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Modeling and Forecasting of Consumer Price Index of Foods and Non-Alcoholic Beverages in Kenya Using Autoregressive Integrated Moving Average Models

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Abstract

Food and non-alcoholic beverages are highly important for individuals to continue staying alive and living healthy lives. The increase in the prices of food and non-alcoholic beverages experienced across the world over years has continued to make food and non-alcoholic beverages not to be accessible and affordable to individuals and families having a low income. The aim of this particular research study was to identify how Kenya's CPI of food and non-alcoholic beverages could be modelled using Autoregressive Integrated Moving Average (ARIMA) models for forecasting future values for the next two years. The data used for the study was that of Kenya's CPI of food and non-alcoholic beverages for the period starting from February 2009 to April 2024 obtained from the International Monetary Fund (IMF) database. The best specification for the ARIMA model was identified using Akaike Information Criterion (AIC), root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE) and mean absolute scaled error (MASE) and assessing whether residuals of the model were independent and normally distributed with a variance that is constant an whether the model has most of its coefficients being significant statistically. ARIMA (3, 1, 0) (1, 0, 0) model was identified as the best ARIMA model for modeling Kenya's CPI of food and non-beverages for forecasting future values among the ARIMA models considered. Using this particular model, Kenya's CPI of food and non-alcoholic beverages was forecasted to increase only slightly with time to reach a value of about 165.70 by March 2026.

Keywords

Consumer Price Index, Food and Non-Alcoholic Beverages, Autoregressive

Integrated Moving Averages, Modeling and Forecasting

1. Introduction

Individuals cannot go without food and water for days and continue staying alive and living healthy lives. This makes food and non-alcoholic beverages to be regarded as one of the basic needs of a person [1]. The scarcity of food is identified as one of the factors that used to make early humans have short life spans [2]. In addition to enhancing the physical wellbeing of a person, food and non-alcoholic beverages also enhance a person's psychological wellbeing, leading to lower levels of depression, anxiety and stress [3]. The increase in prices of food and non-alcoholic beverages experienced across the world over years has continued to make food and non-alcoholic beverages not to be accessible and affordable to individuals and families having a low income. In many countries of the world, especially those in Sub-Saharan Africa, individuals and families having a low income are forced to go without food and non-alcoholic drinks for days or consume only a single meal a day, which makes it difficult for them to continue staying alive and having a healthy living [4].

Kenya has been experiencing strong and stable growth in its economy over the years, outperforming the regional average of 5% for eight consecutive years from 2012 to 2019 [5]. The country, however, continues to be among countries with an economy that is not highly developed and has a very high level of poverty. Kenya's gross domestic product (GDP) is only US$95 billion, which makes the country to be grouped among countries with lower-middle income status [6]. The percentage of people living below the national poverty line in Kenya that could be finding it difficult to access and afford basic needs such as food and shelter are indicated to be as high as 33.6% overall, 37.0% in rural areas and 26.0% in urban areas [7].

Consumer price index (CPI) of food and non-alcoholic beverages is a good indicator of how prices of food and non-alcoholic beverages have been changing over time in a country to make food and non-alcoholic beverages more or less accessible and affordable to poor people. When prices of consumer goods such as foods and non-alcoholic beverages change over time, CPI of food and non-alcoholic beverages indicate how consumers need to adjust their spending to be as well off with the new prices as they were with the old prices. This is because CPI is an index that is constructed by comparing aggregate costs of a representative basket of goods and services, such as food and fuel, with the costs of the same basket in a selected base period within an economy [8]. The aim of the present research study was to examine how the CPI of food and non-alcoholic beverages in Kenya could be modelled using autoregressive integrated moving averages (ARIMA) models for forecasting its future monthly values for the next two years. This is important for identifying the need for more food security monetary and fiscal policies intended to make food and non-alcoholic beverages accessible and affordable to poor people in Kenya.

