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RESEARCH

Chickpea Price Dynamics in *Maharashtra*: Evidence from Seasonal Indices, Cointegration and ARIMA Forecasting

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ABSTRACT

Purpose: *Chickpea (Cicer arietinum L.) is a vital pulse crop in India, contributing 46.62% to the nation's pulse production. This study was to analyse the seasonal behaviour, price trends, and market integration of chickpea across major Agricultural Produce Market Committees in Maharashtra.*

Research Method: *Secondary data for monthly arrivals and prices of chickpea were analyzed over years 2005-06 to 2022-23 to capture both short- and long-term fluctuations in chickpea arrivals and prices in Maharashtra. Seasonal indices were estimated by using the moving average method, while ARIMA models were applied for price forecasting. Model adequacy was validated through accuracy measures such as RMSE and MAPE to ensure reliable forecasts. For market integration, Johansen multiple co-integration trace tests were employed while pairwise Granger causality tests were conducted with diagnostic checks to ensure robustness of causal inference.*

Findings and Values: *Seasonal indices revealed a peak in chickpea arrivals during February to April, coinciding with post-rabi harvest, and a reverse trend in prices, which were highest during July to October. The price forecasting, showing reliable performance with projected price peaks in winter due to reduced market inflow. Johansen co-integration tests confirmed a long-run equilibrium relationship among prices in Latur, Daryapur, Hinganghat, Amravati, and Nagpur markets, indicating strong market integration. Both bidirectional and unidirectional price linkages, with Latur, Hinganghat, and Nagpur emerging as key price-leading markets. The findings highlight the importance of market intelligence in stabilizing prices and enhancing farmers' income through efficient marketing, thereby reducing volatility and promoting sustainable growth of the agricultural sector.*

Keywords: *ARIMA, Arrivals, Chickpea, Forecasting, Maharashtra, Price*

INTRODUCTION

Chickpea (*Cicer arietinum* L.), commonly known as gram or Bengal gram, is one of the most important food legumes cultivated globally, particularly in South Asia. Anon (2021) reported that in India, chickpea occupies a prime position among pulse crops, contributing about 46.62% to the total pulse production. As a rich source of protein, chickpea plays a vital role in supplementing cereal-based diets, especially for the predominantly vegetarian population of the country (Tiwari & Shivhare 2018). It is used in a wide variety of food products such as sweets, condiments, and vegetables and is widely recognized for its health benefits. Pulse proteins are notably high in lysine but low in sulfur-containing amino acids, making them an effective complement to cereals and a practical

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approach to combating protein malnutrition among vegetarian populations, particularly children and nursing mothers (Graham & Vance 2003).

Among the various grain legumes cultivated in India, chickpea is the dominant crop grown during the rabi season. India is the world's largest producer and consumer of chickpeas, accounting for approximately 75% of global production in 2023. During 2020–21, chickpea was cultivated on 9.99 million ha, producing 11.91 million tonnes with a productivity of 1192 kg ha^{-1}. India's chickpea production is projected at around 11.30 million tonnes in 2025, keeping supplies steady but still below demand. Prices are expected to hover near the Minimum Support Price (MSP), with imports and buffer stock management playing a crucial role in stabilizing the market.

Anon (2021) reported that *Maharashtra* led the country in terms of area under cultivation, covering 2.231 million ha and producing 2.396 million tonnes with a productivity of 1074 kg ha^{-1}. The expansion of chickpea cultivation in both the state and the country can be attributed to increased irrigation facilities, adoption of improved varieties, and the use of modern production technologies (Singh 2016). In *Maharashtra*, chickpea accounted for 55.45% of the total pulse production (4.321 million tonnes) during the same period.

Price instability is a critical risk in agriculture, as seasonal gluts, weather variability, and policy shocks often lead to volatile prices, adversely affecting farm income and investment decisions (Wibowo *et al.* 2023). Such instability undermines farmers' confidence to invest in productivity-enhancing technologies, restricts access to credit, and disproportionately affects smallholders who lack effective risk-management instruments (Von & Tadesse 2012, Wibowo *et al.* 2023).

Fluctuating prices significantly influence farmers' decisions regarding both production and marketing. For sustainable agricultural development and the economic security of farmers, accurate price forecasting is essential. If future trends in arrivals and prices can be anticipated, farmers may plan the marketing of their produce to coincide with favorable price periods, thereby improving their income.

