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Econometric analysis of price fluctuations in onion crop using SARIMA model

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Abstract:
The focus of the present study is to model and forecast the conditional monthly prices of onion in Pakistan by applying SARIMA(p,d,q)(P,D,Q)s model. Secondary data of monthly average prices were collected from Pakistan Bureau of Statistics (PBS). The data were first checked for stationarity though ADF test and found non-stationary hence, first difference was taken to make the data stationary. The differenced prices were then modeled by applying Box-Jenkins methodology. Different specifications of seasonal ARIMA i.e., SARIMA models were used and the most suited model was selected based on the AIC, BIC, and the white noise property of the residuals resulted from all the candidates models. SARIMA $(1,1,1)(1,0,1)_{12}$ was selected as the best model and used to forecast the future prices. On an overall basis, the forecasted prices showed an increasing trend with the peaked prices in September-October which is due to the demand and supply gap of onion in the markets. It is concluded that such verities of onion should be grown which are available in market during the peak price months so that the price hike can be controlled. The present study can be further improved by applying structural change model.

Key words:Econometric modelling, Forecasting, Onion, Seasonal ARIMA.*

1. Introduction

Onion (Allium Cepa L) is one the important condiments widely used in all households all the year round and is used insoups and sauces as well (PARC, 2017). Recent research has suggested that onions in the diet may play a part in preventing cardiac disease and other ailments (Tang, *et al.*2017). Many researchers believe that onions originated in central Asia. Other research suggested that onion were first grown in Iran and West Pakistan. Most researchers agree that the onion has been cultivated for 5000 years or more. Since onions grew wild in various regions, they were probably consumed for thousands of years and domesticated simultaneously all over the world (NAO, 2019). Onion is now cultivated in most part of the world, including India, Malaysia, Indonesia, Burma, Philippines, China, Egypt, west and East Africa, tropical South and Central America and the Caribbean (AMIS, 2017).

Onion is commercially grown on an area of 131.4 thousand hectares with the production of 1.8 million tones. It is grown almost in all provinces of Pakistan. Especially in Sindh province of the country, the study area is one of the major onion growing districts (Khokhar, 2018).The area and production of onion in different countries vary over years. The trends in area and production under onion crop have been modeled and forecasted by many researchers of South Asian countries, especially Pakistan (Sultan et al. 2015), India (Mishra et al. 2013) and Bangladesh (Hossain et al. 2017) by using ARIMA(p,d,q) model.

Just like area, production, and consumption, there has been observed a great fluctuation in the prices of onion. From 1981-82 to 2011-2012, the wholesale prices of onion in Hyderabad market were increased @ 8.82% per annum (Fatima, *et al.* 2015). Further, onion prices had been under pressure for the last few months. Retailers had already increased prices due to the demand and supply gap of onion in the vegetable markets especially during the months of September and October every year. Traders said they had been procuring imported onion (from Afghanistan and Iran) during these months. Even the import of onion from neighboring countries like Iran and Afghanistan are mostly failed to provide any relief to the consumers as traders further pushed up prices of staple foods (Khan, 2019).

The price of onion fluctuates over seasons due to the variations in production and market arrivals. Thus, modelling and forecasting the monthly price behavior over the years is of much practical importance. Fluctuations of onion price are matter of great concern among farmers, consumers, policy makers as well. Price forecasting involves making estimate of the future values of variables of interest using past and present information (Kumar, *et al.*2011). So, the accurate forecast is extremely important for efficient monitoring and planning. The price fluctuations in seasonal crop are extensively modeled through ARIMA and SARIMA time series models. These models were also found to be the best forecasting model by giving minimum values of forecast errors (Darekar et al. (2016), Shruthi (2015), Kumar et al. (2011)).ARIAM and SARIMA are used in univariate analysis; their multivariate versions are VAR and SVAR which are widely used to model the multivariate time series such as identification of determinants of Inflation (Mohanty and John, 2015).

Keeping in view the above mentioned facts regarding the huge price fluctuations in onion crop, the present research is carried out to model and forecast the price fluctuations in onion crop using ARIMA or SARIMA(p,d,q) model and to suggest the possible ways to overcome these price fluctuations.

2. Materials and methods

This section is divided into two subsections; the first section is devoted to the collection of the data set as well as the statistical software used to analyze the date set in this research while the second section briefly describes the methodology used to achieve the objectives of the present study.

2.1 Data collection and statistical software

The secondary data used in the present study consist of monthly average prices of onion which were collected from the official website of the Pakistan Bureau of Statistics (http://www.pbs.gov.pk). The data span from November, 2012 to October, 2019 which yielded 84 observations (Appendix A). The collected data were analyzed using MINITAB version 19.

2.2 Methodology

The collected data were first checked for the presence of the unit root (non-stationarity). For this purpose, Augmented Dickey Fuller (ADF) test is used. If the p-value of the ADF-test statistic is greater than the significance level, the null hypothesis cannot be rejected which lead to conclude that the data series is not stationary. Differencing is the way used to achieve stationarity of the time series. Once the condition of stationarity is fulfilled, the resulting data will be analyzed by using the Box-Jenkins ARIMA (SARIMA) approach. Before describing the Box-Jenkins approach, a brief about these two models (ARIMA and SARIMA) is given as under:

2.2.1 Autoregressive Integrated Moving Average (ARIMA) model

ARIMA(p,d,q) model uses the historic data and decomposes it into autoregressive (AR(p)) lags of the time series and moving average (MA(q)) lags over past errors. Therefore, ARIMA model has three parameters i.e., AR(p), I(d) and MA(q) and compactly can be written as ARIMA(p,d,q). A non-seasonal stationary time series can be modeled as a combination of past values and the errors which can be denoted as ARIMA(p,d,q) or can be expressed as follows:

$$X_t = \varphi_\circ + \varphi_1 X_{t-1} + \varphi_2 X_{t-2} + + \varphi_p X_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \theta_q e_{t-q}$$

$\varphi_0, \varphi_1, ...,\varphi_p$ are the autoregressive parameters, $\theta_1, \theta_2, ...,\theta_q$ are the moving average parameters, $X_{t-1}, X_{t-2}, ...,X_{t-p}$ are the lagged values of the dependent variable $e_{t-1}, e_{t-2}, ...,e_{t-q}$ are the lagged values of the stochastic error term.

