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Time Series Analysis and Forecasting of Household Products' Prices (A Case Study of Nyeri County)

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Abstract: Inflation has a significant impact on both consumable and non-consumable products and plays a critical role in determining the cost of living. The study aimed to investigate the trend of household consumable and non-consumable prices over the past three years and identify the best ARIMA model for future price predictions. The results showed that consumable goods played a greater role in determining the national inflation compared to non-consumable goods. A relationship was found between the changes in local-level prices and national monthly inflation rates, with consumable goods being fitted to an ARIMA (1,2,2) model and national inflation rates to ARIMA (3,1,0). Non-consumable goods were found to be a white noise. The models were found to be adequate in forecasting changes in prices, with their validity confirmed by the Box-Ljung test and autocorrelation coefficients of model residuals. This study demonstrated the importance of analyzing changes in products' prices at a local level and how it affects the national inflation rate. In future, similar studies can be carried out in different counties and with a more comprehensive model to investigate the impact of the COVID-19 pandemic on the prices of household consumable and non-consumable goods at the local level.

Keywords: ARIMA Model, Consumable Goods, Non-Consumable Goods, Inflation

1. Introduction

1.1. Background of the Study

In 2019, Kenya had a population of 53 million people, with 73% of them living in rural areas. The country is 530,367 sq. km in size and has 18% arable land, but only 0.037% (as of 2003) of it is irrigated. The population density is 94 people per sq. km. The age dependency ratio is 71 and the population is growing at a rate of 2.3% per year, which is putting pressure on resources and hindering economic progress. The average life expectancy is 64 for men and 69 for women and the total fertility rate is 4 children per woman. Kenya's gross domestic product in 2019/2020 was around 95.50 billion US dollars, with a real GDP per capita of 1238 USD. The Kenyan economy has been growing well, with an average real GDP growth rate of 5.7% from 2015-2019, making it one of the fastest-growing economies in sub-Saharan Africa.

Inflation is one of macroeconomic indicators which become an important issue among economists. Inflation is the tendency rise in average price in general as stated in (Mankiw, 2001). According to Mankiw, also, inflation may be noted by increase in prices of product and services more so the household consumables [18]. Price inflation can also be viewed from another perspective where the price of a commodity stays the same, but the quantity received decreases over time. For example, in low-cost snacks like chips and chocolate bars, the product weight dwindles while the cost remains constant. Loayza & Schmidt-hebbel conducted a study exploring the relationship between inflation and cost of living. The findings revealed a direct correlation between the two variables, suggesting that as inflation increases, so does the cost of living. To address this issue, governments implement various economic policies aimed at stabilizing prices. These policies can range from adjusting monetary policy to implementing price controls.

The authors of the study emphasize the importance of effective economic policy in controlling inflation and preserving the purchasing power of citizens [16]. Inflation is a crucial issue among economists, defined as the increase in average prices. It affects the cost of living and the government implements policies to control inflation. The Central Bank of Kenya has a target range of 2.5-7.5% inflation and price stability is a core objective of monetary policy.

As a topic of study, inflation has received broad attention in academic and policy literature over the past many years. Parkin et al s stated that inflation is a key indicator of Central Banks when formulating monetary policies [20]. Fisher et al noted that when price inflation is rising at a faster pace than desired/expected, a central bank will likely tighten monetary policy by increasing interest rates [11]. In an ideal world, this would encourage savings through higher returns and slow spending, which would slow price inflation.

According to Maiti & Bidinger, the major objective of the monetary policy is to control the inflation rate. Policymakers often measure inflation with an aggregate price index [17]. Nevertheless, an aggregate price index is based on an aggregate consumption bundle and on average prices for various goods and services. Knowing the inflation rate of prices helps one to know and assess the impact at the household level.

Carta et al. discovered that their software for forecasting product prices was more accurate than traditional methods and provided valuable market trend and consumer behavior information. The software uses ARIMA to create a personalized forecast of future product prices [4].

In this study, data from a local general shop will be used to estimate the change in price of household consumable products. The study will consider the prices of maize flour, sugar and rice from wholesalers.

1.2. Statement of the Problem

Despite numerous measures such as economic policies and interventions put through to control increase in products' prices, inflation has continued to affect people adversely. The increase in prices due to inflation lowers the purchasing power of people, particularly those with steady sources of income, thereby lowering their standard of living and savings. The need for more money to purchase goods and services causes a decline in savings and results in less investment and capital formation.

Granted, expected (future) inflation is the primary when designing and implementing monetary policies towards stabilizing prices by Central banks. It is well understood that a better understanding of the relationship between change in prices of consumable and non-consumables goods and inflation is important when formulating policies targeting the low-income earners. However, the available statistical methods study changes in prices at macro-level which may not reflect the same at micro-level. This study seeks to compare change in prices at the national level with the same at micro-level (local retail shop). The study seeks to analyze the national monthly inflation rate and trend of prices of the consumable and non-consumable goods from a retail shop over the last three years.

1.3. Objective of the Study

The general objective of this study is to perform time series analysis and forecasting of prices of consumable and non-consumable products at a local retail shop in Kenya. The specific objectives are to:

1) Analyze the trend and national monthly inflation rate of consumable and non-consumable goods.
2) Compare the national inflation rate with the changes in prices at the local retail shop level.
3) Forecast future prices of the selected household consumable and non-consumable goods using the ARIMA model.

1.4. Scope of the Study

The research work will apply sale prices of consumable and non-consumable goods at a local shop in Nyeri county during a study period spanning between December 2017 and January 2021. The change of products prices will also be compared with national monthly inflation rates as reported by Kenya National Bureau of Statistics (KNBS). The prices will be fitted in a time series models which will then be used to forecast the consumable and non-consumable products.

1.5. Justification of the Study

Due to the importance of price stabilizing policies on household consumable products, it is paramount to understand inflation rates both at macro and micro levels. A gallery of literature only studies the effect of inflation at national level disregarding its effect at consumer level. It is against this backdrop that this research work seeks to understand the rate of inflation at household level.

Therefore, this research work will provide a different perspective on how inflation affects house consumable prices. This paper will serve as a source of knowledge in the field of time series and most importantly the study is expected to raise the interest of scholars to work on inflation at micro-level of the economy-delocalization of inflation rates. It will also serve as a basis for further study in the field.