The ARIMA (Auto Regressive Integrated Moving Average) model was employed to forecast chickpea prices in *Maharashtra* by capturing underlying patterns in historical time-series data. The model combines three components: autoregressive (AR) for past value relationships, integrated (I) for differencing to achieve stationarity, and moving average (MA) for past forecast errors. Model identification was carried out using the autocorrelation and partial autocorrelation functions, followed by parameter estimation and diagnostic checking to ensure model adequacy. Finally, the validated ARIMA model was used to generate short-term forecasts, providing actionable insights for market planning and price-risk management.

In this context, the present study was undertaken to analyze trends in arrivals and prices of chickpea in major markets of *Maharashtra*, estimate seasonal indices, forecast future prices, and assess market integration using co-integration analysis.

MATERIALS AND METHODS

The present study utilized secondary data on arrivals and prices of chickpea collected from 70 Agricultural Produce Market Committees (APMCs) in *Maharashtra*. An eighteen-year period from 2005–2006 to 2022–2023 was selected to capture both short- and long-term fluctuations in chickpea arrivals and prices in *Maharashtra*, encompassing key phases of market reforms, MSP revisions, procurement expansion, and changing cropping patterns, while ensuring inclusion of the most recent available data.

For the purpose of detailed analysis, five prominent markets, namely *Latur, Daryapur, Hinganghat, Amravati,* and *Nagpur*, were purposively selected out of 70 APMCs. The selection was made on the basis of their highest average arrivals of chickpea during the preceding five years, which establishes them as the leading and representative markets in the state. Since these markets handle a substantial share of chickpea trade, they were considered appropriate for analyzing the price–arrival dynamics, thereby providing more reliable and representative results for the study area.

Monthly and yearly data on arrivals and modal prices were obtained from the AGMARKNET portal of the Directorate of Marketing and Inspection, Government of India. The data were analyzed to compute seasonal indices for arrivals and prices, forecast future prices using ARIMA models, and assess the long-run relationships among prices in key markets using Johansen co-integration and Granger causality tests.

Seasonal indices

To identify intra-year seasonal variations, seasonal indices for monthly arrivals and prices of chickpea were calculated using the moving average method (Kendall & Stuart 1976). The seasonal indices help understand monthly fluctuations around the average (Elucidate 2025). It is computed using the following formula (Siegel 2016):

$$\text{Seasonal Index}_{\text{Arrivals}} = \frac{\text{Actual average arrivals for the month}}{\text{Moving average arrivals for the month}} \times 100 \quad (1)$$

$$\text{Seasonal Index}_{\text{Prices}} = \frac{\text{Actual average prices for the month}}{\text{Moving average prices for the month}} \times 100 \quad (2)$$

These indices provide insights into peak arrival months and price behavior over the year, assisting farmers and policymakers in decision-making.

Price forecasting using ARIMA

Price forecasting was performed using the Autoregressive Integrated Moving Average (ARIMA) model, also known as the Box–Jenkins methodology (Box & Jenkins 1970). The ARIMA model is expressed as ARIMA (p, d, q), where p represents the order of autoregression (AR); d, the degree of differencing required to make the series stationary and q, the order of moving average (MA).

The AR component captures the relationship between an observation and a specified number of lagged observations. The I component makes the series stationary through differencing, while the MA component models the dependency between an observation and a residual error from a moving average model applied to lagged observations (Gujarati & Porter 2009). Model selection was guided by multiple performance criteria, including the highest coefficient of determination (R^2), and the lowest values for Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE), as recommended by (Sherly *et al.* 2025).

Co-integration analysis

i) Johansen Co-integration

Johansen multiple co-integration trace tests were used for indicating the long run relationship between the price series of major five markets (on the basis of arrivals) i.e. *Latur, Daryapur, Hinganghat, Amravati* and *Nagpur*.

$$P_t = \sum_{i=1}^{k} A_i P_{t-1} + \mu + B_t + \varepsilon_{ti} \quad (t = 1, 2, 3, \ldots, T) \quad (3)$$

The procedure for estimating the co-integration vectors is based on error correction model (ECM) given by

$$\Delta P_t = \mu + \pi P_{t-1} + \sum_{i=1}^{k-1} r_i P_{t-i} + \beta \mu_t + \varepsilon_t \quad (4)$$

