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## TREND ANALYSIS OF PRICE INFLATION ON MAIZE IN MEKELLE CITY, ETHIOPIA

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**Abstract:** The major endeavor of this research paper is to demonstrate the time series analysis of price inflation of maize in Mekelle city. The statistical technique that we have applied to investigate the data is time series analysis. Consequently, time series method that would use to test stationarity by using Dickey-Fuller Test and Stationary during differencing (second order differencing). By using R software the comprehension of time series analysis, trend analysis, and Box-Jenkins models are made for this data. A total of 60 months of price inflation of maize was incorporated in this study. From the Box-Jenkins model evaluation, the ARIMA (2,2,1) was found the preeminent model. AIC method of evaluation was applied to select the preeminent model from the alternative and also considering Box-Jenkins methodology monthly retail prices were forecasted for one year. The outcomes be evidence for that the trend of price inflation of maize is fragment like (constant). In conclusion, the studies guide to forecasting the price inflation of maize of year 2019 G.C.

**Keywords:** Box-Jenkins model; price inflation; Maiz; ARIMA; forecasting.

**2010 AMS Subject Classification:** 62M10.

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## 1. INTRODUCTION

Inflation is definite as grow in the common price level. In further expressions, prices of several goods and services such as household, clothes, grocery, transportation, and fuel must be increasing in regulate for inflation to occur in the overall financial system. If prices of just a small amount of types of commodities or services are growing up, there isn't essentially inflation. It is a measure of how prices change with time. When the price level rises, each unit of currency buys fewer goods and services; consequently, inflation reflects a reduction in the purchasing power per unit of money a loss of real value in the medium of exchange and unit of account within the economy.

It is important when the economy is not running at capacity, meaning there is unused labor or resources, inflation theoretically helps increase production. More dollars translates to more spending, which equates to more aggregated demand. In turn, triggers more production to meet that demand.

The problem of inflation has global, international, national and also local issue in today. At the global level, inflation has rise both because of supply side issues as well as demand side factors .At the same time, it is useful to bear in mind that many developing countries like Ethiopia are facing to the challenge of addressing high inflation.

If inflation were rapid enough, shortages of goods as consumers begin hoarding out of concern that prices will increase in the future, people's savings and assets lose value (wealth) rapidly, pensions and salaries become pretty much worthless, and mostly affect the poor and unemployed because they are unable to afford the basic necessities. And also high inflation rates tend to cause uncertainty and confusion leading to less investment. It is argued that countries with persistently higher inflation tend to have lower rates of investment and economic growth.

We take this context into account; the price of agricultural products is also increase in Mekelle city. So the study would be to see the effect of price inflation on maize which has a high problem on consumers in Mekelle city.

NRI (2017), showed that farmers storing grains in the certified warehouses under usually checked prices disseminated via the phones before making marketing decisions. There was strong evidence of seasonality in the use of marketing information system, peaking around the harvest season when most farmers consider selling their products but subsequently tailing off. Mendez-Ramos et al (2017) distinguish between 'primary' and 'manufactured' agribusiness, on

the back of empirical analysis showing the huge and rising significance of agribusiness trade in the growth of developing countries in recent decades. Divanbeigi et al (2016) summarise how structural transformation has taken place within the agriculture sector through modernization and technical change, rising productivity, and increasing integration with other sectoral activities.[4][5][10][13]

For this study, the data was a secondary data that collected in Mekelle city from, Tigray Agricultural marketing promotion (TAMP), on price inflation maize recorded for 5 years from years 2014 to 2018 G.C, September to August as a monthly data of 60 observations.

In this paper, Section 2, carries the ARIMA model building using Box-Jenkins methodology. Section 3 presents the final results discussion. Finally, Section 4 reveals the conclusion and recommendations of this study.

## **2. BOX-JENKINS METHODOLOGY**

Box-Jenkins methodology is one of the finest commonly applied time series forecasting methods in implementation.

### **2.1. Box-Jenkins Model**

The Box-Jenkins Model is a mathematical model designed to forecast data from a specified time series. And also can analyze many different types of time series data for forecasting. Its methodology uses differences between data points to determine outcomes. Overall the methodology allows the model to pick out trends, using autoregression, moving averages and level of differencing in order to generate forecasts.

Where autoregression or Autoregressive (p) it is the number of terms in the model that describe the dependency among successive observations and it can measure by autocorrelation graph. Moving averages (q) is the number of terms that describe the persistence a random shock from one observation to next it can be measured by partial autocorrelation graph. In this study we identify an appropriate Box-Jenkins process or model,

#### **Stages in building a Box-Jenkins time series model.**

##### **2.1.1. Model Identification**

To apply Box-Jenkins methodology on a time series data, before any analysis, the data should be checked for stationary. This involves determining the order of the model required to capture the dynamic features of the data. Graphical procedures are used to determine the most appropriate

specification (Making sure that the variables are stationary, identifying seasonality, and the use of plots of the autocorrelation and partial autocorrelation functions).

### 2.1.2. Estimation of parameters

This involves estimation of the parameters of the model specified in Model Identification. The most common methods used are maximum likelihood estimation and non-linear least-squares estimation, depending on the model and its objective is to minimize the sum of squares of errors.

### 2.1.3. Validation Process

This involves model checking, that is, determining whether the model specified and estimated is adequate. Thus: Model validation deals with testing whether the estimated model conforms to the specifications of a stationary univariate process. It can be done by over fitting and residual Diagnosis checking.

