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Price instability, seasonal index and modelling for major vegetables in India

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Abstract

Vegetable production plays a pivotal role in the horticulture industry, yet the availability of vegetable crops remains unpredictable. Seasonal volatility contributes to unclear supply, resulting in price fluctuations. This study aimed to assess the seasonal indices and price instability of key vegetables in India using the Cuddy-Della Instability Index and the Ratio to Moving Average approach. Monthly price series spanning January 2010 to December 2021 were collected from the AGMARKNET website. Seasonality in the price series was examined using the Kruskal-Wallis test. The results indicated that potatoes exhibited moderate instability, while onions and tomatoes displayed high instability. The onion price series demonstrated the highest seasonal indices in October, November, and December. Wholesale and retail prices were lowest in April, May, and June. October and November marked the peak wholesale and retail prices for potatoes, with the lowest prices recorded in February and March. July and August were the months with the highest wholesale and retail tomato prices, while February and March saw the lowest prices. The ARIMA model, applied to de-seasonalized price series, estimated factors excluding the seasonal component. Recognizing these price patterns enables farmers, policymakers, and government sectors to take necessary precautions against sudden price changes.

Key words: Cuddy-Della instability index, Kruskal-Wallis test, ratio to moving average approach, seasonal indices, price instability, ARIMA

Introduction

Agriculture and horticulture have always been elements of human society. As technology advances, smart farms are becoming increasingly pervasive in recent years. The foundation of any country's economy and success is its agricultural sector. The importance of the agriculture market is demonstrated by the fact that in India, the agriculture industry accounts for 17.32% of GDP (NSO, 2020). Unpredictable occurrences like drought and flood can influence the prices of agricultural products, affecting the entire market and causes significant losses for farmers, suppliers, exporters, and other stakeholders. The year with a poor crop, which results in considerable debt, has the biggest impact on farmers.

Crop prices are unpredictable, especially for vegetables. The government frequently finds itself on the verge of achieving its dual goals of maintaining remunerative prices for farmers and reasonable pricing for consumers regarding the three basic vegetables—tomato, onion, and potato. They are primarily seasonal crops. The market is flooded with a large share of them during the harvest season. In India, crops including tomato, onion, and potato (TOP) are considered staple foods. Yet, because TOP crops are all highly perishable and have storage and transportation issues and postharvest losses, the management of these crops is at high risk (Purohit, 2021). But consumption is spaced out over the year. Vegetable prices fluctuate throughout the year because of inelastic demand and seasonal output (Kamble and Tiwari, 2019). The income levels of crop growers and the prices consumers pay are uncertain due to price fluctuations. The price fluctuation of these TOP crops affects domestic life in this nation (Kumar and Joshi, 2016). The Ministry of Food Processing Industries of the Government of India launched the Operation Green programme with the aim of stabilising the supply of TOP crops in India by ensuring their availability throughout the year without price fluctuation (Kumar *et al.,* 2012).

Therefore, the current study was framed with the following objectives to assess: (i) price instability, (ii) seasonal indices, and (iii) de-seasonalized series forecasting. We hypothesised that (i) the price series of TOP crops is more unstable, and (ii) seasonality is present in the price series of TOP crops. A sound price policy in India must be developed after careful consideration of the behaviour of wholesale and retail prices over time.

Materials and methods

Secondary data entirely support the current investigation. The secondary data was taken from January 2010 to September 2022 to draw a significant conclusion about the instability in India's monthly wholesale and retail prices of onion, potato, and tomato. The AGMARKNET website was used to collect the monthly wholesale and retail prices.