Kuhe and Egemba [9] investigated how Nigeria's annual CPI could be modelled in order to forecast its future values. The data used for the study was for the period starting from 1950 to 2014 analyzed using ARIMA technique. Results obtained indicated that Nigeria's annual CPI was integrated into order 1 because it was non-stationary before the first differences were computed and stationary after the first differences were computed. Specific model identified as being the best for modeling Nigeria's annual CPI in order to predict its future values was ARIMA (3, 1, 0) model. Using this particular model, Nigeria's annual CPI was forecasted to increase steadily over the six-year period starting from 2015 to 2021. Ibrahim & Olagunju [10] investigated how Nigeria's monthly CPI could be modelled to have its future values accurately forecasted. The data used was for the period starting from January 2009 to December 2019 analyzed using ARIMA modeling approach. Results obtained indicated that Nigeria's monthly CPI was also integrated into order one and ARIMA (2, 1, 2) model was the best model for fitting the data to have its future values forecasted. Using this particular model, Nigeria's monthly CPI was also forecasted to increase steadily over months in the future.

Norbert *et al.* [11] investigated how Rwanda's monthly CPI could be modelled for forecasting its future values using monthly CPI data for the period starting from February 1995 to December 2015 analyzed using the Box and Jenkins methodology. The specific model that fitted the data much better than the other models considered to produce more accurate forecasts was the ARIMA (4, 1, 6) model. Using this particular model, Rwanda's CPI was forecasted to increase continuously over months for the year 2016. Mia *et al.* [12] investigated how Bangladeshi's CPI could be modelled to have its future values accurately forecasted using annual CPI data for the period starting from 1986 to 2018 analyzed using the ARIMA approach. Results obtained indicated that Bangladeshi's CPI was integrated of order two because it started to be stationary only after the second differences were computed. Specific ARIMA model that fitted the data better than the other ARIMA models considered was the ARIMA (2, 2, 0) model. Using this particular model, Bangladeshi's annual CPI was forecasted to increase continuously with time for the period starting from 2019 to 2025.

Using the ARIMA technique, Mwanga [13] examined how Uganda's monthly CPI could be modelled to have its future values forecasted as accurately as possible. The data analyzed was for the period starting from January 2010 to December 2020. Results obtained indicated that Uganda's monthly CPI was integrated of order one because it was stationary only after being differenced ones and was best modelled using a seasonal ARIMA (1, 1, 1) $(0, 1, 1)_{12}$ model without a constant. Using this particular model, Uganda's monthly CPI was projected to fluctuate between 4.7% and 6.0% for the twelve months of 2021. Mohamed [14] investigated how Somaliland's monthly CPI could be modelled to achieve forecasts that are as accurate as possible for its future values. Specific method used was the ARIMA approach and the data analyzed was for the period starting from January 2013 to

December 2020. Somaliland's CPI was identified to be integrated of order one because it was stationary only after having its first differences were computed and was best modelled using the ARIMA (0, 1, 3) model with its values being forecasted to have an upward trend over months in the future.

2. Methodology

2.1. Data

This study used the monthly consumer price index (CPI) of food and non-alcoholic beverages in Kenya that was not seasonally adjusted or harmonized. The data was for the period starting from February 2009 to April 2024 obtained from the International Monetary Fund (IMF) database. Number of observations in the dataset was 183 because the data did not have values that were missing for any of the months. The period before February 2009 was not considered because its data on Kenya's CPI of foods and non-alcoholic beverages was not available. Analyzed data was visually assessed for stationarity using time series plot, Autocorrelation Function (ACF) plot and Partial Autocorrelation Function (PACF) plot. The data was then assessed for stationarity empirically using Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests. Non-stationary time series was differenced until stationarity was achieved.

CPI data obtained from the IMF database are of good quality and adequately reliable. Data on measures of price or inflation such as Producer Price Index (PPI) and Consumer Price Index (CPI) found in the IMF's database are collected, aggregated and transmitted to the IMF by national statistical agencies [15]. In the case of Kenya, the data are collected, aggregated and transmitted to the IMF by the Kenya National Bureau of Statistics (KNBS). As outlined in the IMF Data Quality Assessment Framework (DQAF), IMF's statistics department performs quality checks on the submitted data that involve tests for compliance with established formats, examinations for outliers and broad cross-sector consistency checks intended to identify large discrepancies across the datasets and updates to the IMF's database originate solely from official sources [16]. In many cases, there is a steady flow of communication among desk economists, resident representatives and country sources of data that allows the IMF desk staff to constantly update the desk's database. In other cases, missions spend a substantial share of their time in the field collecting and double-checking aspects of the data through tasks such as verifying data in the primary sources and checking the accuracy of basic calculations and their consistency with methodological standards.