### 2.1.4. Forecasting

In this stage we will forecast the future values based on the fitted model in order to predict the coming events

## 2.2. Autoregressive Process (AR (p))

The idea behind the autoregressive models is to explain the present value of the series,  $X_t$ , by a function of  $p$  past values,  $X_{t-1}, X_{t-2}, \dots, X_{t-p}$ . An autoregressive process of order  $p$  is written as:

$$X_t = \varphi_1 X_{t-1} + \varphi_2 X_{t-2} + \dots + \varphi_p X_{t-p} + \omega_t = \sum_{j=1}^p \varphi_j X_{t-j} + \omega_t, j=1, 2, 3, \dots, p$$

where  $\{\omega_t\}$  is white noise, i.e.,  $\{\omega_t\} \sim N(0, \sigma^2)$ , and  $x_t$  is the time series

$\varphi = (\varphi_1, \varphi_2, \dots, \varphi_p)$  is the vector of model coefficients (are autoregressive parameters) and  $p$  is a non-negative integer, and  $\omega_t$  is uncorrelated with  $X_s$  for each  $s < t$ .

The AR model establishes that a realization at time  $t$  is a linear combination of the  $p$  previous realization plus some noise term. For  $p = 0$ ,  $X_t = \omega_t$  and there is no auto regression term.

The lag operator is denoted by  $B$  and used to express lagged values of the process so,

$$BX_t = X_{t-1}, B^2X_t = X_{t-2}, B^3X_t = X_{t-3}, \dots, B^dX_{t-d}.$$

If we define  $\Phi(B) = 1 + \sum_{j=1}^p \varphi_j B^j = 1 + \varphi_1 B + \varphi_2 B^2 + \dots + \varphi_p B^p$ , and the AR( $p$ ) process is given by the equation  $\Phi(B)X_t = \omega_t; t = 1, \dots, n$ .

Where  $\Phi(B)$  is known as the characteristic polynomial of the process and its roots determine when the process is stationary or not.

### 2.3. Moving Average Process (MA (q))

Moving average model of order q (MA (q)): MA (q) can define correlated noise structure in our data and goes beyond the traditional assumption where errors are iid. Under this model, the observed process depends on previous  $w_t$ 's.

$$x_t = w_t - \theta_1 w_{t-1} - \theta_2 w_{t-2} - \dots - \theta_q w_{t-q}$$

Where:  $\theta_1, \theta_2, \dots, \theta_q$  are constants with  $\theta_q \neq 0$ ;

$w_t$  is Gaussian white noise  $w_n(0, \sigma_w^2)$ . Note that  $w_t$  is uncorrelated with  $x_{t-j}, j = 1, 2, \dots$

In lag operator notation, the MA (q) process is given by the equation:  $x_t = \theta(B)w_t$ ,

Where the moving average operator  $\theta(B)$  is  $\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \dots - \theta_q B^q = 1 - \sum_j^q \theta_j B^j$ .

### 2.4. Autoregressive Moving Average Models (ARMA (p, q))

Combine! ARMA (p, q): i.e the combination of AR (p) and MA (q).

$$x_t = \phi_1 x_{t-1} + \phi_2 x_{t-2} + \dots + \phi_p x_{t-p} + w_t - \theta_1 w_{t-1} - \theta_2 w_{t-2} - \dots - \theta_q w_{t-q}$$

In operator form:  $\phi(B)x_t = \theta(B)w_t$ .

#### Issues in ARMA

**Models Parameter redundancy:** if  $\phi(z)$  and  $\theta(z)$  have any common factors, they can be canceled out, so the model is the same as one with lower orders. We assume no redundancy.

**Causality:** If  $\phi(z) \neq 0$  for  $|z| \leq 1$ ,  $x_t$  can be written in terms of present and past  $w_s$ . We assume causality.

**Invertibility:** If  $\theta(z) \neq 0$  for  $|z| \leq 1$ ,  $w_t$  can be written in terms of present and past  $x_s$ , and  $x_t$  can be written as an infinite auto regression. We assume invertibility.

### 2.5. Autoregressive Integrating Moving Average Models (ARIMA (p,d,q))

ARIMA models are, in theory, the most general class of models for forecasting a time series which can be made to be "stationary" by differencing.

A non-seasonal ARIMA model is classified as an "ARIMA (p,d,q)" model, where:

**p** is the number (order) of autoregressive terms,

**d** is the number of non-seasonal differences needed for stationarity, and

**q** is the number of lagged forecast errors in the prediction equation (order of moving average).

The ARIMA forecasting equation for a stationary time series is a linear (i.e., regression-type) equation in which the predictors consist of lags of the dependent variable and/or lags of the forecast errors. That is: Predicted value of Y = a constant or a weighted sum of one or more recent values of Y and a weighted sum of one or more recent values of the errors.

In terms of  $y$ , the general forecasting equation is:

$$\hat{y}_t = \mu + \phi_1 y_{t-1} + \dots + \phi_p y_{t-p} - \theta_1 e_{t-1} - \dots - \theta_q e_{t-q}$$

Where  $\hat{y}_t$  is level of differencing, the constant is notated by  $\mu$ , while  $\phi$  is an autoregressive operator,  $e$  is a random shock corresponding to time period  $t$ , and  $\theta$  is a moving average operator. The forecasting equation is constructed as follows. First, let  $y$  denote the  $d^{\text{th}}$  difference of  $Y$ , which means:

$$\text{If } d=0: y_t = Y_t$$

$$\text{If } d=1: y_t = Y_t - Y_{t-1}$$

$$\text{If } d=2: y_t = (Y_t - Y_{t-1}) - (Y_{t-1} - Y_{t-2}) = Y_{t-2}Y_{t-1} + Y_{t-2}$$

Here Random-walk and random-trend models, autoregressive models, and exponential smoothing models are all special cases of ARIMA models.