1.6. Organization of the Study

The study is organized into five chapters. Chapter one provides an introduction to the study, including its background, problem statement, methodology, significance, limitations, and organization of the thesis. Chapter two contains a literature review of time series analysis and Box-Jenkins. Chapter three gives a thorough description of the methodology used for time series analysis and forecasting. Chapter four is dedicated to the analysis of weekly and monthly goods prices from 2017 to 2021 using the techniques discussed in chapter three.

2. Literature Review

The literature review focuses on existing theories and models of time series analysis. A time series is a series of data points indexed in order of time, usually with equally spaced points in time. Some examples of time series are stocks' prices, monthly returns, and a company's sales. The aim of time series analysis is to extract information from the behavior of a variable over time and, if relevant findings emerge, to predict its future trend. This literature review focuses on two developing lines of forecasting research that have received limited attention and appear to have significant potential for improved modeling and forecasting accuracy. Dornbusch et al. shows that there are various price indexes which are used to measure inflation. Below are some of the indices [1].

2.1. Consumer Price Index (CPI)

The Consumer Price Index (CPI) is a measure of the average change over time in the prices paid by consumers for a basket of goods and services. It is used to track inflation, as a rise in the CPI over time indicates a higher cost of living and a decrease in purchasing power. The basket of goods and services is periodically updated to reflect changes in consumer spending patterns. The CPI is widely used by governments, central banks, and economists as an indicator of inflation and is used to adjust various financial and economic data, such as Social Security payments and income tax brackets.

2.2. Producer Price Index (PPI)

The Producer Price Index (PPI) is a measure of the average change in selling prices received by domestic producers for their output. It is a measure of inflation at the wholesale or producer level, reflecting changes in the prices of goods and services produced by businesses before they reach consumers. The PPI is used to analyze changes in the prices of raw materials, intermediate goods, and finished goods, providing insight into the inflationary pressures faced by producers. Bryan, M., Cecchetti, in their work indicate the importance of the CPI in monetary policy discussions and decision-making. The Federal Reserve, for instance, often uses the CPI as a benchmark to evaluate the effectiveness of monetary policy, as inflation is a critical aspect of economic stability and growth [9].

Inflation is a critical measure for central banks in setting monetary policy. If inflation rises faster than desired, central banks may raise interest rates to curb spending and encourage savings, ultimately slowing inflation. Parkin and Bryant (1993) emphasized the significance of inflation in monetary policy decision.

In the paper done by Meyler, & Kenny, the authors examine the use of ARIMA (AutoRegressive Integrated Moving Average) models to predict inflation in Ireland. They analyze the performance of different ARIMA models and compare their results to other methods. The authors found that ARIMA models were effective in forecasting inflation in Ireland and provided useful insights into the relationships between inflation and other macroeconomic variables [19].

According to Karanja & Kuyvenhoven, they examine the evolution of producer prices in Kenya and the impact of economic reforms on these prices. The authors use an ARCH-M (Autoregressive Conditional Heteroskedasticity with Mean) model to analyze the data and make inferences about the relationship between producer prices and economic reforms. The authors also analyzed how market reforms impacted the evolution and volatility of the prices of certain consumer goods such as flour and tea leaves in Kenya. Milk and maize were used as representatives of food items while coffee and tea were used to represent non-food traded commodities. The study found that real producer prices for coffee, tea, and maize experienced a significant decline during the study period, while milk prices saw an increase [14]. The authors Etuk et al., describe the methodology used to analyze the rainfall data and fit the SARIMA models, including the identification of the appropriate model order and the estimation of the model parameters. They also present the results of their analysis, including the diagnostic checks to assess the adequacy of the SARIMA models and the accuracy of the model forecasts [2].

There are other research works which have used ARIMA models in prediction of stock prices. Authors in Personal & Archive analyzed and showed how CPI of non-food and food stuffs related to the national CPI. They also which periods in the study period that non-food and food CPI determined the national CPI the most [21]. The authors Moazzam & Ali Kemal, they utilized time series methods in their study of the factors affecting inflation in Pakistan. They analyzed data to determine the relationship between money supply, oil prices, and inflation in the country. The results of their study indicated that both money supply and oil prices play a significant role in determining inflation in Pakistan [24].

Time series analysis and forecasting has turned out to be a key tool in applications in business management activities. Among the most effective approaches for analysing time series data is the model introduced by Box and Jenkins, Autoregressive Integrated Moving Average (ARIMA). In a study by Profile used Box-Jenkins methodology to build ARIMA model on evolution of unemployment rate during the period 1998-2007 monthly data. Box-Jenkins combines both autoregressive models and moving averages. The study believes that the most adequate model for unemployment and inflation rate is ARIMA [22].

ARIMA is commonly applied in the energy sector, such as the work done by Conejo et al., where they used ARIMA along with wavelet transform to forecast electricity prices on a weekly basis [10]. Jiang et al., and Ozturk & Ozturk also used ARIMA models to predict coal consumption in China and energy consumption in Turkey, respectively. [13, 25] Many studies have previously explored the idea of ensuring the input data of an ARIMA model is stationary and has regular seasonal patterns. In general, when it comes to time series forecasting, Brockwell and Davis emphasize the importance of removing trends or seasonality from the time series being considered [8]. The Adfuller Test, introduced by

Taylor et al., can be used to determine whether a time series is stationary or not. Stationary time series are considered good for statistical analysis and prediction [23]. Other researchers have focused on finding the correct parameters for an ARIMA model to work effectively. For example, Jenkins and Reinsel introduced the Box and Jenkins method for calculating ARIMA's input parameters (p, d, q) [12]. Ke and Zhang discussed techniques such as ACF, PACF, and others used in ARIMA [15].

3. Research Methodology

The chapter concentrates on the techniques employed to prepare, clean, examine, and represent the cost data of household products obtained from a local store in Nyeri county. The data was manually recorded into a Microsoft Excel spreadsheet from weekly receipts and included the date of supply, names of goods supplied, quantities, and prices in Kenyan shillings from December 2017 to January 2021. The data preparation and organization were done using STATA-16, and the analysis was performed using the R programming language.