Where, $\gamma_i = -(I - \Pi_1 - \ldots - \Pi_T)$; $i = 1, 2, \ldots, K-1$; $\Pi = -(I - \Pi_1 - \ldots - \Pi_k)$; μ is the constant, t is the time or trend variable, and ε_t is the error term.

ii) Granger causality test To study the direction of causality for the selected time, the Granger causality test was employed. It involves the estimation of the simple form of vector autoregressive model (VAR) as given below:

$$\ln P_t^A = \sum_{i=1}^{n} \delta_i \ln P_{t-1}^B + \sum_{j=1}^{n} \vartheta_j \ln P_{t-j}^A + \mu_{At} \quad (5)$$

$$\ln P_t^B = \sum_{i=1}^{n} \phi_i \ln P_{t-i}^B + \sum_{j=1}^{n} \partial_j \ln P_{t-j}^A + \mu_{Bt} \tag{6}$$

Where, P_t is the price and subscripts A and B indicate the two markets. T is the time trend. μ_A and μ_B are the error terms of both the models.

RESULTS AND DISCUSSION

The seasonal indices reveal distinct seasonal fluctuations, with prices generally rising during lean supply months and declining during peak arrival periods. This indicates a clear pattern of seasonal behavior in the markets, driven largely by production cycles and demand variations. However, the price forecasts show the trends by projecting the prices in the coming months, highlighting both the upward and downward movements consistent with historical patterns. Accordingly, seasonal indices and price forecasts of chickpea were examined in this study to analyze the behavior of arrivals and prices.

Seasonal indices of arrivals and prices of chickpea in major markets of Maharashtra

The seasonal indices of chickpea arrivals and prices in key APMCs viz.; *Latur, Daryapur, Hinganghat, Amravati,* and *Nagpur* are presented in Table 1. The analysis revealed a distinct seasonal pattern in both arrivals and price behavior, consistent with harvest and market dynamics observed in previous studies (Gupta *et al.* 2018, Gaikwad *et al.* 2025). The peak arrival period was found to be concentrated between February and April, coinciding with the post-rabi harvest season. The highest indices of chickpea arrivals were recorded in March across most markets, with values of 258.13% in *Latur*, 348.89% in *Hinganghat*, 315.48% in *Amravati*, and 341.22% in *Nagpur*, indicating a sharp influx of produce into these markets during this period. In contrast, *Daryapur* APMC registered the peak arrival in February, with an exceptionally high index of 444.73%, the highest among all observed markets. Such concentrated post-harvest arrivals are common for rabi crops like chickpea, due to synchronized harvesting and immediate marketing needs (Gaikwad *et al.* 2025).

Conversely, the lowest indices of arrivals were noted during December, with *Latur* (19.18%), *Daryapur* (9.39%), *Amravati* (20.79%), and *Nagpur* (9.92%) all showing minimal market inflow, indicative of the lean pre-harvest season.

The seasonal price indices exhibited comparatively less fluctuation than arrivals, but still reflected an inverse relationship with the volume of arrivals. Typically, chickpea prices were higher during the off-season months of July to October, when market arrivals were low. The highest price indices were observed in July at *Hinganghat* (114.62%), August at *Daryapur* (111.80%), September at *Amravati* (111.83%), and October at *Latur* (110.33%) and *Nagpur* (109.84%). This seasonal behavior reflects the typical supply–demand dynamics, where lower arrivals in lean months result in higher prices (Noonari *et al.* 2015).

In contrast, the lowest price indices were generally recorded during peak arrival months. Specifically, March witnessed the lowest price indices in *Latur* (90.73%) and *Daryapur* (88.56%), while January had the lowest in *Hinganghat* (81.16%) and *Nagpur* (88.55%). *Amravati* recorded its minimum price index in June, a pre-monsoon period often marked by limited storage and speculative trading.

These findings underscore a well-established pattern: high seasonal indices of arrivals were concentrated during the harvest season (February to April), which coincided with lower price indices. Conversely, off-season months exhibited higher price indices due to lower arrivals, reaffirming earlier observations in pulse marketing behavior (Satishkumar *et al.* 2020, Gaikwad *et al.* 2025).

Forecasting of chickpea prices

Using monthly chickpea price data spanning 18 years (2005–2022) from five major markets in *Maharashtra*, price forecasts were generated up to December 2023 employing the ARIMA (AutoRegressive Integrated Moving Average) model. The ARIMA approach has been widely

Table 1. Seasonal indices of arrivals and prices of chickpea in major markets.