## 2.6. Trend Analysis

Trend analysis quantifies and explains trend and patterns in a "noisy" data over time. The trend is an up wards or down wards shift in a data set over time. It fits general trend model to time series data and provides forecast the linear, quadratic, exponential growth or decay and s-curve model. The appropriate model is selected by using different measures of accuracies like mean absolute percentage error (MAPE), mean square error (MSE) and mean absolute error (MAE). We choose the one with minimum Mean absolute percentage error (MAPE) as the appropriate model for each category. And also we eliminate the components in order to measure the trend.

### 2.6.1. Mean Absolute Percentage Error (MAPE)

Also famous as mean absolute percentage deviation and it is a appraisal of prediction accuracy of a forecasting method in statistics. It regularly expresses accuracy as a percentage, and is defined by the principle:

$$\text{MAPE} = \frac{100\%}{n} \sum_{t=1}^n \left| \frac{A_t - F_t}{A_t} \right|,$$

Where  $A_t$  is the actual value and  $F_t$  is the forecast value. The difference between  $A_t$  and  $F_t$  is divided by the actual value  $A_t$  again. The absolute value in this calculation is summed for every forecasted point in time and divided by the number of fitted points  $n$ . multiplying by 100% makes it a percentage error.

### 2.6.2. Mean Square Error (MSE)

The MSE assesses the superiority of an estimator\_(i.e., a mathematical function mapping a sample of data to an estimate of a parameter of the population from which the data is sampled) or a predictor.

If  $\hat{Y}$  is a vector of  $n$  predictions generated from a sample of  $n$  data points on all variables, and  $Y$  is the vector of observed values of the variable being predicted, then the within-sample MSE of the predictor is computed as:

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

### 2.6.3. Root Mean Square Error (RMSE)

Is a frequently used measure of the differences between values (sample or population values) predicted by a model or an estimator and the values observed. The RMSE represents the square root of the second sample moment of the differences between predicted values and observed values or the quadratic mean of these differences.

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

### 2.6.4. Mean Absolute Error (MAE)

It is also called mean absolute deviation and it is the average of the absolute value, or the difference between actual values and their average value, and is used for the calculation of demand variability. It is expressed by the following formula:

$$\text{MAE} = \sum_{i=1}^n \left| \frac{x_i - \bar{x}}{n} \right|,$$

Where  $x_i$ : Performance value for period  $i$

$\bar{x}$ : Average value

$n$ : Number of data.

Here we choose the one with minimum Mean absolute percentage error (MAPE) as the appropriate model for each category. And also we eliminate the components in order to measure the trend.

### 2.7. Akaike Information Criterion (AIC)

Akaike's information criterion (AIC) compares the quality of a set of statistical models to each other. It will take each model and rank them from best to worst. The "best" model will be the one that neither under-fits nor over-fits. Therefore, once you have selected the best model. Akaike's Information Criterion is usually calculated with software.

The basic formula is defined as:

$$\text{AIC} = -2(\log\text{-likelihood}) + 2K$$

Where:

K is the number of model parameters (the number of variables in the model plus the intercept).

Log-likelihood is a measure of model fit. The higher the number, the better the fit. This is usually obtained from statistical output.

### **2.8. Bayesian Information Criterion (BIC)**

Bayesian information criterion (BIC) or Schwarz Criterion is a criterion for model selection among a finite set of models; the model with the lowest BIC is preferred. It is based, in part, on the likelihood function and it is closely related to the Akaike information criterion (AIC). When fitting models, it is possible to increase the likelihood by adding parameters, but doing so may result in over fitting. The BIC resolves this problem by penalizes the complexity of the model (the number of parameters in the model). This penalty for additional parameters is stronger than that of the AIC.

$$\text{BIC} = -2\ln(L) + k\ln(n)$$

Where:

n = the number of data points in x, the number of observations, or equivalently, the sample size;

k = the number of free parameters to be estimated. If the estimated model is a linear regression, k is the number of regressors, including the constant.

L = the maximized value of the likelihood function for the estimated model.

### **2.9. Forecasting**

Forecasting is the process of making predictions of the future based on past and present data and most commonly by analysis of trends. Forecasting may represent a prediction as to what might happen to one particular such as price of maize next year or in five year time or it may by a prediction as to the future of a much more complex entity such as the economy.

Forecasting also refers to the using of knowledge use have at one moment of time to estimate what will happen at another moment of time. The forecasting problem is created by the interval of time between the moments. Maize inflation price forecasting refers to the statistical analysis of the past and current movement in a given time series to as to obtain clues about the future pattern of the movement. By using the quadratic trend model ARIMA we can forecast the future.[1][2][3]



### 3. RESULTS AND DISCUSSION

The data analyzed are data on inflation of maize price in January of 2014 to August 2018 in Mekelle city. In this research, we used **R** software for Data analysis of the monthly price inflation of maize in Mekelle city.

#### 3.1 Time Series Analysis

Research results with Software **R** i.e. the first phase is the identification of the model. At this stage identification of the model is the first step that to make a plot of the data.

Graphically the plot of maize price inflation with respect to time was given below.