Instability index: By de-trending the price series, the Cuddy-Della Index observes the direction of the instability (Cuddy and Valle, 1978). It is a superior metric for capturing price fluctuations in agriculture. The Cuddy-Della index (CDI) was calculated as follows:

$$CDI = CV\sqrt{1-\bar{R}^2}$$

Where, CV is the coefficient of variation, and is adjusted coefficient of determination. The ranges of CDI (Sihmar, 2014) are given as follows:

S. No	Range of CDVI	Instability
1	0-15	Low
2	15< - 30	Medium
3	30<	High

Seasonality

Kruskal wallis test (H_0 : There is a seasonality in the series**;** H_a: There is no seasonality in the series)

The Kruskal-Wallis test is a strong substitute for the one-way analysis of variance. Although the independence of random error is necessary, nonparametric ANOVA does not assume that random error is normal.

The test is typically applied to k years of data $\{x_i\}_j$. Each year, j = 1, 2,..., k is made up of 12 observations (one for each month), which are indexed by i = 1_j, 2_j,... 12_j.

The test statistic is given by $Q = \frac{SS_t}{SS_e}$

Where $SS_t = (N-1)\sum_{j=1}^{g} n_i\,(\bar{r}_{.j} - \bar{r})^2$ and $SS_e = \sum_{j=1}^{g}\sum_{i=1}^{n_j}(r_{ij} - \bar{r})^2$

Analysis of seasonal components: To examine seasonal pricing behaviour, time series data on monthly wholesale and retail prices were used. The pricing behaviour was analysed using the following methodologies:

Ratio to moving average method (Gupta and Kapoor, 1997)**:**

The following steps were used to compute the seasonal indices.

Step I: The original data will be used to generate the centred 12-month moving average. These centre 12-month moving averages have both a trend and a cyclical component.

Step II: The original data should be divided by the centred moving average.

P=TSCI

$$\frac{P}{MA} = \frac{TSCI}{TC} X100 = (S\times I)100$$

Step III: By averaging the data for each month over the years that are included in Step II, the irregular component was removed. A monthly seasonal index will be calculated by multiplying the average value by 100.

Step IV: The seasonal indices should add up to 1200. If the value is greater or less than 1200, a correction factor (K = 1200 / S) is used to adjust it. Where K is the correction factor and S is the sum of seasonal indices.

ARIMA: Inclusion of autoregressive and moving average processes is more favourable for achieving greater flexibility of actual time series data, which starts with the combination of autoregressive and moving average processes denoted as ARMA (p,q) and indicated by: $\varnothing(B)\,y_t = \theta(B)\,\varepsilon_t$

Where $\varnothing(B) = 1 - \varnothing_1 B - \varnothing_2 B^2 - \ldots \varnothing_p B^p$

and $\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q$

In which B - the backshift operator expressed by B(= ;p – order of AR; q – order of MA

The Box-Jenkins Autoregressive Integrated Moving Average (Box and Jenkins, 1976) model was developed by including "differencing" in the ARMA model, which is indicated by ARIMA (p, d, q), which is written as

$$\Box\cos^{-1}\theta^d Y_t = C + \phi_1 \Box^d Y_{t-1} + \ldots + \phi_p \Box^d Y_{t-p} + \varepsilon_t + \theta_1\varepsilon_{t-1} + \ldots + \theta_q \varepsilon_{t-q}$$

In which, ~ N (0,).

The assumption of residuals was checked by Ljung-Box test (Ljung and Box, 1978).

Ljung-Box test (H_0: There is no autocorrelation in the residuals; H_a: There is autocorrelation in the residuals)

$$Q = n(n+2)\sum_{k=1}^{m}\frac{\hat{r}_k^2}{n-k} \sim \chi_m^2$$

Where the residual series' estimated autocorrelation at lag k, and m is the number of lags being tested.

Results and discussion

Descriptive statistics of all the price series are given in Table 1. All the price series are positively skewed and leptokurtic. It means that extreme outliers are more common in the price series. The coefficient of variation also confirms the high degree of chaos in the price series. Figs. 1 and 2 show India's wholesale and retail price series of major vegetables, respectively.