2.2.2 Seasonal Autoregressive Integrated Moving Average (SARIMA) model

The seasonal ARIMA model incorporates both non-seasonal and seasonal factors in a multiplicative model. One shorthand notation for the model is (Chatfield, 2002): ARIMA(p,d,q)×(P,D,Q)$_S$, with p = non-seasonal AR order, d = non-seasonal differencing, q = non-seasonal MA order, P = seasonal AR order, D = seasonal differencing, Q = seasonal MA order, and S = time span of repeating seasonal pattern (in a monthly data s = 12).Without differencing operator, the model could be written more formally as;

$$\left(\Phi\left(B^S\right)\varphi\left(B\right)x_t-\mu\right)=\Theta\left(B^S\right)\theta\left(B\right)w_t$$

The non-seasonal components are:

$$AR:\varphi\left(B\right)=1-\varphi_1B-.....-\varphi_pB^p$$

$$MA:\theta\left(B\right)=1+\theta_1B+.....+\theta_qB^q$$

The seasonal components are:

Seasonal $AR:\Phi\left(B^S\right)=1-\Phi_1B^S-....-\Phi_PB^{PS}$

Seasonal $MA:\Theta\left(B^S\right)=1+\Theta_1B^S+....+\Theta_QB^{QS}$

2.3 Box-Jenkins ARIMA approach

The method is appropriate for time series of medium to long length (at least 50 observations). There are four steps of Box-Jenkins methodology: 1). Identification, 2). Estimation, 3). Model Validation/ Diagnostics, and 4). Forecasting. This Box-Jenkins identification method has been used in various fields such as finance (Chatfield, 2002), agriculture (Mishra et al. 2013) and management (Moneta and Rüffer, 2009) and many more. These steps are briefly described as under:

Step # 1. Identification

The identification process is accomplished with the help of plotting the Autocorrelation and Partial Autocorrelation functions i.e., *ACF* and *PACF* of the data with their lagged values. Autocorrelation is defined as the correlation of the data series along with its own lagged values. For example, if $\{Y_t\}$ is the time series then first order autocorrelation is the correlation of $Y_t$withY_{t-1}i.e., $Corr\left(Y_t,Y_{t-1}\right)$. It value ranges from -1 to +1.Yet another important characteristic is a partial auto-correlation function (PACF) which is conditional correlation of Y_{t-k} with $Y_{t.}$ after removing the effects of Y_{t+k-1}. PACF is defined for positive lag only; their values also lie between -1 to +1.

Table 1.Properties of General Time Series models

Model	Stationarity Condition	Invertible Conditions	ACF Pattern	PACF Pattern
AR(p)	Yes	No	Die down	Cuts off after lag *p*
MA(q)	No	Yes	Cuts off after lag *p*	Die down
ARMA(p,q)	No	Yes	Die down	Die down

Table 2.Properties of Specific Pure Time Series Models

ARMA Model	Stationarity Condition	Invertible Conditions	ACF Pattern	PACF Pattern
$(1,D,0)_s$	$-1 < \alpha_s < 1$	None	Die down	Cuts off after 1 seasonal lag
$(2,D,0)_s$	$\alpha_s + \alpha_{2s} < 1$	None	Die down	Cuts off after 1 seasonal lag
$(0,D,1)_s$	None	$-1 < \theta_s < 1$	Cuts off after 1 seasonal lag	Die down
$(0,D,2)_s$	None	$\theta_s + \theta_{2s} < 1$ $\theta_{2s} - \theta_s < 1$ $\theta_{2s} < 1$	Cuts off after 1 seasonal lag	Die down
$(1,D,1)_s$	$-1 < \alpha_s < 1$	$-1 < \theta_s < 1$	Die down	Die down

Table 1 and 2 show the properties of the general time series (ARIMA) models, and specific pure Seasonal time series (SARIMA) models, respectively. These properties include stationarity and invertibility conditions, ACF and PACF patterns that help in identifying the lagged values of the time series data. Besides these, the following various information criteria such as AIC and BIC are used.

Step # 02. Estimation

The estimation procedure involves estimating the model parameters for different values of *p, d* and *q* to fit the actual time series. Maximum Likelihood Estimation (MLE) is used to estimate the unknown values of the model's parameters. MLE works by finding the parameter values that maximize the likelihood function which simply tells you about the likelihood (most likely chances) that with these parametric values the model generate the data set.

After estimation of parameters with different combinations of *p, d,* and *q,* the best fitted model is selected among all the candidates' models. The selection of best fitted model is done after taking into consideration various criteria such as Log-Likelihood (LL) of the model, Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC).