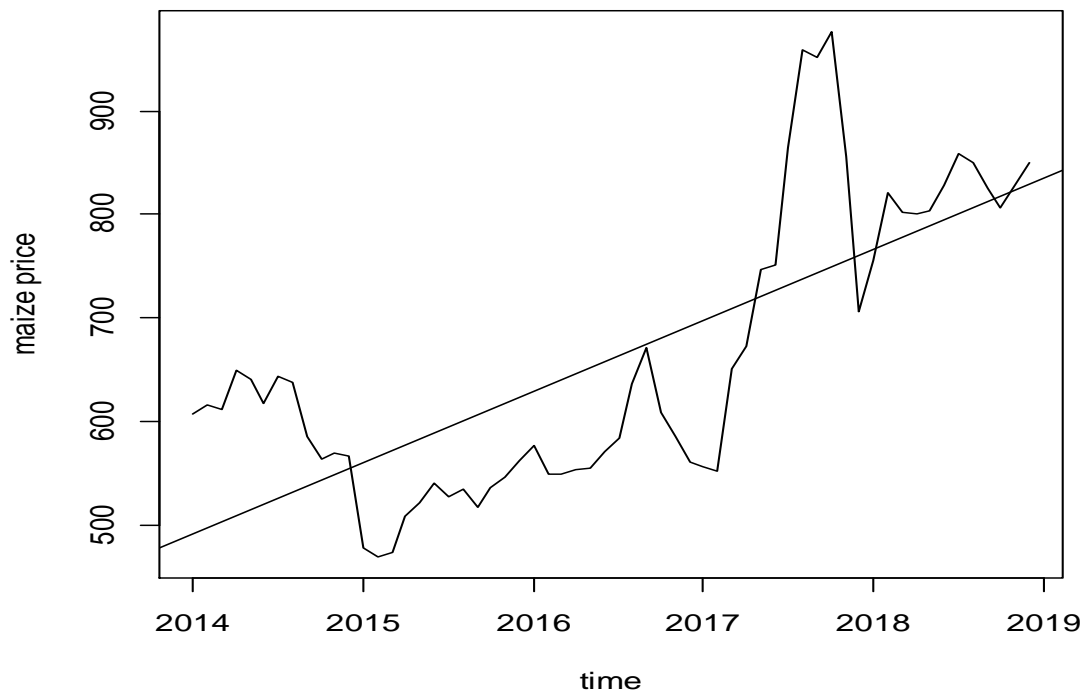


Figure 1: Time plot for Retail Price of maize (birr per qntl) in Mekelle Town

This plot shows the radical change from September 2014 to August 2018 in just five years. As it shows in the above figure, the trend line shows there is increasing pattern in the price of maize with respect to time. (i.e. not stationary). Therefore, we have to change non-stationary time series into stationary time series by taking a successive difference of the price.

### 3.2 Testing Stationary

Augmented Dickey-Fuller (ADF) and Phillips–Parron test (pp) are used to check the stationarity of the time series data (observation), but in this study we used Augmented Dickey-Fuller (ADF) to check the stationarity. And the forecasting equation is given by  $\Delta y_t = Y_t$  (for  $d=0$ )

Table 1: Augmented Dickey-Fuller (ADF) test for monthly maize price stationary

Test hypothesis

Augmented Dickey-Fuller Test
Data: maize_pr
Dickey-Fuller = -2.7356, Lag order = 3, p-value = 0.2774
Alternative hypothesis: stationary

**H<sub>0</sub>**: the data is not stationary (the data needs differencing) Vs

**H<sub>1</sub>**: the data is stationary (the data doesn't need differencing)

By using the Augmented Dickey-Fuller test the original data is not stationary, because p values (0.2774) which are greater than alpha value (0.05) so reject the null hypothesis, and concluded that the data is not stationary.

### 3.3 Stationary through Differencing

In order to convert non-stationary series to stationary, differencing method can be used.

(forecasted equation for  $d=1$ :  $\Delta Y_t = Y_t - Y_{t-1}$ ) Then the test is as follows:

Table 2: Augmented Dickey-Fuller test after differencing ( $d=1$ ) changed to stationary of monthly maize price.

Augmented Dickey-Fuller Test
Data: diff (maize_pr)
Dickey-Fuller = -4.0902, Lag order = 3, p-value = 0.01184
Alternative hypothesis: stationary

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Table 3: Augmented Dickey-Fuller test after differencing (d=2) changed to stationary of monthly maize price.

Augmented Dickey-Fuller Test
data: diff(diff(maize_pr))
Dickey-Fuller = -5.6153, Lag order = 3, p-value = 0.01
Alternative hypothesis: stationary

The forecasting equation is constructed as:  $\Delta y_t = (Y_t - Y_{t-1}) - (Y_{t-1} - Y_{t-2}) = Y_{t-2}Y_{t-1} + Y_{t-2}$

As we can see from table 2 and table 3 both the p-values (0.01184 and 0.01) are less than alpha value (0.05). Here more small p-value is after differencing two(d=2), therefore we have more evidence rejecting the null hypothesis, so from this we can conclude that reject the null hypothesis that means the data is stationary after differencing twice rather than once.