3.1. Data Collection Methods

As a way of bookkeeping most shops keep all the receipts from suppliers for reference. This study used the data from the receipts to evaluate the evolution of consumable and consumable products' prices at consumer level. The information was first entered in Ms Excel where it was cleaned and organized into monthly data. The data was reliable since the shop owner was advised to have the receipts well-kept and accurately filled so as not to compromise the quality of data. The products were classified as consumable and non-consumable. Consumables were products that are intended to be consumed such as rice, sugar, maize and wheat flour, cooking fat, tea leaves, breads among others while non-consumables included soaps, tissue papers,

3.2. Calculation of Inflation

The commonly used description of inflation states that inflation is a sustained rise in general price level. In formulas;

$$\pi = \frac{\text{pt}-\text{pt}-1}{\text{pt}-1}$$

where π–inflation (in percentage)

p_t – present price level

p_{t-1} – past price level

3.3. Decomposition of Time Series

Decomposition of time series separates the various components such as trend, seasonal factors, and cyclic component in the time series data. The purpose of decomposition is to calculate the seasonal impacts and create seasonally adjusted estimates. The process involves: (1) estimating the trend and removing it (de-trending) through subtraction (for additive decomposition) or division (for multiplicative decomposition), and (2) estimating the seasonal factors by adjusting the seasonal effects to average 0 (for additive) or 1 (for multiplicative).

3.4. Our Approach

In this section describes the process of developing an algorithm that will be customized to model the change in prices. More specifically, a time series model with a set of features will be used to model the data. An ARIMA parameters (p, d, q) with the lowest MAPE will be used to forecast the products' prices. The following section will describe how to develop an ARIMA model.

3.5. ARIMA (Autoregressive Integrated Moving Average)

The ARIMA (Autoregressive Integrated Moving Average) model is a commonly used method in time series analysis that uses a combination of three components (AR, I, and MA) to fit to time series data and make predictions about future points in the series. The ARIMA model is specified by three parameters (p, d, q), which affect the AR, I, and MA components respectively. The purpose of the ARIMA model is to fit to time series data, such as monthly prices of consumable products over time, and make predictions about future points in the series.

3.5.1. Autoregressive Model (AR)

An autoregressive (AR) model is a statistical model that uses previous values of a time series to predict future values. The model assumes that current values of the time series are dependent on past values and a random error term. The number of past values used in the model is represented by the order of the AR model, denoted by "p" in ARIMA (p,d,q). The autoregressive term in the model captures the linear relationship between the current value and past values of the time series. The AR(p) model is defined as.

$$\text{X}_\text{t} = \text{c} + \text{p} \sum_{i=1}^{p} \varphi\, \text{Xt} - 1 + \epsilon\text{t}$$

3.5.2. Integrated (I)

The I component of ARIMA stands for Integrated and refers to the number of times the time series needs to be differenced to become stationary. Differencing involves subtracting consecutive values in the time series to eliminate trends and make the data have a constant mean and variance. The degree of differencing is indicated by the value of d in the ARIMA notation (p, d, q). ARIMA models only work with stationary data, so differencing is a crucial step to prepare the data for analysis. To perform differencing, the change between consecutive observations is calculated as:

$$y' = y_t - y_{t-1}$$

where yt, $yt{-}1$ are consecutive values of the series at time t and t-1 is computed, resulting in the differenced series y'.
value of the series at time t.

Moving Average model (MA).

The moving average model MA(q) is a technique used to model univariate time series. It involves taking the linear regression of the current value of the series against the current and past noise terms. The model is denoted by MA(q), where q refers to the order of the moving average.

The MA(q) model is defined as.

$$X_t = \mu + \epsilon_t + \theta\epsilon_{t-1} + \cdots + \theta\epsilon_{t-q}$$

here μ is the mean of the series, θ1... θq are the parameters of the model and ϵ_tis white noise.

3.6. Model Identification and Evaluation

The identification and evaluation of a time series model is a multi-step process. First, the stationarity of the time series is tested using the augmented Dickey-Fuller test. Next, the size of clusters of correlated and partially correlated entries in the time series is determined by finding the values of p and q. The ARIMA model is then specified based on the stationarity and p and q values. The parameters of the ARIMA model are estimated using the Box and Jenkins method, and the model's performance is evaluated using metrics such as mean squared error or accuracy.

3.6.1. Autocorrelation Function (ACF)

Covariance and correlation are statistical techniques that will be used to deduce whether two variables are linearly related and to what extent their relationship is. On the other hand, Auto- correlation and auto covariance are techniques which measure the linear relationship between two lagged values of a time series X_t i.e. the relationship between; X_t and X_{t-1}, X_{t-1} and X_{t-2}.

A significant part of time series analysis focuses on explaining the autocorrelation in the data, even though trend and seasonality are the main systematic features in many time series.

3.6.2. Partial Autocorrelation Function (PACF)

The Partial Autocorrelation Function (PACF) measures the correlation between two variables, while taking into account the values of other variables. In the context of time series analysis, the PACF measures the correlation between observations separated by k time units (Xt and $Xt-k$), after adjusting for the influence of other observations with shorter lags ($X_{t\text{-}1}$, X_{t-2}..., $X_{t\text{-k-}1}$). Essentially, the PACF represents a conditional correlation, meaning it takes into account the values of other variables.

3.6.3. Model Adequacy (Box-Ljung test)

The Box-Ljung test is used to assess the lack of fit of a time series model. The test is performed on the residuals of a time series model after fitting an ARMA(p, q) model to the data. The test evaluates m autocorrelations of the residuals. If the autocorrelations are close to zero, it means the model exhibit lack of fit.

H_0: The model does not exhibit lack of fit.

H_a: The model exhibits lack of fit.

To find the optimal ARIMA model for the product prices, we will carry out the following steps:

Test stationarity, which also helps in determining the appropriate d value.

Determine p and q using PACF and ACF respectively. The results from PACF and ACF provide an upper limit for iteratively fitting the model.

Choose the best ARIMA parameters (p, d, q) based on the minimum Mean Squared Error (MSE), calculated as:

$$\text{MSE} = \frac{1}{\text{n}}\sum_{\text{i}=1}^{n}(\text{Y} - \hat{\text{Y}})^2$$

where Ŷ is a vector of n predictions, and Y is a vector of observed values for the variable being predicted.

4. Results and Discussions

This chapter present and analysis and findings according to the objective of the study which include analysis of change in consumable and non-consumable products at consumer level of the economy, comparisons of the change in price over the study period with national monthly inflation as reported by Kenya National Bureau of Statistics (KNBS) and then forecast the prices. Pre- processing and model identification and evaluation was carried out in R programming and charts generated using MS Excel.