2.2. Models

Univariate models assessed for model fit and forecast accuracy using Kenya's CPI of foods and non-alcoholic beverages were the ARIMA models. ARIMA models captures autocorrelation within a time series variable and have three parts, which are the autoregressive (AR) part, the order of differencing (I) part and the moving averages (MA) part. Order of differencing (I) part indicates the number of times that a time series variable needs to be different for it to become stationary. AR part captures autocorrelation in the time series variable directly using its values for previous periods and MA part captures autocorrelation in the time series variable indirectly using error terms of the previous periods as indicators of unexplained fluctuations [17]. A general mathematical presentation of an ARIMA (p, d, q) model estimated for a time series variable y_t like the one on Kenya's CPI of foods and non-alcoholic beverages is as given by the equation below. In the equation, Δd is the order of differencing needed to make the non-stationary time series analyzed stationary, β_i, $i = 1, 2, \ldots, p$ are coefficients of the AR part of the model and γ_j, $j = 1, 2, \ldots, q$ are coefficients of the MA part of the model.

$$\Delta^d y_t = \sum_{i=1}^{p} \beta_{t-i} \Delta^d y_{t-i} + \sum_{j=1}^{q} \gamma_j u_{t-j} + u_t \tag{1}$$

The initial ARIMA model considered was identified using the ACF and PACF plot. Other ARIMA models considered were obtained by adding higher order AR and/or MA part to the initial ARIMA model considered. Parameters of the ARIMA models considered were estimated using the maximum likelihood (ML) estimation method. The models considered were assessed for model fit using Akaike Information Criterion (AIC) and forecasting accuracy using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and Mean Absolute Scaled Error (MASE). The ARIMA model identified as the best for modeling Kenya's CPI of food and non-alcoholic beverages was also assessed for residuals that were independent ACFs, residuals having constant variance using ARCH LM test and residuals having a normal distribution using Shapiro-Wilk test. For modeling purposes, the data was divided into a training set having 80% of the observations for the period starting from February 2009 to March 2021 and a testing set having the other 20% of the observations for the period starting from April 2021 to April 2024. All statistical analyses were conducted using R software.

3. Results and Discussions

For the period investigated, Kenya's CPI of foods and non-alcoholic beverages ranged from 41.6 to 163.15 with a mean of 91.88 and a standard deviation of 35.28. Distribution of the data is also skewed positively (*Skewness* = 0.41) and highly flat (*Kurtosis* = −0.92). A natural logarithm transformation was used to reduce the positive skewness of the data before ARIMA models were estimated to forecast future values of Kenya's CPI of food and non-alcoholic beverages. **Figure 1** contains the time series plot (left), ACF plot (middle) and PACF plot (right) obtained for Kenya's CPI of food and non-alcoholic beverages. For the period investigated, Kenya's CPI of foods and non-alcoholic beverages had an upward trend making the variable not to be stationary. Results obtained from the ADF test for stationarity indicated that the time series variable on Kenya's CPI of foods and non-alcoholic beverages was non-stationary because of having a unit root (ADF = −2.590, p = 0.330). Results obtained from the KPSS test for stationarity, on the other hand, indicated that the time series variable on Kenya's CPI of foods and non-alcoholic beverages was non-stationary because of having a deterministic trend (KPSS = 3.698, $p = 0.010$).