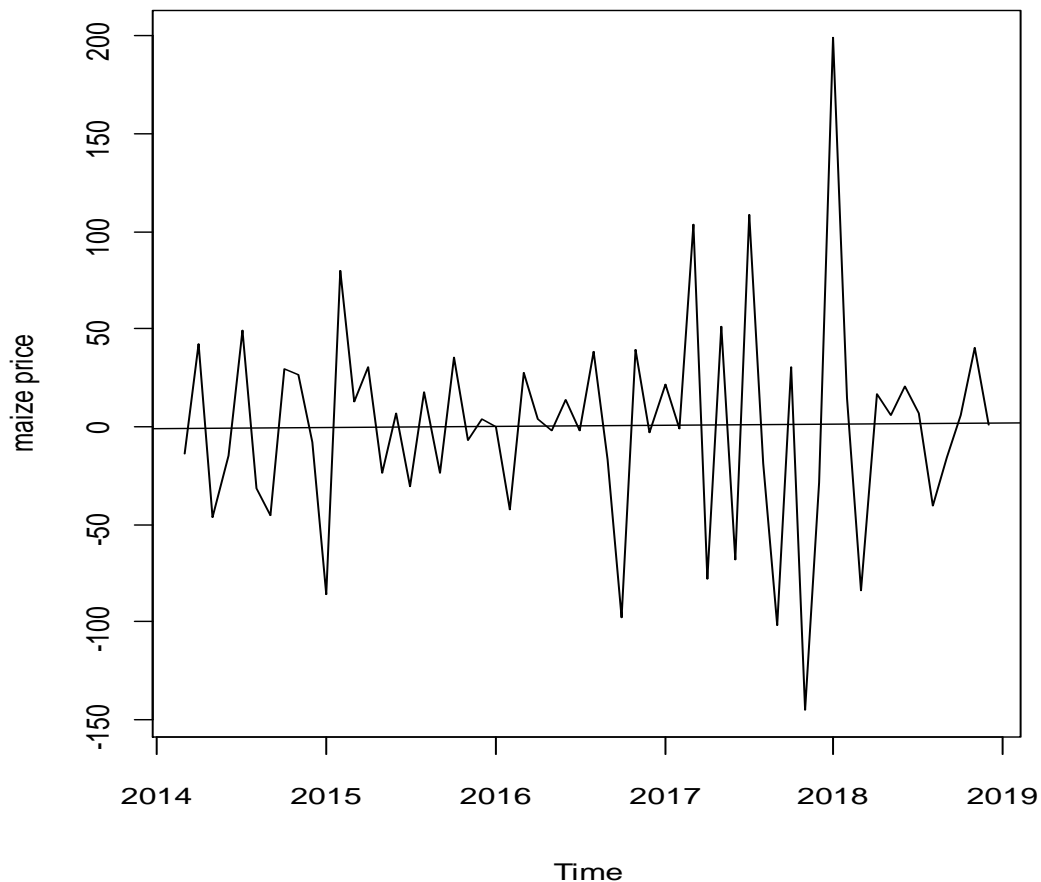


Figure 2: time series plot of monthly maize price inflation after differencing

As we can see from figure 2 the series fluctuates about the mean. This means that it does not trend away or drift away from the mean and the trend line shows there is a constant pattern in the price of maize with respect to time (the time plots appears similar at different points). Because of this reason the time series is stationary.

### 3.4. Trend Analysis on Maize-Price Inflation

Table 4: Summary table for price of maize in Mekelle city, and its measure of accuracy.

Measures of accuracy					
ME	RMSE	MAE	MPE	MAPE	MASE
0.2879998	64.28444	47.19973	-15.47734	376.8735	0.6996862

The above table shows that the measures of accuracy for price of maize inflation of the differenced (after differencing,  $d=2$ ), means that after the data is stationary.

### 3.5 Box-Jenkins Modeling

The basic steps Box-Jenkins procedures are analyzed in the following way:-

#### 3.5.1 Model Identification

To apply Box-Jenkins modeling on a time series data, before any analysis, the data should be checked for stationary. A stationary series is the one that does not contain trend i.e. it fluctuates around a constant mean. As we have seen from the time plot of Figure 2, the monthly retail price of maize has linear trend and also has a constant trend line patterns. This shows that the series is stationary and stable. Therefore, now let us examine ACF and PACF for model identification.

#### 3.5.2 Autocorrelation Function of Monthly Maize Price Inflation

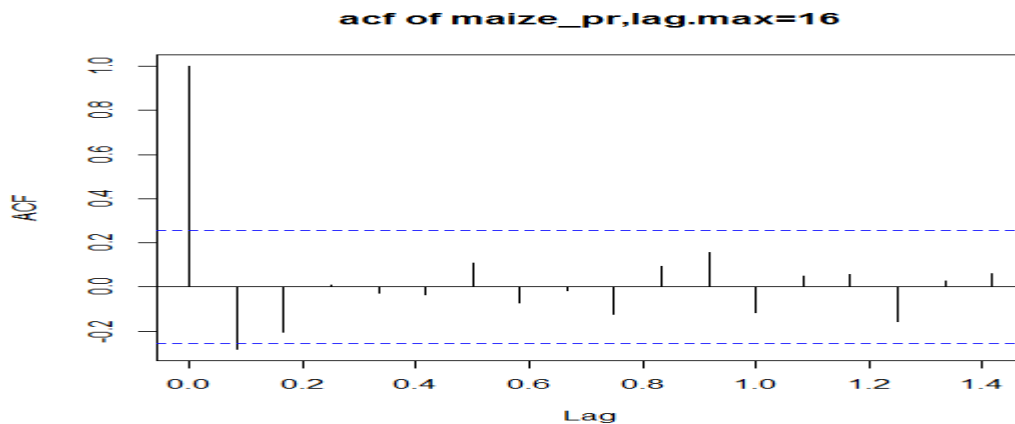


Figure 3: plot of autocorrelation function for stationary data after differencing ( $d=2$ )

We see from the correlogram that the autocorrelations for lags 1 out side of the significance bound, and that the autocorrelations tail off to zero after lag 1. The autocorrelations for lag 1 are negative. So we must test the MA model to check the model adequacy. That is, the total monthly maize price inflation under the autocorrelations graph shows there is one point that out side the lower bounds that is MA (1). Meaning, disseminations' of the monthly total maize price inflation is not balance or equal.

### 3.5.3 Partial Autocorrelation Function: For Monthly Maize Price Inflation

The partial autocorrelation plot is also commonly used for model identification in Box and Jenkins models.