Step # 03. Model validation/ diagnostics

In this step, white noise property of the selected model is checked. This is carried out by plotting ACF and PACF of the residuals resulted from the model. It should be noted that all the ACFs and PACFs must lie within the confidence bounds of 2S.E. If some of the autocorrelations are large, the values of *p* and/or *q* are adjusted and the model is re-estimated. Mostly, the Ljung-Box test is used for checking the white noise property of the residuals (Enders, 2015).Instead of testing independence at each distinct lag, this test is performed collectively over the number of lags, therefore, known as portmanteau test. The test statistic is formulated as follows;

$$Q_{MK} = \frac{T(T+2)\sum_{m=1}^{M} \hat{\rho}_{ek}(m)}{T-m}$$

where $\hat{\rho}(m)$ the estimated sample autocorrelation at lag m and T is the sample size. The null hypothesis of no significant autocorrelations is tested against the alternative that at least one of these autocorrelations is not equal to 0. Mathematically;

$$H_0;\ \hat{\rho}_e(1) = \hat{\rho}_e(2) = \ldots. = \hat{\rho}_e(m) = 0$$
$$H_A;\ \hat{\rho}_e(1) = \ldots. = \hat{\rho}_e(m) \neq 0$$

Step # 04. Forecasting

Forecasting is simply defined as assessing the magnitude of future observations based on past data set. The main assumption of the forecasting is that the past pattern of the data will continue in the future. In the present study, the out-of-sample point forecasts for the next twelve months were generated.

3. Results

This section describes the results obtained after analysis of data under study. Figure 1 shows the time plot of monthly average prices of onion in district Hyderabad from Nov, 2012 to Oct, 2019. There are clear fluctuations in the prices of onion during the study period. On overall basis, an increasing trend in the prices can be seen very clearly from 2012 to 2019 which is indicative of the non-stationarity in the prices. Besides, the largest price hike can be observed during October, 2017 which was due to the ongoing conflicts between India and Pakistan that led the policy makers to stop any kind of export and import with India. The second largest price hike can be observed during the third quarter of 2019 which was due to the heavy rains in the onion growing areas which destroyed its production resulting in the sharp rise in prices.

Table 3shows the descriptive statistics and the results of the ADF test. The large difference between the maximum and minimum value shows high range in the prices. The mean of the prices is Rs. 36.005 with the variance is Rs. 213.430. The large value of variance shows the greater variability in the prices of onion. As stated earlier that onion prices indicate a significant trend which is the evident of non-stationary structure in the time series data which can be confirmed from the results of the ADF-test. The p-value (0.457) of the test statistic is greater than the selected level of significance (α = 0.05), therefore, failing to reject the null hypothesis of a unit root. This shows that the first difference of the prices should be taken to make them stationary hence, the parameter "d" in ARIMA(p,d,q) will take the value 1 i.e. d = 1.

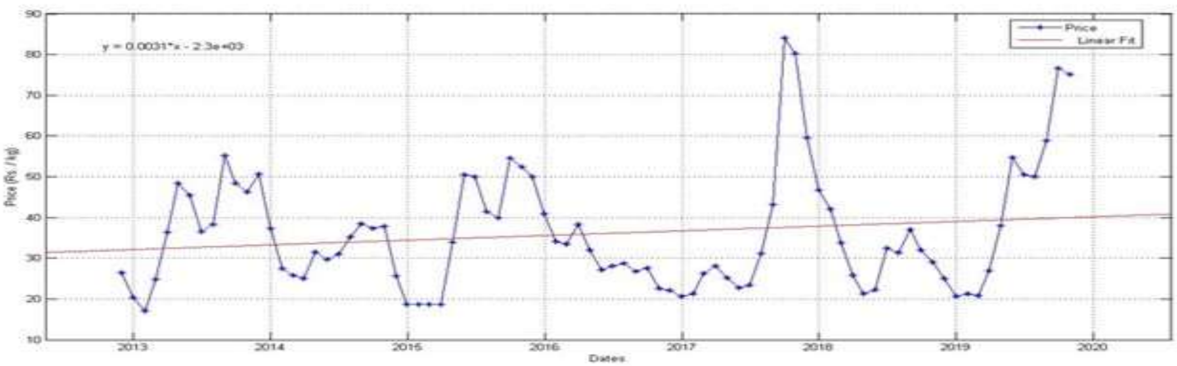
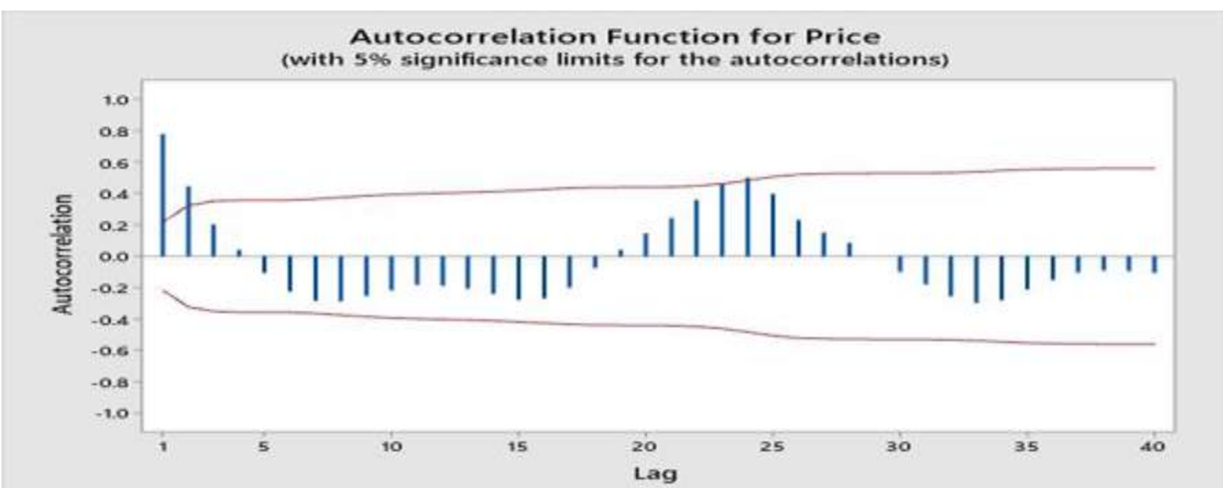