Table 1. Descriptive statistics for price series

Crop	Onion		Potato		Tomato	
Price	WS	Retail	WS	Retail	WS	Retail
Mean	2024.84	25.37	1424.41	18.49	2050.26	26.49
SE	92.67	1.04	42.64	0.50	73.11	0.85
Median	1728.05	21.66	1327.58	17.68	1754.90	23.58
SD	1146.26	12.86	527.43	6.17	904.34	10.51
Kurtosis	5.73	5.59	3.37	2.52	0.78	0.77
Skewness	1.98	1.93	1.43	1.21	1.13	1.11
Range	7445.97	84.11	3123.80	35.80	4153.40	48.14
Minimum	790.89	10.84	656.27	8.79	846.09	11.77
Maximum	8236.86	94.95	3780.07	44.59	4999.49	59.91
CV (%)	56.60%	50.69	37.02	33.36	44.11	39.67

WS= Wholesale

The instability measured through the Cuddy-Della instability index for wholesale and retail prices in onion, potato and tomato of India has been shown in Table 2. It was revealed from the results of the Cuddy-Della index that wholesale and retail prices for onion and tomato were highly instable. Similar results were found in the oilseed price series in the Amreli district of Gujarat (Dudhat *et al.,* 2021). But wholesale and retail prices for potato were medium-instable.

Table 2. Instability of the price series

Crop	Onion		Potato		Tomato	
Price	CDI	Instability	CDI	Instability	CDI	Instability
Wholesale	50.40	High	24.59	Medium	36.17	High
Retail	44.04	High	19.78	Medium	31.24	High

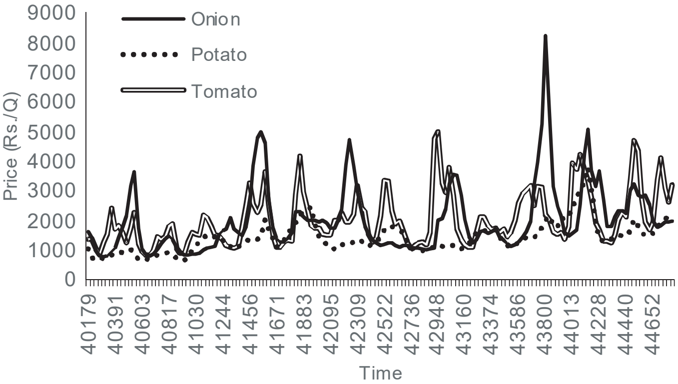

Fig 1. Actual wholesale price series of major vegetables in India

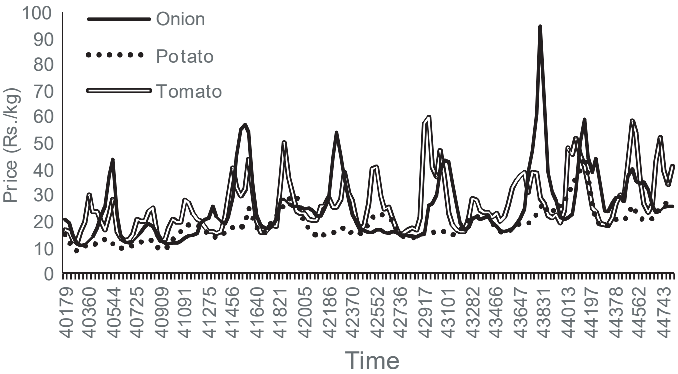

Fig 2. Actual retail price series of major vegetables in India

The nonparametric Kruskal-Wallis test was employed to detect seasonality in the price series of all crops. In Table 3, the Kruskal-Wallis test yielded a *P*-value of less than 0.01 for both wholesale and retail prices of all crops, confirming the presence of seasonality. Additionally, Figures 1 and 2 further illustrate this seasonality. Similarly, Debasish (2012) conducted a similar analysis to test seasonality in stock price series.