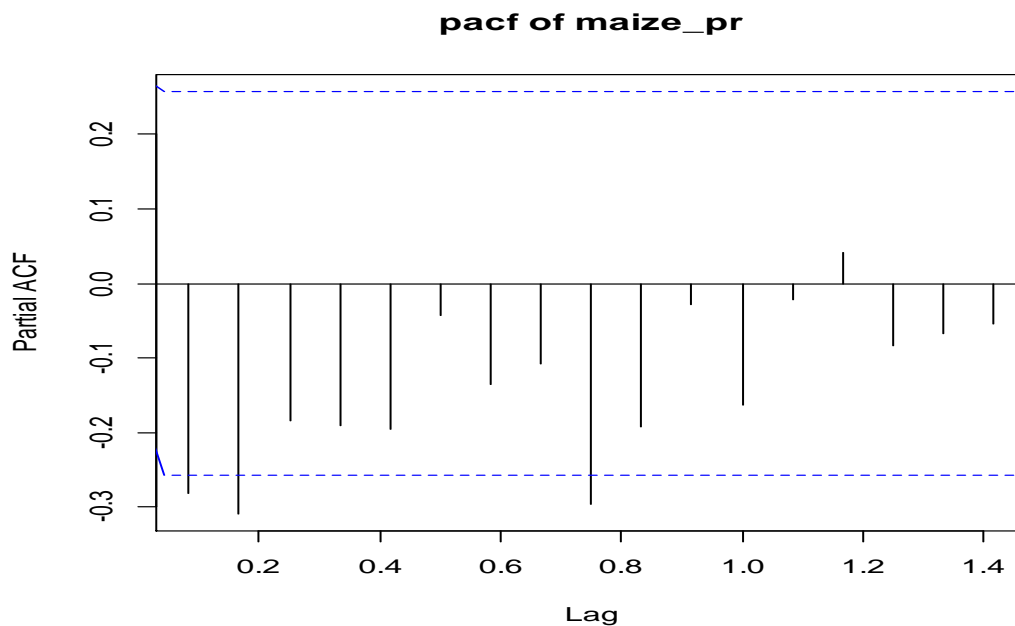


Figure 4: plot of partial autocorrelation function for stationary data after differencing ( $d=2$ ).

Similarly, from figure 4 the partial autocorrelation graph, we see that the partial autocorrelation at lag 1 and at lag 8 are not in the significance bounds (has 2 lagged numbers).

So we must test the AR model to check the model adequacy. That is, the total monthly monthly maize price inflation under the partial autocorrelations graph shows there are two points that out side the lower bounds that is AR (2). Meaning, disseminations' of the monthly total maize price inflation is not balance or equal.

### 3.5.4 ARIMA Process

#### Selecting a Candidate ARIMA Model

If your time series is stationary, or if you have transformed it to a stationary time series by differencing  $d$  times, the next step is to select the appropriate ARIMA model, which means finding the values of most appropriate values of  $p$  and  $q$  for an ARIMA ( $p, d, q$ ) model.

The time series of second differences appears to be stationary in mean and variance, and so an ARIMA ( $p, 2, q$ ) model is probably appropriate for the time series of the maize price inflation of Mekelle town. By taking the time series of second differences, we have removed the trend component of the time series of the maize price inflation at Mekelle town.

By counting the lag of ACF there are 1 lag where the Autocorrelation function two lags so that the order of moving average is ( $q=1$ ) and the order of PACF autoregressive are ( $p=2$ ) and also the correlogram and partial correlogram tail off to zero except those lags we tried before.

So the possibility model to fit the data with differencing twice ( $d=2$ ) are:

ARIMA(1,2,0), ARIMA(0,2,1), ARIMA(1,2,1), ARIMA(2,2,1), and ARIMA(2,2,0).

By using AIC, we obtain the appropriate model, as follow.

Table 5: AIC Model selection for monthly maize price inflation

<p>Arima(1, 2, 0)</p> <p>Coefficients:</p> <p>ar1</p> <p>-0.6498</p> <p>s.e. 0.1000</p> <p>sigma^2 estimated as 13237: log likelihood = -345.48, aic = 694.95</p>
<p>Arima(0,2,1)</p> <p>Coefficients:</p> <p>ma1</p> <p>-0.9998</p> <p>s.e. 0.0439</p> <p>sigma^2 estimated as 7609: log likelihood = -331.72, aic = 667.43</p>

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<p>Arima(1, 2, 1)</p> <p>Coefficients:</p> <pre> ar1  ma1 -0.5165 -1.0000 s.e. 0.1126 0.0449 sigma^2 estimated as 5466: log likelihood = -323.02, aic = 652.04 </pre>
<p><b>Arima(2,2,1)</b></p> <p>Coefficients:</p> <pre> ar1  ar2  ma1 -0.7557 -0.4461 -1.0000 s.e. 0.1178 0.1171 0.0461 sigma^2 estimated as 4280: log likelihood = -316.77, <b>aic = 641.54</b> </pre>
<p>Arima(2, 2, 0)</p> <p>Coefficients:</p> <pre> ar1  ar2 -1.016 -0.5558 s.e. 0.109 0.1078 sigma^2 estimated as 8957: log likelihood = -334.91, aic = 675.83 </pre>

From table 5 results of AIC above ARIMA (2, 2, 1) is appropriate for model of monthly maize price because AIC is the lowest for this model than others. The value is aic = 641.54 (lowest AIC value is the best.)

### 3.6. Parameter estimation for monthly maize price inflation

Once the order of ARIMA (p, d, q), model has been specified the next step is estimating parameters.

Final Estimates of Parameters.

**arima(x = ddmaize\_pr, order = c(2, 2, 1))**

Coefficients:

```

ar1  ar2  ma1
-0.7557 -0.4461 -1.0000
s.e. 0.1178 0.1171 0.0461

```

sigma^2 estimated as 4280: log likelihood = -316.77, **aic = 641.54**

As mentioned above, if we are fitting an ARIMA (2, 2, 1) model to our time series, it means we are fitting an ARMA (2, 1) model to the time series of second differences.