Fig. 1. Monthly average prices of onion: November, 2012 – October, 2019

Table 3. Summary statistics of monthly average prices of onion with ADF-test results

Min.	Max.	Mean	Variance	Skewness	Kurtosis	ADF-Test	
						Statistics	p-value
17.090	84.060	36.005	213.430	1.238	4.475	-2.185	0.457



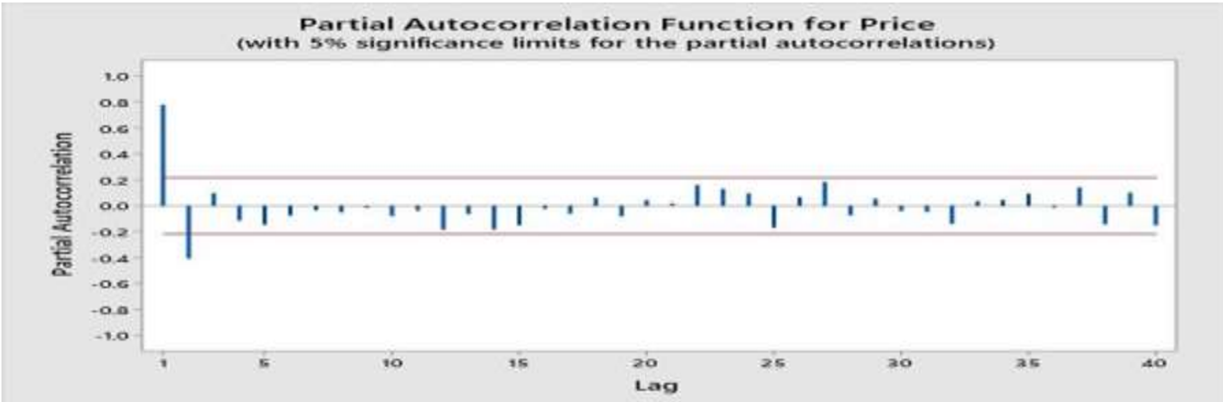


Fig.2. Plot of ACFs and PACFs of monthly average prices of onion

The ACFs and PACFs of the monthly average prices are plotted in Figure 2. The ACF plot dies down in a sine wave fashion while the PACF of the data also cuts off after 2 lags indicating that the value of lag orders “p” in the autoregressive process is 2. Figure 3 shows the time plot of differenced data. It can be easily seen from the figure that the first difference of the data made the monthly average prices stationary and the existence of seasonality is also clearly evident from the figure. The statement regarding the stationarity can be further verified from the ADF test again whose results are shown in the following Table 4**.** The smaller p-value (0.001) of the test statistics than the significance level rejects the null hypothesis of a unit root. The same results regarding achieving the stationarity after taking first difference of the onion prices in India were also reported by Kumar *et al.* (2011).

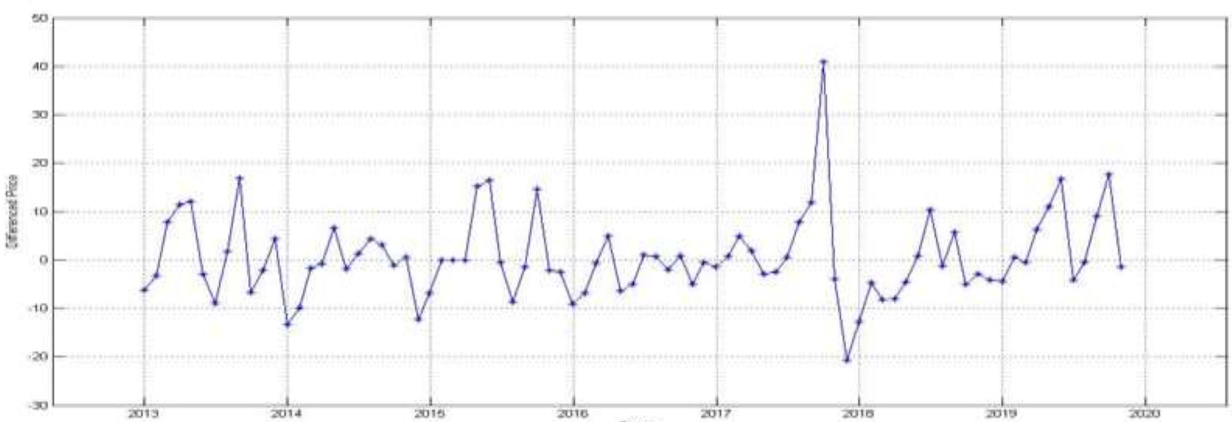


Fig. 3. Plot of first difference of monthly average prices of onion

Table 4. Summarystatistics of differenced prices of onion along with ADF-test

Min.	Max.	Mean	Variance	Skewness	Kurtosis	ADF-Test	
						Statistics	p-value
-20.66	40.93	0.59	75.23	1.36	7.56	-6.618	0.001

Furthermore**,** the ACFs and PACFs of the differenced data are plotted in Figure 4. The ACF dies down after one lag while the PACF cuts off after two lags which is indication that p = 2. So, for the non-seasonal p and q are concerned, the behavior of ACF and PACF suggested that p =2 while q = 0 is suitable lag order for the non-seasonal part of the SARIMA model. Seasonality can be clearly observed from the plot of the first differenced data. However, the visual inspection of the ACF and PACF can be quite inconclusive and misleading, same is the case here in this study. The ACF and PACF of the differenced price data are unable to find the seasonality as no seasonal lag is higher than the bounds of ±2S.E.