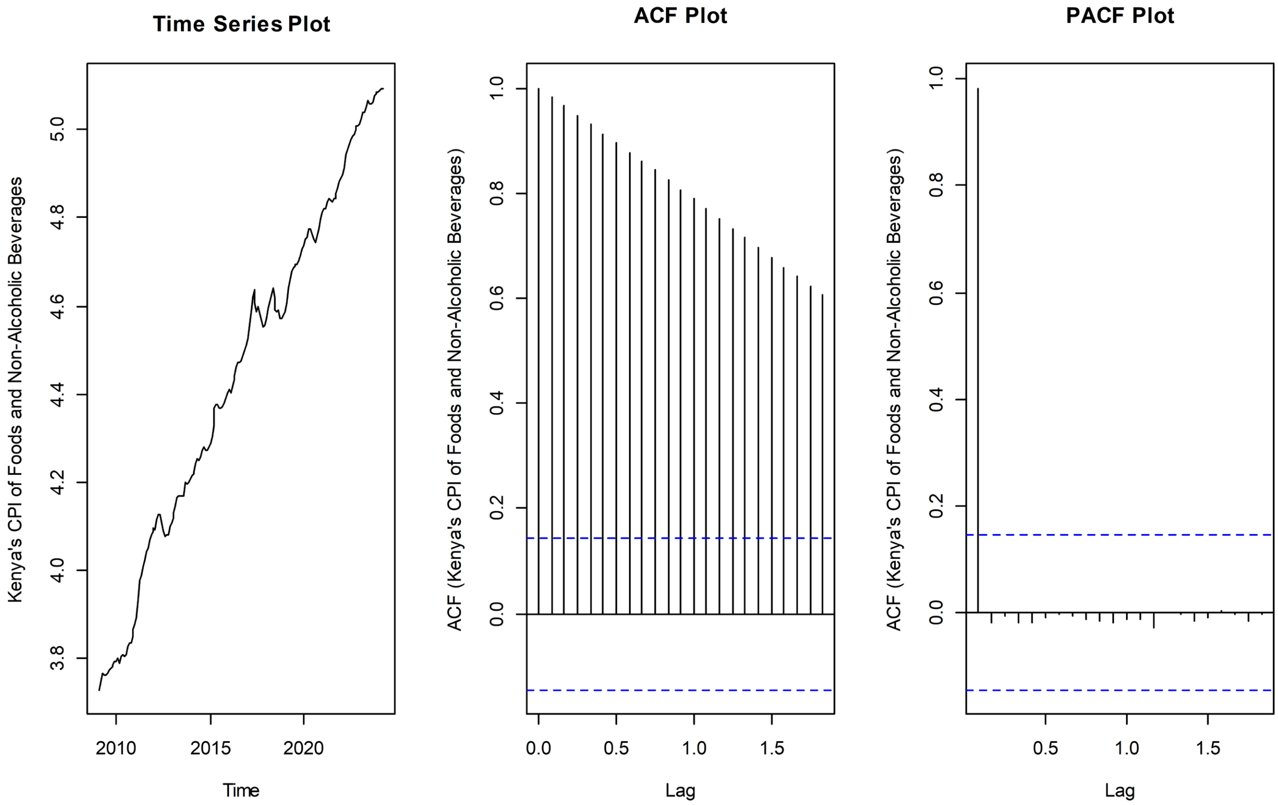

Figure 1. Time Series Plot (Left), ACF Plot (Middle) and PACF Plot (Right) of Kenya's CPI of foods and non-alcoholic beverages.

Figure 2 contains the time series plot (left), ACF plot (middle) and PACF plot (right) obtained for first differences of Kenya's CPI of food and non-alcoholic beverages. For the period investigated, first differences of Kenya's CPI of foods and non-alcoholic beverages did not have a trend that could make the variable not to be stationary. Results obtained from the ADF test for stationarity indicated that the first difference of the time series variable on Kenya's CPI of foods and non-alcoholic beverages was stationary because of not having a unit root (ADF = −5.992, $p = 0.010$). Results obtained from the KPSS test for stationarity, on the other hand, indicated that the first difference of the time series variable on Kenya's CPI of foods and non-alcoholic beverages was stationary because of not having a deterministic trend (KPSS = 0.057, $p = 0.100$). Kenya's CPI of foods and non-alcoholic beverages is, therefore, integrated into order one because it needs to be differentiated into only one for it to become stationary.

The ACF plot with significant spikes at lag 0, 1, 5, 6, 11, 12, 13, 16, 17 and 18 and PACF plot with significant spikes at lags 0, 1, 4, 9 and 19 were obtained for the stationary time series on first differences of Kenya's CPI of foods and non-alcoholic beverages indicate seasonality. The plots, however, fail to show any pure

AR or MA process. As a starting point, ARIMA (1, 1, 0) (1, 0, 0) was considered because AR part appeared to dominate in the long run as indicated by a decaying ACF. Other ARIMA models considered were ARIMA (2, 1, 0) (1, 0, 0), ARIMA (1, 1, 1) (1, 0, 0), ARIMA (2, 1, 1) (1, 0, 0), ARIMA (2, 1, 2) (1, 0, 0), ARIMA (3, 1, 0) (1, 0, 0), ARIMA (3, 1, 1) (1, 0, 0), ARIMA (3, 1, 2) (1, 0, 0) and ARIMA (3, 1, 3) (1, 0, 0) because of a possible need include MA terms and other AR terms in the modeling of Kenya's CPI of foods and non-alcoholic beverages to achieve the best possible model fit and forecast accuracy.