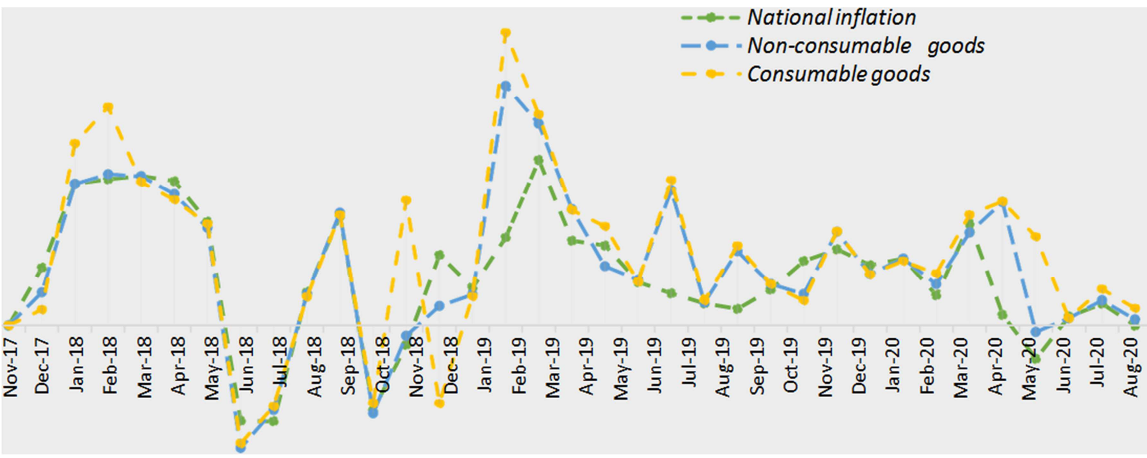

Figure 1. *Evolution of Consumable and non-consumable products' prices and national inflation rates.*

4.1. Evolution of Consumable and Non-Consumable Prices, and National Monthly Inflation

From the (Figure 1 above), it is evident there is a naïve relationship between prices of consumable and non-consumable products prices and national monthly inflation. It is also evident that prices of consumable goods influence inflations more that non-consumable products. In other words, consumable products prices move more closely to national inflation prices than prices of non-consumable products. For instance, between November 2017 and May 2018, between January 2019 and May 2019, and between March 2020 and June 2020, high inflation recorded may be largely contributed to increase in prices of consumable products during the periods. Reduced inflation rates were also attributed to the movement of prices of consumable products downward. For instance, between May 2018 and August 2018 there was a drastic downward movement which may be largely credited to the reduction of prices of consumable products. It is also clear that prices of consumable products prices are more volatile than prices of non-consumable products. Definitively, the prices of food products fluctuate more over time as compared to non-food products. This may explain the visible relationship between consumable products' prices and monthly national inflation as reported by Kenya National of Bureau of Statistics (KNBS).

4.2. Determining Stationarity of Time Series Using Augmented Dickey Fuller test (ADF Test)

The Augmented Dickey Fuller (ADF) test is a statistical method used to determine if a time series is stationary or not. It is a commonly used test in analyzing the stationarity of a series. The process of finding the appropriate form of stationarity begins with the estimation of unit root with the ADF test. The null hypothesis of the ADF test is that the time series is non-stationary (has a unit root). If the null hypothesis is rejected, it means the data are stationary around a zero mean and can be used for modeling and forecasting prices. However, if the time series is non-stationary, differencing should be applied until stationarity is achieved. From Table 1 below, we found that prices of consumable products and national monthly inflation to be non-stationary-the p value was less than 5%. Stationarity of national inflation rates was achieved after second differencing (d=2, ADF statistic=-4.4415, p-value=0.001) and first differencing of time series of prices of consumable products (d=1, ADF statistic = -3.9831, p-value= 0.02097).

Table 1. *ADF results (stationarity check results).*

Time series	Augmented Dickey- Fuller statistics	P-value	Decision
National inflation rates	-3.3675	0.07707	Not stationary
Prices of consumable products	-3.4729	0.06161	Not stationary
Prices of non-consumable products	-3.9831	0.02097	Stationary

4.3. Model Identification and Evaluation

The first step is decomposition of the series in trend, seasonality and random component that make up the time series. Secondly, fit the series into time series model and there after undertaking post-estimation diagnostic to check for the adequacy of the model. Here, we use Box-Ljung Box test on the estimated model.

4.3.1. National Monthly Inflation Rate

In the section, we explain the decomposition work for national monthly inflation rate. It is not clear from the chart whether has been a consistent trend, either positive or negative. The trend has been alternating during the study period. The missing values prior to May 2018 and past May 2020 is attributed to the fact the calculating trends require some long-term data. With regard to seasonality, there is evidence of seasonality in the chart. If the values of trends, seasonality and random components are summed they result to the observed national monthly series. Using the Autocorrelation function (ACF) plot and partial autocorrection function (PACF), ARIMA (1,2,2) is the best model to fit national inflation rates. There is a drastic reduction in autocorrelation after the second bar (q=2) and there is steep reduction of partial autocorrelation after the first bar (p=1). This is in agreement with the model to determine using a combination of ARIMA (p,d,q) components with the lowest log likelihood or Akaike Information Criterion (AIC).