Usually, monthly data have seasonality of twelve months; the seasonal difference of the differenced price data with seasonal index of 12 months was calculated. Figure 5 shows the time plot of the seasonal difference of the first difference data. This plot shows the stability in the mean at both the seasonal and the non-seasonal levels. The ACF and PACF of the seasonal difference of the first differenced data are plotted in Figure 6. A critical look at the seasonal lags show that both ACF and PACF spikes at seasonal lag 12 dies down to zero for the other seasonal lags, suggesting that P = Q = 1 would be needed to describe these data as coming from a seasonal autoregressive and moving average process.

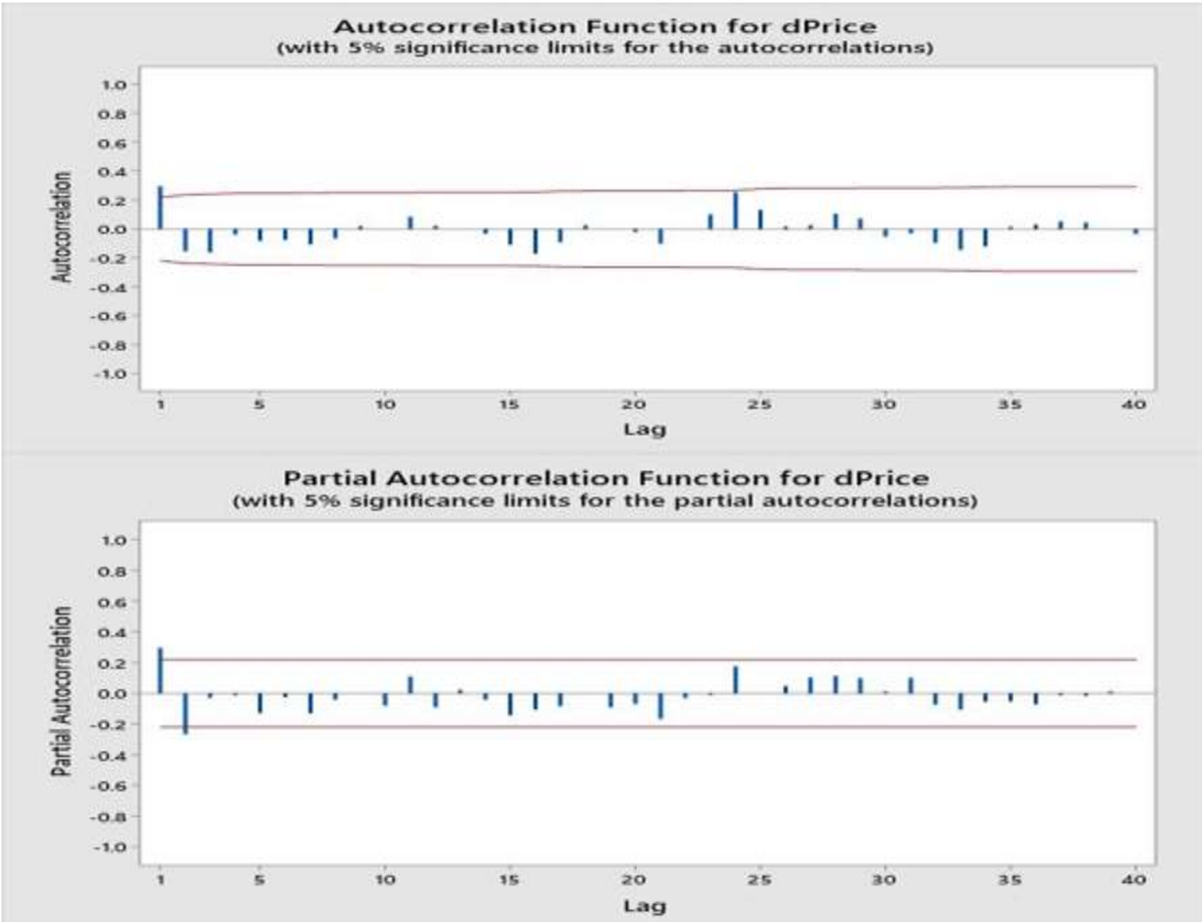


Fig.4. ACFs and PACFs of differenced monthly average prices of Onion

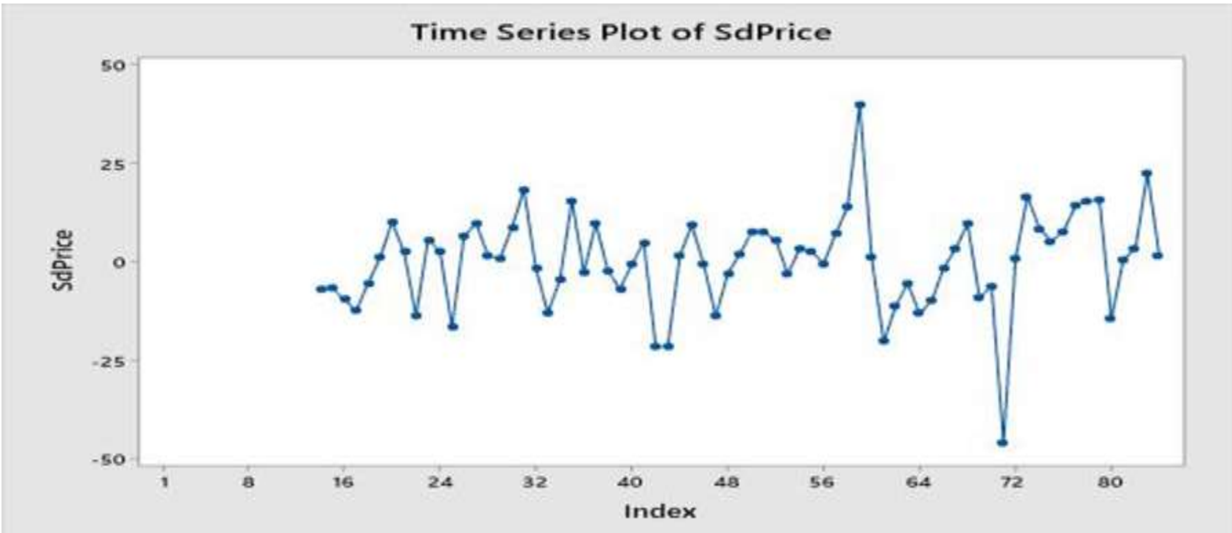


Fig.5. Plot seasonal difference of the first differenced prices of onion

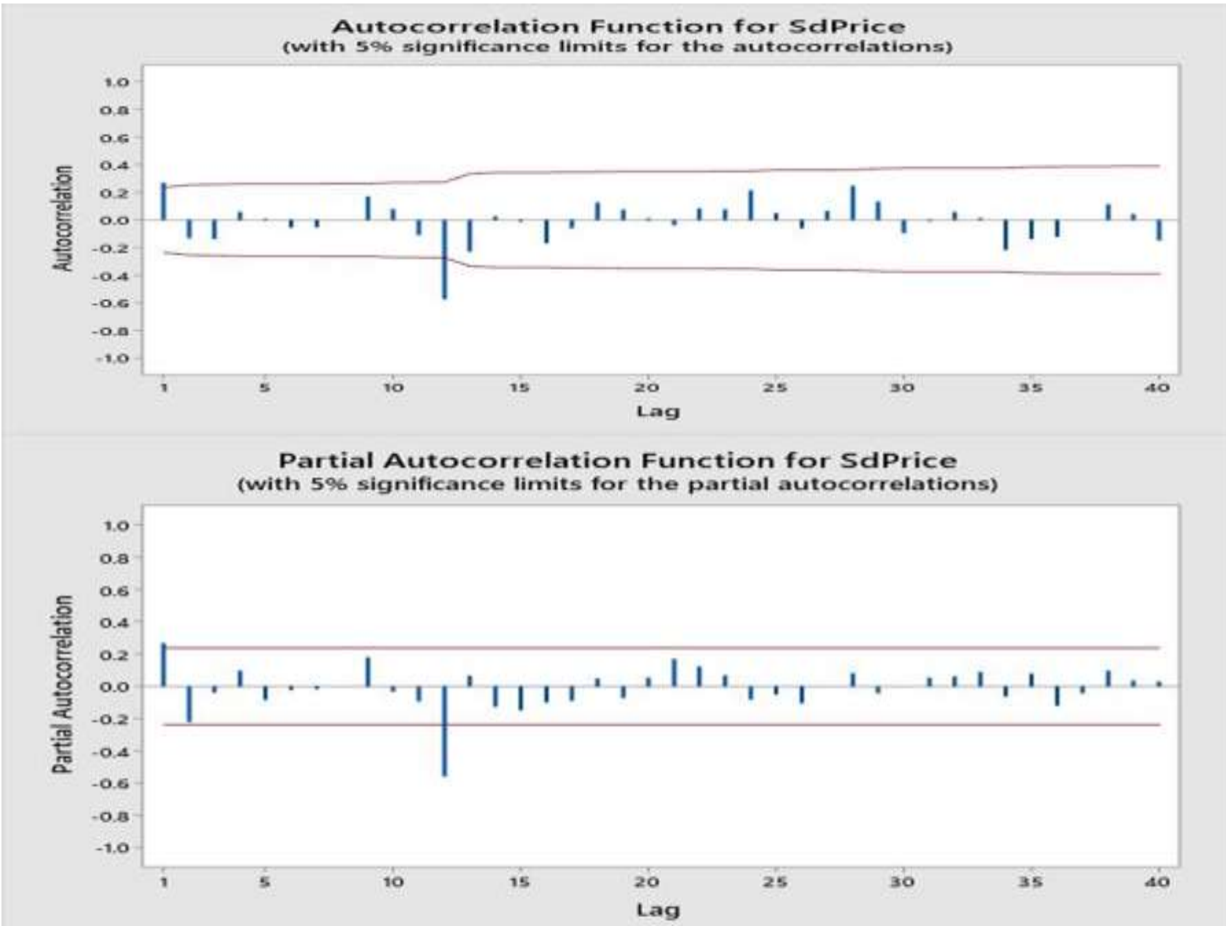


Fig. 6.ACFs and PACFs for seasonal difference of first differenced prices

Based on the behavior of the ACF and PACF of the first differenced data and seasonally differenced data for selecting the lag order of both the non-seasonal the seasonal parameters, the following four candidates' models are estimated. These models along with their AIC and BIC values are presented in Table 5.

Table 5.AIC and BIC values for four SARIMA Models

S. No.	SARIMA Model	AIC	BIC
1	(1,1,1)(1,0,1)	8.5598	8.7045
2	(1,1,1)(0,0,1)	8.6839	8.7996
3	(1,1,1)(1,0,0)	8.6834	8.7992
4	(2,1,0)(1,0,1)	8.5752	8.7199

It can be clearly seen for Table 5 that both the AIC and BIC select the same model i.e., SARIMA(1,1,1)(1,0,1) since the lowest values of AIC and BIC are reported for this model. Furthermore, the parameters estimates along with their t-values and the Ljung-Box results are reported in the following Table 6. It can be seen from the table that all the parameters of the selected model SARIMA$(1,1,1)(1,0,1)_{12}$ are significant and the residuals from the selected model do not show the presence of any significant autocorrelation as shown in the Figure 8.