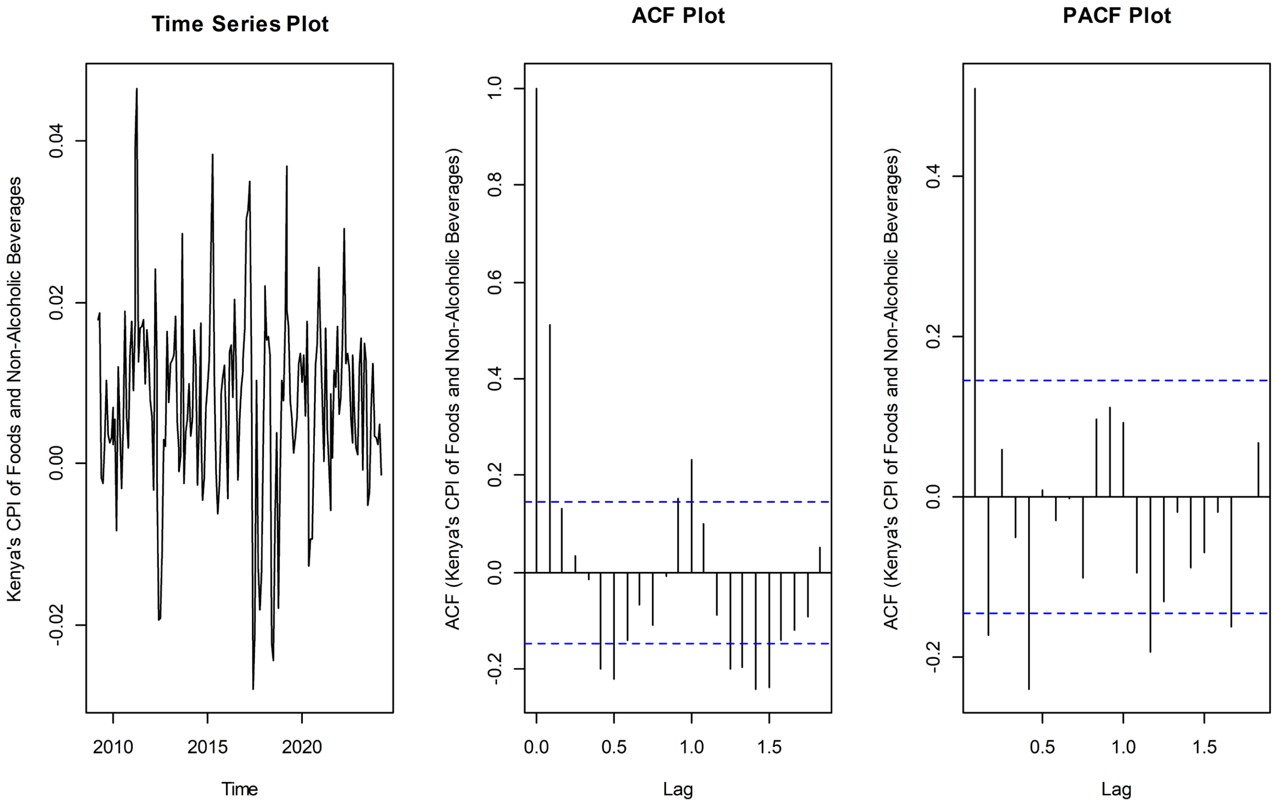

Figure 2. Time Series Plot (Left), ACF Plot (Middle) and PACF Plot (Right) of the first differences in Kenya's CPI of foods and non-alcoholic beverages.