Table 3. Seasonality test for the price series

Price	Wholesale Price			Retail Price		
Crop	Statistics	*P* value	Inference	Statistics	*P* value	Inference
Onion	56.07	<0.01	Seasonality	58.34	<0.01	Seasonality
Potato	71.65	<0.01	Seasonality	75.86	<0.01	Seasonality
Tomato	51.16	<0.01	Seasonality	53.80	<0.01	Seasonality

During the study period, the seasonal indices of wholesale and retail prices of onion, potato and tomato in India are presented in Table 4. For onion, the peaks of both wholesale and retail prices were found in October, November, and December. Similarly, the lowest wholesale and retail prices were found in April, May, and June. For potato, the peaks of both wholesale and retail prices were found in October and November. Similarly, the lowest wholesale and retail prices were found in February and March. For tomato, the peaks of both wholesale and retail prices were found in July and August. Similarly, the lowest wholesale and retail prices were found in February and March. Anjoy and Paul (2019) also separated the seasonal factor from the monthly onion price series.

Factors other than seasonality are separated by de-seasonalization. The total data set of the de-seasonalized series was divided into a training set and a testing set. A training set was used for model building, and a testing set was used to estimate the model's forecasting ability. The last 12 observations were kept as the testing set, while the remaining observations were kept as the training set. The KPSS test (Kwiatkowski *et al.,* 1992) was employed to determine the stationarity of the de-seasonalized price series and is reported in Table 5. All the de-seasonalized price series were non-stationary. Hence, differencing was required to make a stationary series. ACF, PACF, and the number of times differencing the series to make a stationary were used to get possible orders in ARIMA model fitting. According to the minimum values of AIC and BIC, the best model was chosen for all the de-seasonalized price series. ARIMA (2,1,2), ARIMA (1,1,2), and ARIMA (2,1,2) were fitted for deseasonalized wholesale price series of onion, potato and tomato, respectively. Similarly, ARIMA (0,1,2), ARIMA (2,1,2), and ARIMA (1,1,2) were fitted for de-seasonalized retail price series of onion, potato, and tomato, respectively.

Table 4. Seasonal indices of the price series

Crop	Onion		Potato		Tomato	
Price	WS	Retail	WS	Retail	WS	Retail
January	1.17	1.16	0.91	0.93	0.86	0.87
February	0.99	0.99	0.82	0.84	0.68	0.71
March	0.81	0.84	0.81	0.83	0.65	0.69
April	0.70	0.73	0.86	0.87	0.70	0.73
May	0.67	0.70	0.92	0.93	0.78	0.80
June	0.73	0.75	0.99	0.99	0.95	0.95
July	0.84	0.85	1.06	1.05	1.40	1.36
August	1.02	1.01	1.09	1.08	1.33	1.31
September	1.15	1.13	1.10	1.09	1.16	1.15
October	1.26	1.23	1.14	1.13	1.18	1.17
November	1.35	1.32	1.22	1.19	1.27	1.23
December	1.32	1.29	1.08	1.07	1.03	1.02

Table 5. Results of KPSS test for the price series

Crop	Wholesale Price			Retail Price		
	Statistics	*P* value	Inference	Statistics	*P* value	Inference
Onion	0.76	0.01	Non-stationary	0.87	0.01	Non-stationary
Potato	0.61	0.02	Non-stationary	0.69	0.01	Non-stationary
Tomato	0.60	0.02	Non-stationary	0.67	0.01	Non-stationary

Tables 6 and 7 show the best model's parameter estimates, significance, and standard error for de-seasonalized wholesale and retail price series, respectively. The results of the Ljung-box

Table 6. Parameter estimates of fitted model for all the wholesale price series

Crop		Onion	Potato	Tomato
Fitted model		ARIMA (2,1,2)	ARIMA (1,1,2)	ARIMA (2,1,2)
Parameters	AR (1)	0.65* (0.15)	0.71* (0.07)	0.86* (0.21)
	AR (2)	0.08* (0.14)	-	-0.15* (0.18)
	MA (1)	-0.39* (0.12)	-0.42* (0.07)	-0.65* (0.20)
	MA (2)	-0.56* (0.13)	-0.54* (0.06)	-0.32* (0.20)
AIC		2272.63	2334.63	2379.39
BIC		2287.75	2346.73	2394.51
Ljung-Box test statistic (*P* value)		7.91 (0.79)	8.72 (0.72)	14.17 (0.28)
Training set	RMSE	409.92	505.31	581.82
	MAE	256.35	289.72	341.34
Testing set	RMSE	478.38	548.83	642.78
	MAE	289.67	328.18	395.28