Table 6.Model estimates along with Ljung-Box Test Results

SARIMA $(1,1,1)(1,0,1)_{12}$						
Type	Coefficient	S.E Coefficient	t-value	p-value	Ljung-Box Test	
					Q-Stat	p-value
AR1	0.261	0.109	2.39	0.019	$(12.22)_{12}$	0.141
SAR	0.981	0.030	32.42	0.000	$(20.33)_{24}$	0.438
MA1	-0.250	0.111	-2.26	0.027	$(33.53)_{36}$	0.393
SMA	0.895	0.108	8.29	0.000	$(46.00)_{48}$	0.390
SARIMA$(1,1,1)(0,0,1)^{12}$						
Type	Coefficient	S.E Coefficient	t-value	p-value	Ljung-Box Test	
					Q-Stat	p-value
AR1	-0.046	0.282	-0.160	0.870	$(6.45)_{12}$	0.694
MA1	-0.442	0.256	-1.720	0.088	$(18.64)_{24}$	0.608
SMA	0.018	0.122	0.150	0.882	$(25.90)_{36}$	0.806
					$(38.63)_{48}$	0.737
SARIMA$(1,1,1)(1,0,0)_{12}$						
Type	Coefficient	S.E Coefficient	t-value	p-value	Ljung-Box Test	
					Q-Stat	p-value
AR1	-0.045	0.280	-0.160	0.872	$(6.49)_{12}$	0.690
SAR	-0.031	0.122	-0.250	0.801	$(18.67)_{24}$	0.606
MA1	-0.443	0.255	-1.740	0.086	$(25.94)_{36}$	0.804
					$(38.80)_{48}$	0.731
SARIMA$(2,1,1)(1,0,1)_{12}$						
Type	Coefficient	S.E Coefficient	t-value	p-value	Ljung-Box Test	
					Q-Stat	p-value
AR1	-0.154	0.374	-0.41	0.681	$(9.44)_{12}$	0.307
AR2	-0.435	0.340	-1.28	0.205	$(21.02)_{24}$	0.396
SAR	0.9870	0.0474	20.81	0.000	$(32.02)_{36}$	0.466
SMA	0.851	0.113	7.51	0.000	$(44.19)_{48}$	0.463

The same results can also be confirmed from the Q-stat and p-values of the Ljung-Box test which are presented in the last two columns of Table 6. The test statistics and the p-values are reported for different lags such as 12, 24, 36 and 48. It can be seen that all the p-values are greater than the selected a-level for all the reported lag values showing that residuals from the selected model behave like a white noise.

4.2 Point forecast with SARIMA(1,1,1)(1,0,1) model

After the successful selection of the best model and its diagnostic checking, the next step in the Box-Jenkins methodology is the produce the point forecasts from the selected model for the some future values. The point forecasts for the prices of Onion were calculated for the next 12 months i.e. from November, 2019 to October, 2020. Values of these point forecasts along with the 95% confidence limits are graphically shown in the Figure 9. The point forecasts are showing mix pattern i.e., decreasing one for the first few months i.e. from Nov-2019 to Jan-2020 and then continuously increasing for the remaining months i.e., from February, 2020 to October, 2020.

