trends, and times of relative price stability or deflation are indicated by downward trends. For firms, investors, and politicians to comprehend the dynamics of inflation and modify economic policies appropriately, these insights are essential.

The research discovered that there was a unit root present since the data was non-stationary before differencing. Differentiating the data, however, caused it to become stationary, which made it possible to build and estimate several time series models, including ARIMA. This is necessary to get accurate estimates and an understanding of the behavior of inflation in the Tanzanian economy.

The ACF and PACF for the inflation rate indicate that past inflation rates have a considerable influence on current rates. The ACF and PACF plots showed autocorrelation coefficients at specific lags. This autocorrelation's persistence emphasizes how crucial it is to take historical data into account when assessing and projecting Tanzanian inflation. The autocorrelation coefficients rapidly decreased to almost zero upon differencing, suggesting a more flexible and dynamic economic environment. This suggests that historical rates of inflation in Tanzania have little bearing on current rates, enabling more successful inflation control through economic policy.

Based on the stationarity of the data and lags observed in the ACF and PACF plots, ARIMA (1,1,1) and ARIMA (2,1,1) models were selected for forecasting inflation in Tanzania. These models capture both short-term and longer-term influences on inflation dynamics, contributing to more reliable predictions. The model selection process revealed that MA components play a significant role in explaining inflation behavior, while AR components were not statistically significant. This suggests that recent past MA values of inflation have a substantial impact on current levels, emphasizing the importance of considering recent data for accurate forecasting.

Diagnostic analyses of the ARIMA models' residuals revealed encouraging findings, with the residuals primarily resembling white noise. This suggests that there is less opportunity for additional development because the models successfully captured the underlying structure in the data. Overall, the models showed adequate representation of Tanzanian inflation dynamics, while certain diagnostic tests suggested conditional heteroskedasticity in the residuals and a small positive autocorrelation. Practically speaking, the models are reliable because of the high p-value in the Portmanteau (Q) test, which provides strong evidence that the residuals are white noise.

The findings of this study provide valuable insights into inflation dynamics within the Tanzanian economy, offering essential guidance for policymakers, businesses, and investors. The analysis revealed the cyclical nature of inflation, emphasizing the importance of adaptable economic policies to navigate fluctuations and maintain price stability. The selection of ARIMA models for forecasting inflation, supported by rigorous analysis and diagnostics, presents a robust framework for understanding and predicting inflation behavior in Tanzania. By incorporating recent past moving average values and accounting for significant autocorrelation, these models offer a reliable tool for economic planning and decision-making. Moving forward, policymakers can leverage these insights to formulate proactive strategies aimed at managing inflation, promoting economic growth, and ensuring financial stability in Tanzania's dynamic economic landscape.

5. Conclusion and Recommendations

5.1 Conclusion

This study centered on modeling and forecasting INFL in Tanzania, employing advanced time series techniques. The primary aim was to create an accurate model for INFL and provide reliable forecasts. The analysis began with a detailed examination of the INFL data set, revealing inherent fluctuations. To identify the right model, stationarity tests were conducted, confirming that differentiating the data was essential. ARIMA (1,1,1) and ARIMA (2,1,1) models were then selected, demonstrating favorable parameter estimation and diagnostic results.

This study effectively constructed ARIMA (1,1,1) and ARIMA (2,1,1) models to represent Tanzania INFL trends. These models exhibited strong statistical significance and provided reliable insights into future INFL patterns. By adhering to rigorous diagnostic checks, this study ensures the chosen models properly capture the hints within the INFL dataset, contributing to a more accurate understanding of INFL dynamics.

5.2 Recommendations

To further enhance forecasting and modeling attempts, several recommendations arise. Firstly, researchers may explore more sophisticated models or hybrid approaches that incorporate additional economic indicators. Regular updates of the models are vital to keep pace with evolving economic conditions. Policymakers can leverage these forecasts for practical decision-making, particularly in the domain of monetary and fiscal policies. Data quality must be upheld, and public awareness of INFL forecasts can promote financial literacy and informed decision-making.

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