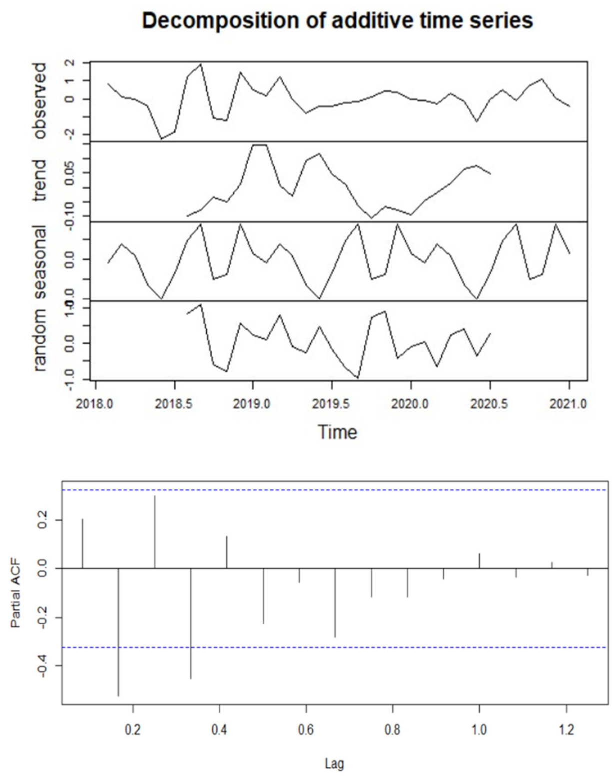

Figure 2. *Decomposition plot of national inflation.*

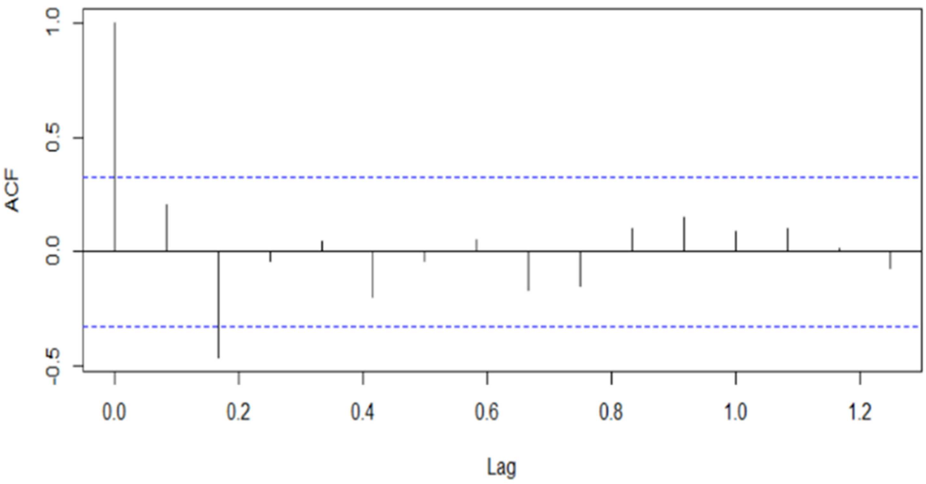

Figure 3. *ACF plot for the National Inflation.*

The model becomes:

$$Y_t - 0.4772\, Y_{t-1} = e_t - 0.0573\, e_{t-1} - 0.9426\, e_{t-2}$$

The histogram and normal probability plot of residuals of monthly inflation rates indicate that the normal distribution provides an adequate fit for this model (Figure 4 below).

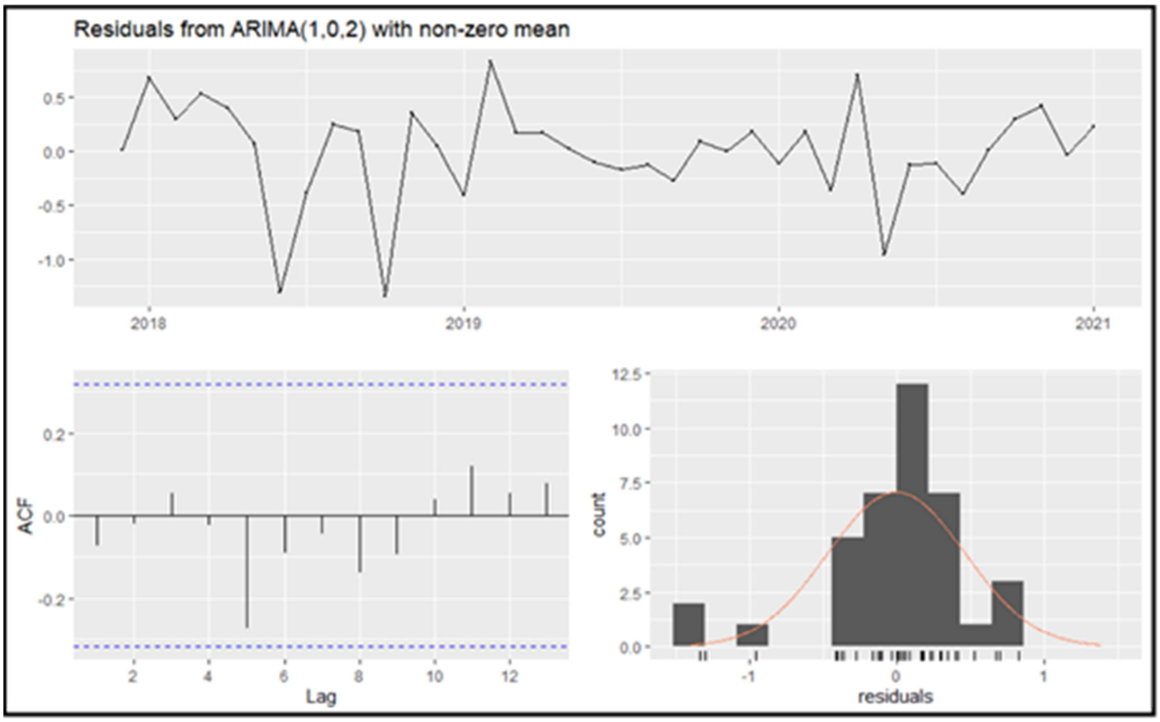

Figure 4. *Residuals plots of national inflation's ARIMA model.*

We apply the Box-Ljung test to the residuals from the ARIMA (1,2,2) model fit to determine whether residuals are random. From Table 2 below, the Box-Ljung test of national inflation rate shows that the first 7 lag autocorrelations among the residuals are zero (p-value = 0.1405), indicating that the residuals are random and that the model provides an adequate fit to the data.

Table 2. *Residual test results (National Inflation Rates).*

Test name	Test Statistic	Degrees of freedom	p-value
Ljung-Box test	6.9141	4	0.1405

Table 3. *ARMA results (National Inflation Rates).*

Model type	Coefficient	Standard error
AR1	0.4772	0.1533

Model type	Coefficient	Standard error
MA1	-0.0573	0.1125
MA2	-0.9426	0.1097
	log likelihood = -32.14, aic = 72.27	

4.3.2. Change in Prices of Consumable Products

For prices of consumable goods, the trend is relatively smooth, despite several fluctuations over time it remained constant over the study period. With regard to seasonality, the prices of consumable goods exhibit seasonality which occurs at the end of every year. ARIMA (3,1,0) is shown to have the lowest log likelihood and Akaike Information Criteria (AIC). Using PACF it is evident that there exists an autocorrelation between the current price and the previous subsequent consumable products' prices.