Month	*Latur*		*Daryapur*		*Hinganghat*		*Amravati*		*Nagpur*	
	Arrivals	Prices	Arrivals	Prices	Arrivals	Prices	Arrivals	Prices	Arrivals	Prices
January	32.41	94.61	109.42	94.60	3.69	81.16	34.74	98.11	9.98	88.55
February	134.99	95.80	444.73	93.17	75.48	97.66	197.89	95.04	126.83	94.14
March	258.13	90.73	235.90	88.56	348.89	99.56	315.48	90.37	341.22	93.90
April	214.10	93.47	127.24	99.12	268.75	104.85	212.03	101.27	261.19	91.92
May	201.13	99.93	96.82	97.07	162.92	104.10	143.47	100.23	188.44	99.94
June	171.81	97.66	63.04	97.91	145.33	99.07	105.21	91.62	104.36	99.29
July	61.42	104.14	25.20	104.37	100.55	114.62	31.98	91.99	63.02	105.87
August	33.95	108.60	16.00	111.80	47.70	106.66	31.21	102.37	40.11	106.66
September	24.64	109.18	16.98	104.48	18.54	92.05	30.83	111.83	24.89	104.12
October	23.88	110.33	30.24	107.88	10.37	95.91	43.32	105.89	20.11	109.84
November	24.38	99.32	25.04	103.45	9.93	110.66	33.06	109.93	9.94	107.22
December	19.18	96.24	9.39	97.60	7.86	93.69	20.79	101.35	9.92	98.54

recognized for its effectiveness in capturing temporal patterns and providing reliable short-term forecasts in agricultural commodity markets (Box & Jenkins 1976, Gupta *et al.* 2018).

ARIMA model selection

On the basis of Autoregressive component (p), differentiation (d) and moving average components (q), various possible combinations of model were identified. Among these models, the best fit model was chosen based on the highest R^2, and the lowest values of MAPE, MAE and RMSE (Table 2). Tables 3 to 5 present the actual and forecasted monthly prices of chickpea in the major markets of *Maharashtra* for the period January 2022 to December 2023. The results are divided into two parts: (i) months for which both actual and predicted prices are available (January 2022–January 2023), and (ii) months with only forecasted values (February 2023–December 2023).

In addition to criteria such as R^2, MAPE, MAE, and RMSE, the difference (%) i.e. the percentage change of actual prices over the predicted prices was estimated to check the accuracy of the results given by the ARIMA model.

Across the five selected markets viz; *Latur*, *Daryapur*, *Hinganghat*, *Amravati*, and *Nagpur, Maharashtra*, the forecasting model demonstrated consistently close alignment between actual and predicted chickpea prices, with most deviations within a $\pm 10\%$ range. *Daryapur* and *Hinganghat* demonstrated high forecasting accuracy, with prediction errors typically constrained within $\pm 5\%$, and even near-zero deviations in several months, indicative of reliable short-term model performance. *Amravati* showed moderate accuracy, with most forecast errors within $\pm 5\%$, though slightly larger variations appeared in a few months.

Nagpur, Maharashtra maintained reasonable forecast precision, with most errors within $\pm 10\%$ and minimal deviation in August 2022 (-0.10%). *Latur* experienced greater volatility, with deviations ranging from -26.6% to $+18.0\%$, suggesting that this market might be more influenced by localized fluctuations or structural factors affecting predictability.

The forecasted chickpea prices for the period February–December 2023 exhibited a clear upward trajectory across all five markets under study. Notably, *Latur* was projected to record the highest price range (5,138–5,511/q), reflecting its role as a strategic trading hub with strong demand and relatively lower arrivals compared to other markets. In contrast, *Amravati* market showed the lowest forecasted price range (4,126–4,367/q), likely due to higher local arrivals exerting downward pressure on prices.

This observation is consistent with the negative correlation between arrivals and prices ($r = -0.8183$) earlier reported for *Amravati* market by Andhalkar *et al.* (2011), who found that

Table 2. ARIMA model selection.