* Significant at 0.05 level of probability

Table 7. Parameter estimates of fitted model for all the retail price series

Crop		Onion	Potato	Tomato
Fitted model		ARIMA (0,1,2)	ARIMA (2,1,2)	ARIMA (1,1,2)
Parameters	AR (1)	-	0.78* (0.15)	0.71* (0.07)
	AR (2)	-	-0.07* (0.17)	-
	MA (1)	0.32* (0.08)	-0.47* (0.14)	-0.49* (0.09)
	MA (2)	-0.19 (0.08)	-0.49* (0.12)	-0.47 (0.07)
AIC		916.23	969.88	1007.51
BIC		925.30	985.00	1019.61
Ljung-Box test statistic (*P* value)		10.98 (0.53)	8.28 (0.76)	17.77 (0.14)
Training set	RMSE	4.81	5.63	6.43
	MAE	3.04	3.16	3.82
Testing set	RMSE	5.39	5.82	6.93
	MAE	3.92	3.48	4.28

* Significant at 0.05 level of probability

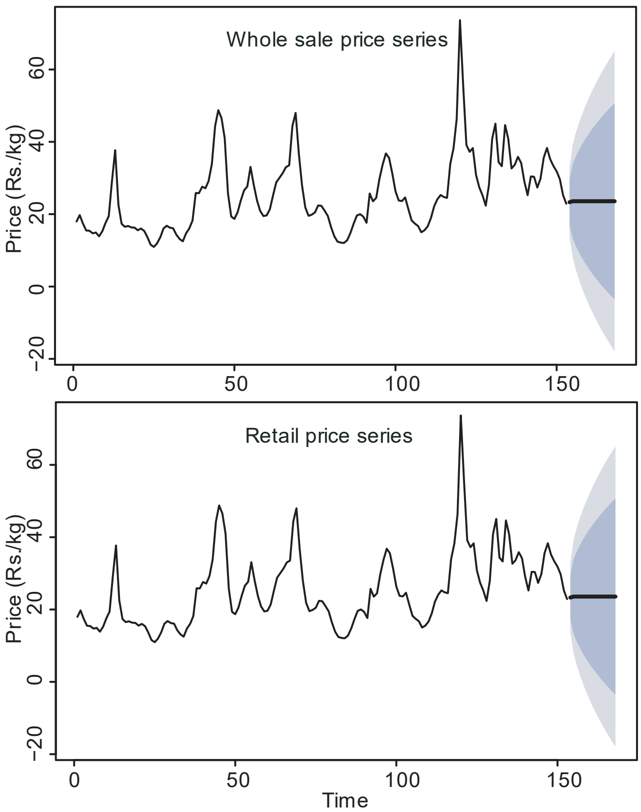

Fig 3. Deseasonalized onion price series and its forecasts

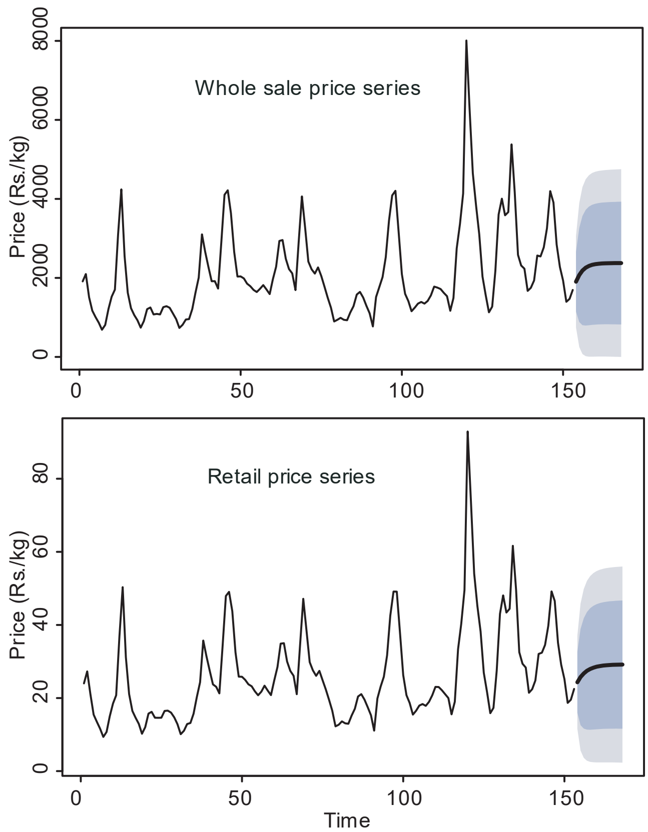

Fig 5. Deseasonalized tomato price series and its forecasts

test showed that all the de-seasonalized price series residuals from the fitted ARIMA model were white noise. Forecasts of de-seasonalized price series were