An ARMA (2, 1) model can be written as:

General form: ARMA (p, q)  $\hat{y}_t = \mu + \phi_1 y_{t-1} + \dots + \phi_p y_{t-p} + e_t - \theta_1 e_{t-1} - \dots - \theta_q e_{t-q}$

Therefore ARMA (2, 1) becomes  $\hat{y}_t - \mu = \phi_1 y_{t-1} + \phi_2 y_{t-2} + e_t - \theta_1 e_{t-1}$

$\hat{y}_t - \mu = \text{phi1} * y_{t-1} + \text{phi2} * y_{t-2} + e_t - (\text{theta1} * e_{t-1}) = -0.7557y_{t-1} + (-0.4461)y_{t-2} + e_t - (-1.0000) e_{t-1}$

Therefore,  $\hat{y}_t - \mu = -0.7557y_{t-1} - 0.4461y_{t-2} + e_t + 1.0000 e_{t-1}$

where  $\hat{y}_t$  is the stationary time series we are studying (the time series of monthly maize price inflation),  $\mu$  is the mean of time series  $\hat{y}_t$ , phi1 and phi2 are parameters to be estimated in autoregressive model, theta1 is parameters to be estimated in moving average, and  $e_t$  is white noise with mean zero and constant variance.

From the output of the “arima()” R function (above), the estimated value of phi1 and phi2 (given as ‘ar1’, ‘ar2’ in the R output) are -0.7557 & -0.4461, and theta1 (given as ‘ma1’ in the R output) is -1.0000 in the case of the ARIMA(2,2,1) model fitted to the time series of monthly maize price inflation at Mekelle city.

### 3.7. Diagnostic Checking

#### 3.7.1. ACF of Residual for Monthly Maize Price Inflation

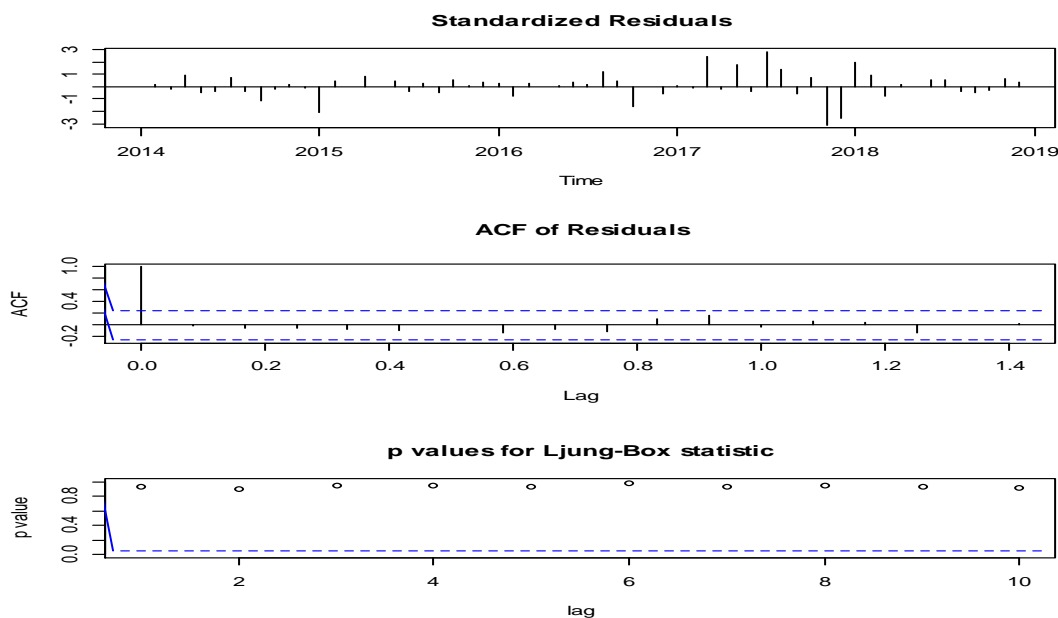


Figure 5: ACF plots of residuals



As we seen from figure 5 autocorrelation of residuals for the lags all are falls inside the 95% confidence bounds indicating that the residuals appears to be random. This leads the model ARIMA (2, 2, 1) is an appropriate adequate for the given data.

### 3.7.2 Modified Box-pierce (Ljung-Box) Chi-Square statistic test for the diagnostic checking

Hypothesis:

Ho: The data are independently distributed Vs

Ha: The data are not independently distributed; they exhibit serial correlation.

Table 6: Modified Box-Pierce (Ljung-Box) Chi-Square statistic

Box-Ljung test
data: ddmaize_pr X-squared = 15.7152, df = 16, p-value = 0.473

From table 6 test statistic (Ljung-Box statistic), since p-value = 0.473 is greater than 0.05, so this indicates that the residual is independent and non-zero autocorrelations (uncorrelated) in the forecast errors for lags 1-16. This implies that, the selected model ARIMA (2, 2, 1) is an appropriate model.

### 3.8. Forecasting Using Arima Model

After identification of the model, estimation of the parameters, and diagnostic checking the next step is forecasting with the appropriate model that have been chosen, for monthly price inflation of maize at Mekelle town. The appropriate model for this data is ARIMA (2,2,1) to obtain the point of forecast. The final model must be rewritten in the original form is described as follows.

$$\hat{y}_t - \mu = \text{phi1} * y_{t-1} + \text{phi2} * y_{t-2} + e_t - (\text{theta1} * e_{t-1})$$

$$\hat{y}_t - \mu = -0.7557y_{t-1} - 0.4461y_{t-2} + e_t + 1.0000 e_{t-1}$$

Forecasts from period 60: of the next one year (twelve months).