Table 1 contains the findings obtained from the analyses conducted to assess the in-sample model fit and out-sample forecast accuracy of the ARIMA models considered. Among the ARIMA models considered, the one that appeared to have the best in-sample model fit was ARIMA (1, 1, 0) (1, 0, 0) model and the one that appeared to have the second best in-sample model fit was ARIMA (3, 1, 0) (1, 0, 0) model. This is because ARIMA (1, 1, 0) (1, 0, 0) model had the smallest AIC value (AIC = −903.85) and ARIMA (3, 1, 0) model had the second smallest AIC value (AIC = −903.66). Specific ARIMA models that appeared to have the best and second best out-sample forecast accuracy were ARIMA (2, 1, 2) (1, 0, 0) model and ARIMA (3, 1, 0) (1, 0, 0) model respectively. This is because ARIMA (2, 1, 2) (1, 0, 0) model had the smallest RMSE (RMSE = 0.161), MAE (MAE = 0.138), MAPE (MAPE = 2.753) and MASE (MASE = 11.943) and ARIMA (3, 1, 0) (1, 0, 0) had the second smallest RMSE (RMSE = 0.162), MAE (MAE = 0.139), MAPE (MAPE = 2.772) and MASE (MASE = 12.024).

Table 1. In-sample model fit and out-sample forecast accuracy of ARMA models considered.

Models	Model Selection Criteria				
	RMSE	MAE	MAPE	MASE	AIC
ARIMA (1, 1, 0) (1, 0, 0)	0.166	0.144	2.866	12.428	−903.85
ARIMA (1, 1, 1) (1, 0, 0)	0.168	0.146	2.898	12.567	−903.20
ARIMA (2, 1, 0) (1, 0, 0)	0.168	0.146	2.894	12.548	−902.60
ARIMA (2, 1, 1) (1, 0, 0)	0.168	0.145	2.891	12.537	−901.88
ARIMA (2, 1, 2) (1, 0, 0)	0.161	0.138	2.753	11.943	−901.04
ARIMA (3, 1, 0) (1, 0, 0)	0.162	0.139	2.772	12.024	−903.66
ARIMA (3, 1, 1) (1, 0, 0)	0.163	0.140	2.790	12.101	−901.72
ARIMA (3, 1, 2) (1, 0, 0)	0.165	0.143	2.842	12.32	−901.40
ARIMA (3, 1, 3) (1, 0, 0)	0.169	0.146	2.908	12.613	−899.55