given in Figs. 3, 4 and 5 for onion, potato, and tomato, respectively. Similarly, Anjoy and Paul (2017) used a de-seasonalized series for ARIMA model fitting for the monthly potato price series.

The current study was conducted to learn about the instability, seasonal indices, and de-seasonalized forecasts of wholesale and retail prices of major vegetables in India. The potato price series was medium-unstable, whereas the onion and tomato prices were extremely volatile. The existence of seasonality is the major reason for this instability. Seasonal indices indicate the direction of price fluctuation within a year for major vegetables in India, and the ARIMA model forecasts factors other than seasonal factors. Finally, farmers, policymakers, and government sectors can prepare for these sudden price changes since they are better aware of price patterns.

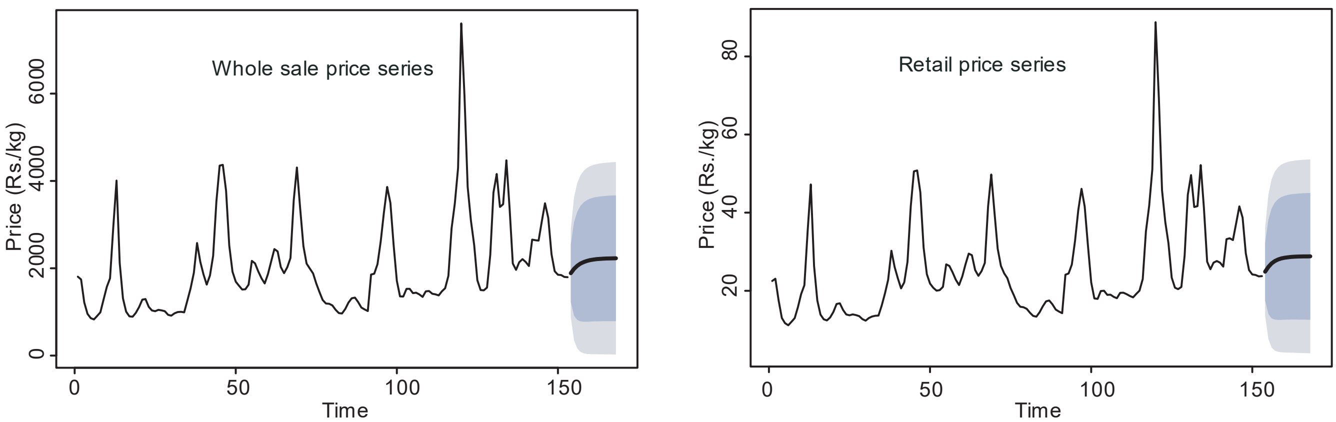

Fig 4. Deseasonalized potato price series and its forecasts

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