Table 7: Forecasted monthly retail price for the year 2019 G.C

forecast(arima(ddmaize_pr,order=c(2,2,1)),12)					
	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
Jan 2019	16.07893	-68.51498	100.6728	-113.2963	145.4542
Feb 2019	22.76050	-64.67575	110.1968	-110.9617	156.4827
Mar 2019	11.49730	-81.97725	104.9718	-131.4597	154.4543
Apr 2019	17.67917	-90.33640	125.6947	-147.5164	182.8747
May 2019	18.68255	-94.77308	132.1382	-154.8329	192.1980
Jun 2019	15.81744	-104.94754	136.5824	-168.8767	200.5115
Jul 2019	18.18578	-111.18371	147.5553	-179.6678	216.0393
Aug 2019	18.32484	-117.37589	154.0256	-189.2115	225.8612
Sep 2019	17.81404	-124.89214	160.5202	-200.4362	236.0643
Oct 2019	18.78877	-130.99175	168.5693	-210.2808	247.8583
Nov 2019	18.93077	-137.27799	175.1395	-219.9699	257.8315
Dec 2019	19.03941	-143.77310	181.8519	-229.9608	268.0397

By default, R will spit out the 80% and 95% prediction intervals.

We can check the accuracy of the forecasted value by using the above 80% and 95% confidence interval (CI) described as follows.

The forecasted value of January for the year 2019 is found between both the 80% and 95% CI i.e 16.07893 is found in 80% of lower CI (-68.51498 ) & the upper CI (100.6728) and also in 95% of lower CI (-113.2963 ) & the upper CI (145.4542), Similarly for the February up to Dec forecasted value is between the lower & the upper confidence interval of the 80% and 95% CI respectively, Since all the forecast values are found between the lower & the upper interval, then we can say (conclude) that forecasted value is accurate.

You can also conveniently plot these forecasts as follows.

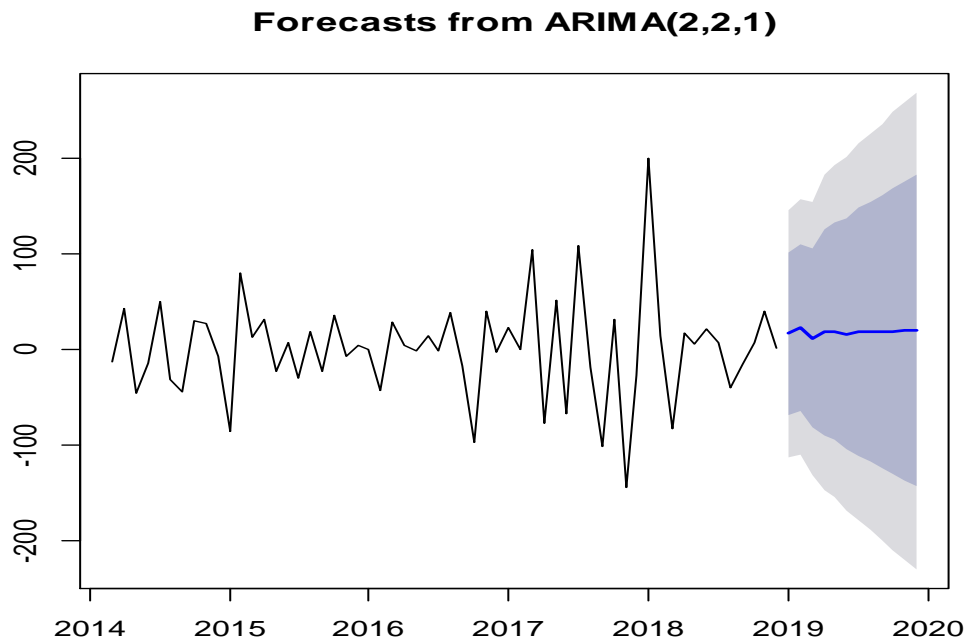


Figure 6: Original and forecast plots of the maize price inflation data

Here the forecasts for Jan 2019 up-to Dec-2019 are plotted as a blue line, the 80% prediction interval as coffee beans shaded area, and the 95% prediction interval as a white shaded area. The ‘forecast errors’ are calculated as the observed values minus predicted values, for each time point. We can only calculate the forecast errors for the time period covered by our original time series, which is 2019-2018 for the maize price inflation data.[6][7][8][9]

## 4. CONCLUSION AND RECOMMENDATION

### 4.1 Conclusion

Based on the analysis conducted in this research on the retail price inflation of maize, the following ideas are extracted and summarized.

Before we applying time series analysis the stationary test of the price inflation of maize data were made ,by using the ducky-fuller test and the test’s found that the original data not stationary. After the stationary for the data tested the order MA and AR are identified by using the ACF and PACF. Then the model is selected by using AIC .Since, ARIMA (2,2,1) for maize price inflation have lower values of AIC it is found to be the most appropriate model to fit the

given data. After the model was fitted the diagnostic checking have been applied by using the ACF residual and Modified Box-Pierce (Ljung-Box) Chi-Square statistic test at 5% level of the significance, so that the model fitted is appropriate for the price inflation of maize. Since the trend line shows there is a constant pattern in the price of maize with respect to time (the time plots appears similar at different points),implies there is no increasing or decreasing their price inflation of maize in Mekelle city, further results that there is relatively similar of monthly maize price inflation over the forecast period.

#### **4.2. Recommendations**

Our study results that the market price of maize relatively similar from month to month as well as from year to year. Therefore, the market price is good in our study Mekelle city and focused on a particular commodity maize, but in fact, there is an increment in price in all commodities thought our country Ethiopia.[11][12][14][15]

Therefore, based on the result of this study government and concerned bodies are recommended to take remedial action that decreases this market price. In this case:

- ◆ The government should interfere in a free market economy to stabilize the market condition.
- ◆ The government should supply maize into the market and sell to the people at a low price.
- ◆ Really Ethiopia uses only summer season (by rain only) to manufacture crops, then it's better to use irrigation farming system to stabilize the price inflation.
- ◆ Introducing modern and improve the way of farming practice is also another action which will stabilize the market price in the long run.

#### **CONFLICT OF INTERESTS**

The author(s) declare that there is no conflict of interests.

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