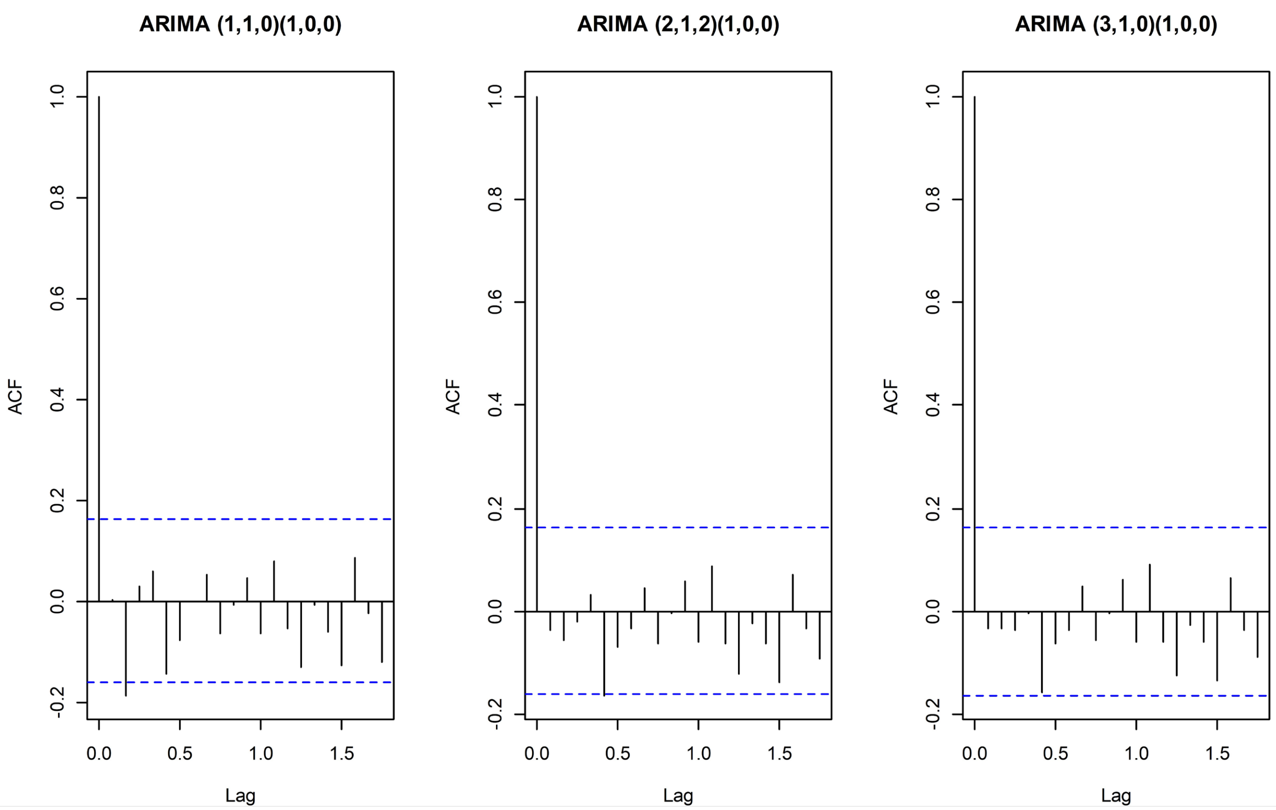

Figure 3. ACF plots obtained for residuals of the ARIMA models considered.

The three models identified to have superior in-sample model fit and out-sample forecast accuracy are assessed for residuals that are correlated using ACFs.

Figure 3 contains the results that were obtained. Although ARIMA (1, 1, 0) (1, 0, 0) has the best in-sample model fit because of having the smallest AIC value, its residuals are not uncorrelated (independent) as indicated by an ACF plot having a significant spike not only at lag 0, but also at lag 2. The other two ARIMA models have residuals that are uncorrelated (independent) as indicated by ACF plots having a significant spike only at lag 0. The two models are assessed for residuals having a variance that is constant using the ARCH tests conducted using the 5% level of significance and residuals having a normal distribution using Shapiro-Wilk test conducted using the 10% level of significance. Results obtained indicated that residuals had a variance that is constant for both ARIMA (2, 1, 2) (1, 0, 0) model (ARCH LM Test χ^2 (12) = 10.374, p = 0.583) and ARIMA (3, 1, 0) (1, 0, 0) model (ARCH LM Test χ^2 (12) = 10.750, p = 0.550). Results obtained also indicated that residuals were approximately normally distributed for both ARIMA (2, 1, 2) (1, 0, 0) model (S-W = 0.981, p = 0.046) and ARIMA (3, 1, 0) (1, 0, 0) model (S-W = 0.981, p = 0.046).

ARIMA (2, 1, 2) (1, 0, 0) model and ARIMA (3, 1, 0) (1, 0, 0) model are assessed for significance of their coefficients. Table 2 contains the findings obtained. For the ARIMA (3, 1, 0), (1, 0, 0) model, estimated coefficients are significant statistically at the 10% level of significance for the seasonal AR1 term (t = 2.978, p = 0.002) and non-seasonal AR1 term (t = 7.814, p < 0.001), AR2 term (t = −1.691, p = 0.091) and AR3 term (t = 1.761, p = 0.078). As for the ARIMA (2, 1, 2) (1, 0, 0) model, estimated coefficient is significant statistically at the 10% level of significance only for the seasonal AR term (t = 2.857, p = 0.004). The best model for modeling Kenya's CPI of food and non-alcoholic beverages to forecast its future values among the ARIMA models considered is ARIMA (3, 1, 0) (1, 0, 0) model.

Table 2. Significance of coefficients estimated for ARMA (2, 1, 2) (1, 0, 0) and ARIMA (3, 1, 0) (1, 0, 0) models.

Coefficients	ARIMA (2, 1, 2) (1, 0, 0)			ARIMA (3, 1, 0) (1, 0, 0)		
	β (SE)	t-value	p-value	β (SE)	t-value	p-value
SAR1	0.251 (0.088)	2.857	0.004	0.253 (0.085)	2.978	0.003
AR1	0.806 (0.853)	0.945	0.345	0.675 (0.086)	7.814	<0.001
AR2	−0.038 (0.465)	−0.082	0.935	−0.169 (0.100)	−1.691	0.091
AR3				0.145 (0.083)	1.761	0.078
MA1	−0.130 (0.841)	−0.154	0.878			
MA2	−0.205 (0.197)	−1.038	0.299			

Using this particular ARIMA model, Kenya's CPIs of food and non-alcoholic beverages are forecasted for the 24 months period starting from May 2024 to April 2026. Figure 4 shows the forecasts obtained and their 80% and 95% prediction intervals. Kenya's CPI of food and non-alcoholic beverages is forecasted to increase only slightly for the period starting from May 2024 to April 2026 when compared to its value by April 2024 to reach a value of 165.70 (95% PI = [124.72, 220.14]) by April 2026.