Table 4. *ARMA results (Consumable Products).*

Model type	Coefficient	Standard error
AR1	-1.0541	0.1529
AR2	-0.8728	0.1783
AR3	-0.3660	0.1500
	log likelihood = -12.91, aic = 35.06	

The equation model becomes:

$$Y_t + 1.0541Y_{t-1} + 0.8728Y_{t-2} + 0.3660Y_{t-3} = e_t$$

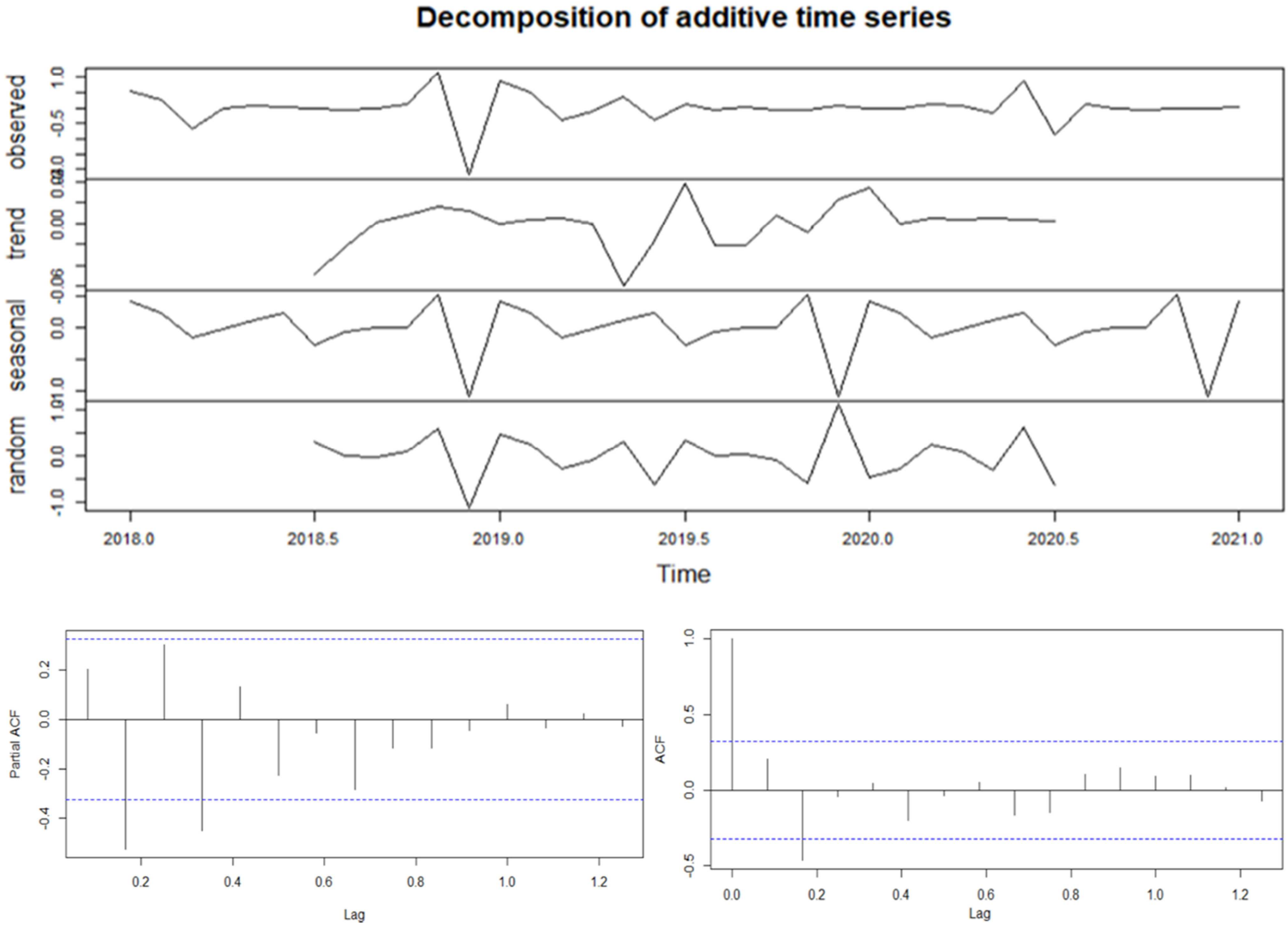

Figure 5. *Decomposition plot of consumable products' price.*

The model fits the series well since there exists no correlation between the model residuals. This is from the ACF plot of residuals of the model in Figure 6 below, where there is no bar that touches the significance lines. In addition, the residuals of the model also seem to fit normal probability model. In the output below, the Box-Ljung test of national inflation rate shows that the first 7 lag autocorrelations among the residuals are zero (p-value = 0.5394), indicating that the residuals are random and that the model provides an adequate fit to the data.

Table 5. *Residual test results (Consumable Products).*

Test name	Test Statistic	Degrees of freedom	p-value
Ljung-Box test	3.1112	4	0.5394

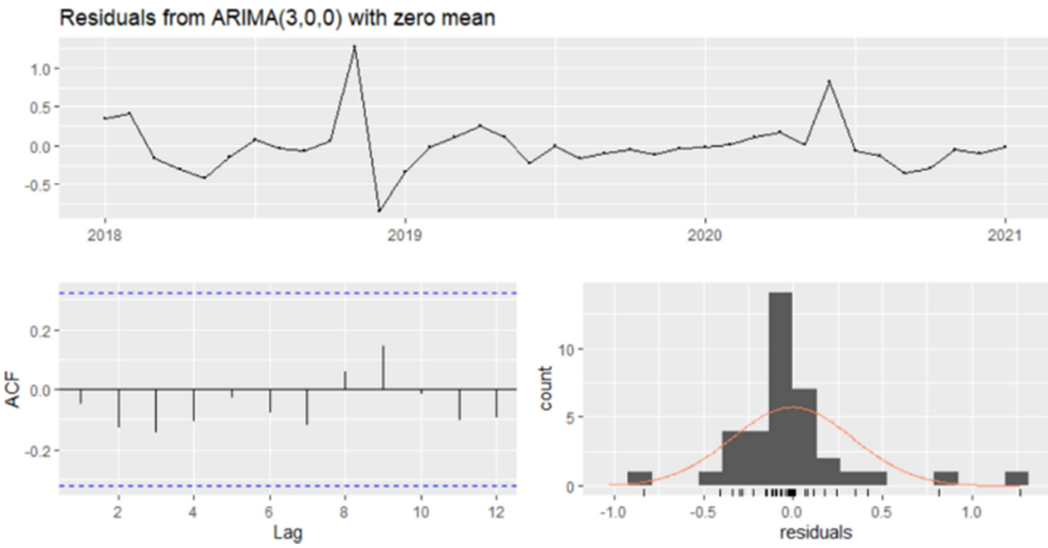

Figure 6. *Residuals plots of consumable product price's ARIMA model.*

4.3.3. Change in Prices of Non-Consumable Products

Unlike prices of consumable products and national monthly inflation rates, prices of non- consumable seem to have had a positive trend during the study period. This is indicated by a positive gradient of trend component after decomposition. The seasonality of the non-consumable products' prices is also noted, where there is a spike of prices at the beginning of every year. Using both ACF and PACF plot is evident that the prices of non-consumable products can be assumed to be white noise. This is also affirmed by a random walk ARIMA (0,0,0) having the lowest log likelihood and Akaike Information Criterion (AIC) values. Again, the residuals of the model fit well on normal distribution plot, and they have no autocorrelation (ACF of residual does not have any significant correlation between the values).