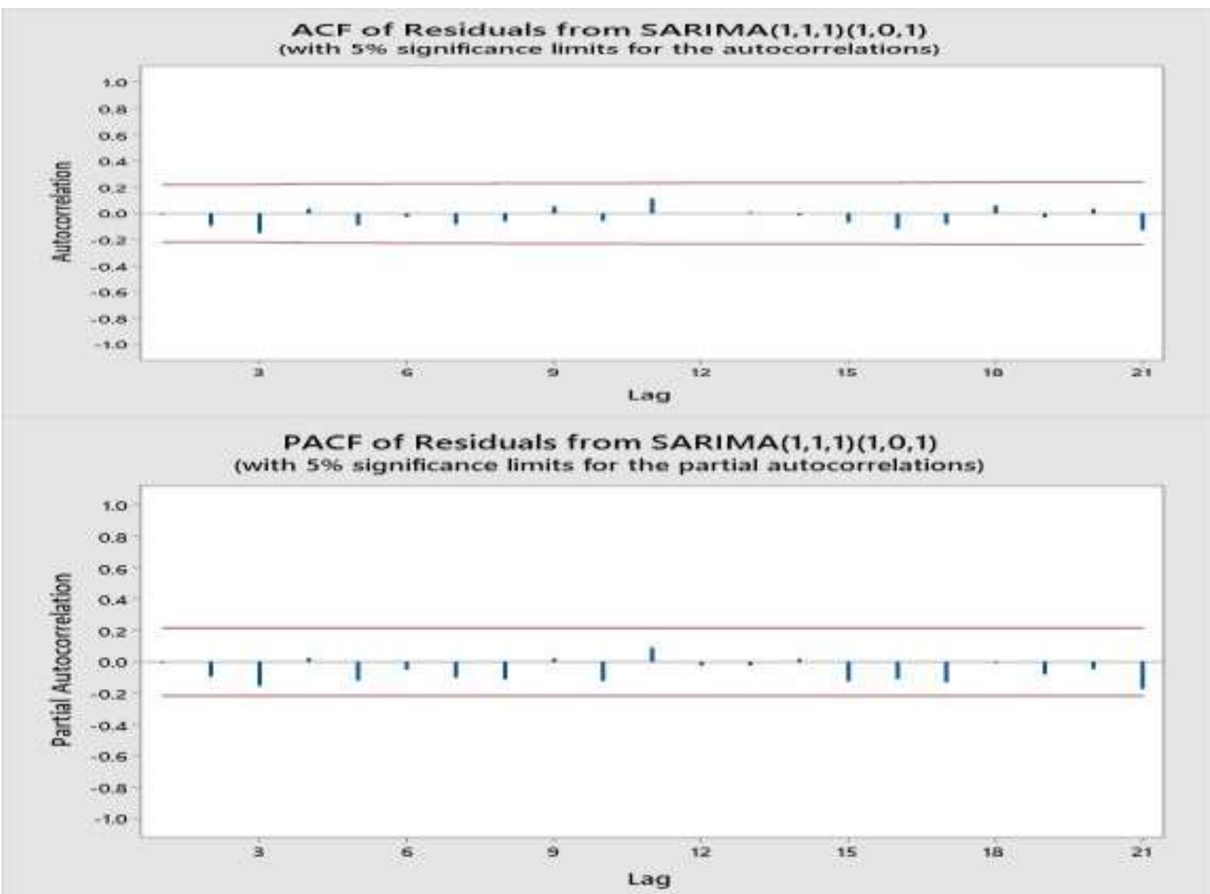


Fig. 8.ACFs and PACFs of residuals from SARIMA(1,1,1)(1,0,1) model

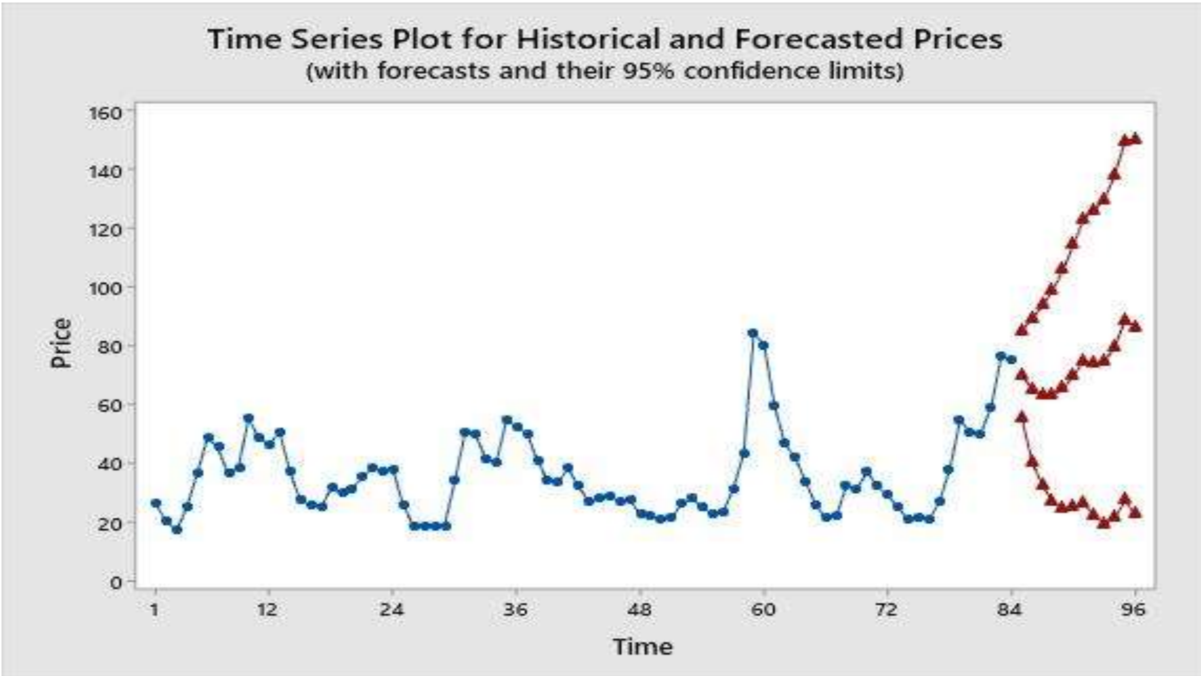


Fig. 9. Plot of original and point forecasts from SARIMA(1,1,1)(1,0,1)$_{12}$ model

5. Conclusion

This study concludes that the there is a great variability in the prices of onion in the selected district overall showing an increasing trend. The prices of onion are changing after every twelve months which shows the seasonality pattern in the prices i.e., the prices are very high during winter while very low during summer. Based on the findings, it can be concluded that the conditional price behavior of onion can be best modeled by using the ***SARIMA(1,1,1)(1,0,1)$_{12}$*** model in the selected district. The forecasts generated from the model which has chosen in order to determine the course of the prices of next few months which showed real onion prices will be decreasing for the next few months i.e., from December, 2019 to February, 2020 and then will continue to increase for majority of the remaining months of 2020.

6. Recommendations

The following recommendations are purely based on the findings of the present study.

- Since it is reported that the prices of onion have found highest during the month of October which is due to decrease in supply, it is recommended that such verities of onion should be grown which are available in market during the month of October so that the price hike can be controlled.

- The similar study can be conducted to further analysis of the seasonal price fluctuations using structural change models.
- Based on the findings of the present study, it is also recommended that the government should device new policies to cop up with this price hike during the spotted months in the study.

7. Compliance with Ethical Standards:

Conflict of Interest: The authors of this research article certify that they have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

Ethical Approval: This article does not contain any studies with human participants or animals performed by any of the authors.

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