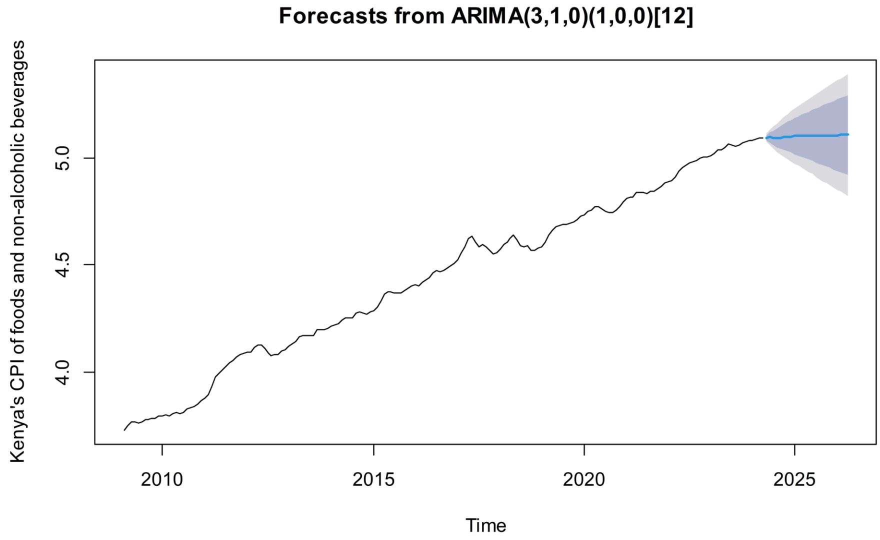

Figure 4. Forecasted Kenya's CPI of food and non-alcoholic beverages for May 2024 to April 2026.

4. Conclusions

The aim of this particular research study was to examine how Kenya's CPI of food and non-alcoholic beverages could be modelled using ARIMA models for forecasting its future values. Specific ARIMA model identified as the best model for modeling of Kenya's CPI of food and non-alcoholic beverages among the ARIMA models considered was ARIMA (3, 1, 0) (1, 0, 0) model. This had the second best in-sample model fit and second best out-sample forecast accuracy. The model also had residual that were independent and normally distributed with a variance that was constant and coefficients that were significant statistically at the 10% level of significance. Using this particular model, Kenya's CPI of food and non-alcoholic beverages was forecasted to increase only slightly for the period starting from May 2024 to April 2026 to reach a value of 165.70 (95% PI = [124.72, 220.14]) by April 2026. The study, therefore, concluded that Kenya's CPI of food and non-alcoholic beverages could be effectively modelled using ARIMA (3, 1, 0) (1, 0, 0) model for forecasting future values. The study also concludes that Kenya should not be expected to experience a sharp increase in the prices of food and non-alcoholic beverage for the period starting from May 2024 to April 2026 if the current trend is to continue. This implies that given the existing food security monetary and fiscal policies in Kenya such as those of smart agriculture intended to increase food production, food and non-alcoholic beverages are not likely to experience large increase in the near future (the next two years) that could make them not to be accessible and affordable to poor people in the country.

Although the present research study used data from a highly credible source and the model used to model it did not violate any of its assumptions, the model used for modeling the data did not consider the influence of other factors, such as consumer spending habits, on Kenya's CPI of food and non-alcoholic beverages. The model identified in this paper is, therefore, appropriate for forecasting Kenya's CPI of food and non-alcoholic beverages only under conventional circumstances. In case of special circumstances, such as a major breakthrough in consumer spending behaviors, the model is likely to be inaccurate in forecasting Kenya's CPI of food and non-alcoholic beverages. Further research is, therefore, necessary for identifying how Kenya's CPI of food and non-alcoholic beverages could be modelled for forecasting future values by considering its values for the previous periods and current and previous values of variables such as consumer spending behavior. For such a study, variance autoregressive (VAR) models and vector error correction (VEC) models should be considered depending on whether the variables analyzed are co-integrated of order one.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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