Table 6. *White Noise Coefficients for Non-Consumable Products.*

Model type	Coefficient	Standard error
Mean	0.1889	0.0946

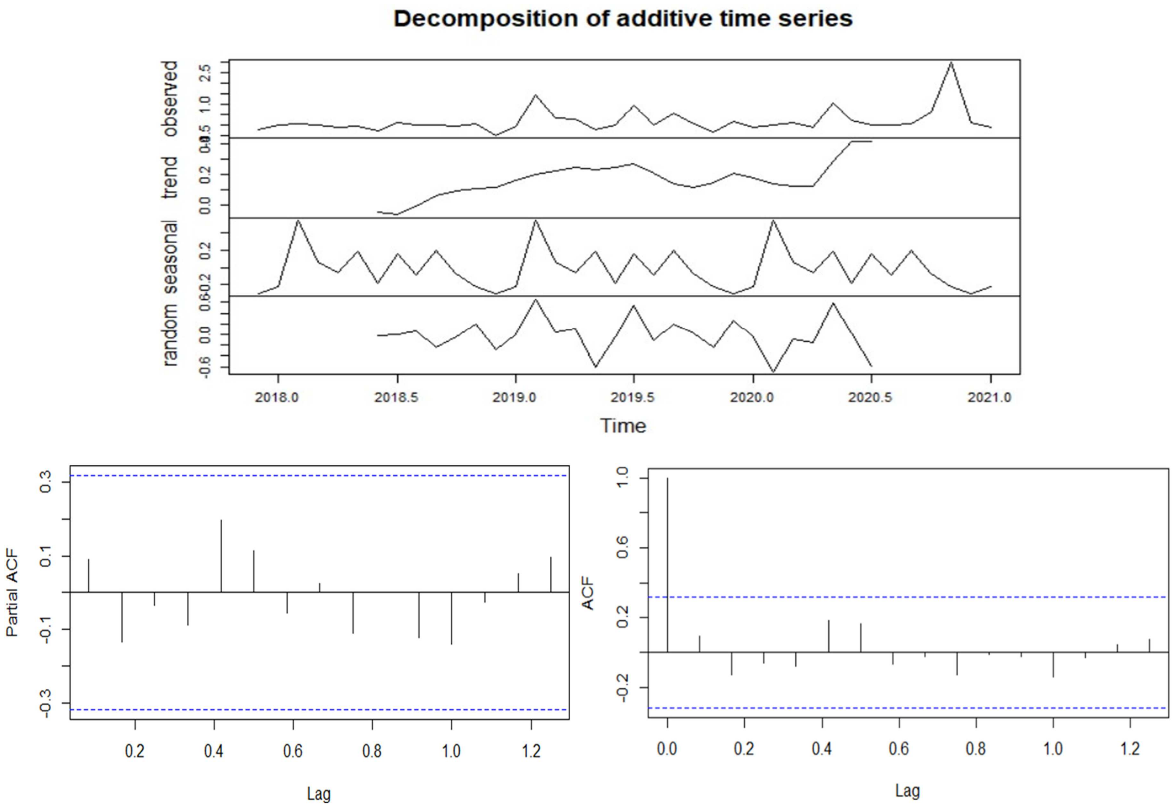

Figure 7. *Decomposition plots of non-consumable products' prices time series.*

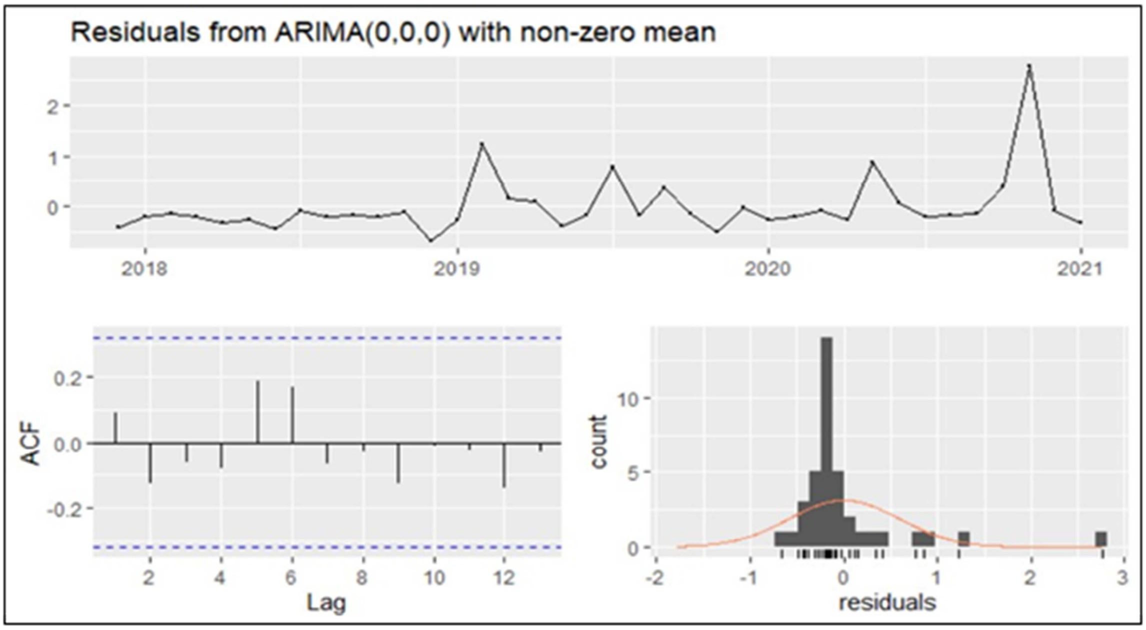

Figure 8. *Residuals plots of no-consumable products prices' ARIMA model.*

Therefore, the model becomes,

$$0.1889 = e_t$$

Table 7. *Residual test results (Non-Consumable Products).*

Test name	Test Statistic	Degrees of freedom	p-value
Ljung-Box test	4.602	7	0.7084

4.4. Forecasting

Fitted models were used to forecast the change in prices and national monthly inflation. Performance of the models were evaluated using several statistics, where they were expected to be as minimum as possible. In other words, the accuracy of the models is pegged on the magnitude of the statistics. It is evident from table 1 below that the model was somewhat a good fit to forecast change in prices for consumable products and national monthly inflation rates. Specifically, the mean error is 0.00 for both models and Mean Absolute Error less than one. In addition, the autocorrelation function of the forecast errors is also significantly small when forecasting both consumable products' prices and national monthly inflation rates.

Table 8. *Error Function Results.*

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
National Inflation	0.00	1.08	0.75	-110.77	578.96	0.90	-0.06
Prices of consumable goods	0.00	0.92	0.51	2320.08	2413.44	1.17	-0.64

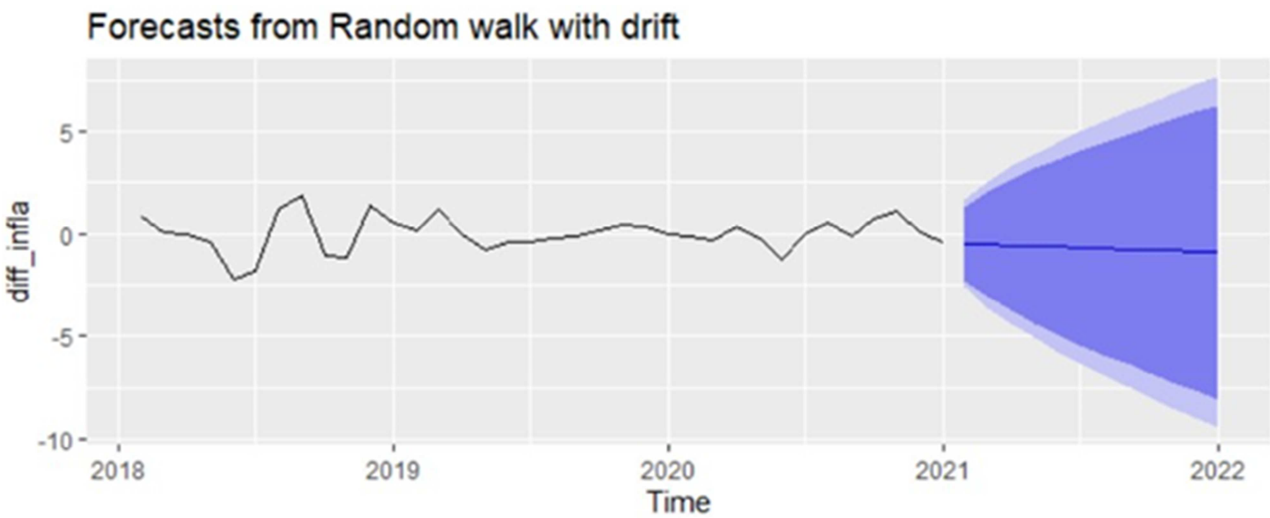

Figure 9. *Forecast plot of the national inflation's ARIMA model.*

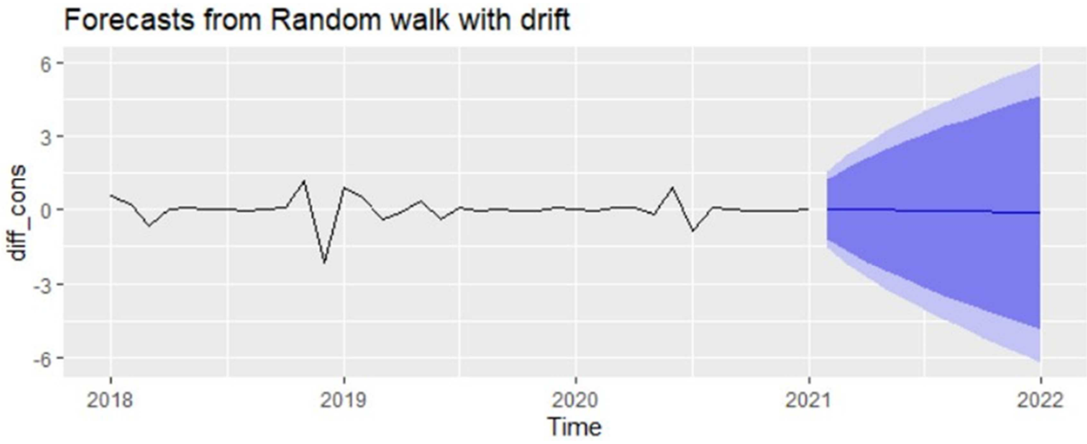

Figure 10. *Forecast plot of consumable products' prices ARIMA model.*

5. Summary, Conclusions and Recommendations

5.1. Summary of the Findings

This chapter summarizes the findings based on the objectives of the study and makes recommendations based on those findings. The main objective of the study was to explore the trend of prices of household consumable and non-consumable over the three years under study and obtain the best ARIMA model that can be used for predictions of future prices. After assessing the relationship between change in prices of consumable goods and the national inflation we found out that consumable products play a greater role in determining the national inflation i.e., they bear a similar trend in a longer period in the year than non-consumable goods.

It was evident that there exists a relationship between change in prices at local level, both consumable and non-consumable products, and national monthly inflation rates as reported by Kenya National Bureau of Statistics (KNBS). However, changes of prices of consumable goods indicated that they contribute more to national inflation rate as compared to non-consumable products.

5.2. Conclusions and Recommendations

The change in prices of consumable products was fitted to an ARIMA (1,2,2) and national monthly inflation rates fitted to ARIMA (3,1,0). For the non-consumable goods, it was found to be a white noise. The findings of this research work are in line with similar work undertaken by (Tyralis & Papacharalampous, 2017; Carta, 2019 & Huwiler & Kaufmann, 2013) [3, 4, 5]. The application of random forest in forecasting the prices and national monthly inflation rates is also employed by Nti et al, 2019 & Budiastuti, 2017) [5, 6]. Their findings also allude to the efficacy of the models in forecasting future change in prices.

In future, researchers may undertake similar research work with more local shops within the same locality and different counties to study whether there are differences between the change in prices over time in different counties. In addition, a more sophisticated model needs to be employed on the data to investigate the effects of COVID-19 pandemic on the price of consumable and non-consumable products at local level.

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