APMC	Fitted model	R^2	MAPE	MAE	RMSE
Latur	ARIMA (2,1,6)	0.91	4.85	223.08	336.84
Daryapur	ARIMA (1,1,6)	0.93	5.17	222.48	385.44
Hinganghat	ARIMA (5,1,5)	0.90	5.76	239.80	386.86
Amravati	ARIMA (1,1,1)	0.86	5.53	219.05	383.23
Nagpur	ARIMA (2,1,2)	0.93	5.75	228.46	324.55

Table 3. Forecasting of chickpea prices in *Latur* and *Daryapur* market (Rs./q).

Year	*Latur*			*Daryapur*		
	Actual price	Predicted price	Difference (%)	Actual price	Predicted price	Difference (%)
Jan-22	6350.00	4660.69	-26.60	4082.69	3942.66	-3.43
Feb-22	4660.95	6334.57	35.91	4554.41	4366.62	-4.12
Mar-22	4660.53	4630.61	-0.64	4649.33	4700.94	1.11
Apr-22	4597.14	4516.40	-1.76	4573.53	4521.14	-1.15
May-22	4480.00	4793.16	6.99	4361.58	4504.69	3.28
Jun-22	4589.20	4728.96	3.05	4318.42	4388.64	1.63
Jul-22	4790.50	4635.13	-3.24	4621.25	4529.37	-1.99
Aug-22	4800.00	4508.26	-6.08	4620.83	4694.41	1.59
Sep-22	4303.53	4908.98	14.07	4238.57	4503.40	6.25
Oct-22	4426.38	5071.21	14.57	4195.63	4453.40	6.14
Nov-22	4432.15	5085.65	14.74	4253.75	4423.49	3.99
Dec-22	4492.50	5302.37	18.03	4215.83	4512.71	7.04
Jan-23	4570.83	5245.06	14.75	4237.50	4609.22	8.77
Feb-23	–	5138.63	–	–	4599.24	–
Mar-23	–	5264.66	–	–	4583.43	–
Apr-23	–	5246.09	–	–	4591.50	–
May-23	–	5327.37	–	–	4616.23	–
Jun-23	–	5430.37	–	–	4639.14	–
Jul-23	–	5309.85	–	–	4652.98	–
Aug-23	–	5361.63	–	–	4662.42	–
Sep-23	–	5424.56	–	–	4673.68	–
Oct-23	–	5394.54	–	–	4688.11	–
Nov-23	–	5510.88	–	–	4703.51	–
Dec-23	–	5492.24	–	–	4717.94	–

higher arrivals generally tend to depress market prices. The intermediate markets such as *Daryapur*, *Hinganghat*, and *Nagpur, Maharashtra* were placed in moderate price bands, with forecasted ranges of 4,599–4,718/q, ~4,392–4,544/q, and 4,633–4,882/q, respectively. This indicates a more balanced interaction of supply and demand in these markets, where arrivals and consumption requirements tend to offset each other.

These findings are consistent with broader market assessments, which highlight that tight supplies and sustained consumption demand have placed upward pressure on chickpea prices, even when rates remain high (Mundus Agri 2025). Additionally, the prevailing mandi price for Kabuli chana in *Maharashtra* (~4,795/q) closely corresponds with the forecasted ranges for central markets like *Amravati* and *Hinganghat*, lending further credibility to the forecasting results (Napanta 2025).

Overall, the results indicate the robustness and suitability of the selected ARIMA models for price prediction (Sharma & Yadav 2020). In addition to this, forecasting analyses by (Chavan *et al.* 2024) demonstrated that ARIMA models could effectively capture short-run dynamics of chickpea prices in *Maharashtra*, supporting the predictive reliability of price behaviour in leading markets like *Latur*.

Table 4. Forecasting of chickpea prices in *Hinganghat* and *Amravati* market (Rs./q).

Year	*Hinganghat*			*Amravati*		
	Actual price	Predicted price	Difference (%)	Actual price	Predicted price	Difference (%)
Jan-22	4156.75	4102.94	-1.29	4296	4364.32	1.58
Feb-22	4309.05	4157.67	-3.51	4483	4413.59	-1.54
Mar-22	4518.33	4407.38	-2.46	4531	4462.53	-1.50
Apr-22	4437.86	4527.33	2.02	4489	4412.35	-1.71
May-22	4121.07	4464.01	8.32	4233	4444.78	5.01
Jun-22	4217.73	4216.65	-0.03	4139	4288.81	3.63
Jul-22	4466.58	4219.36	-5.53	4240	4255.18	0.36
Aug-22	4294.41	4391.88	2.27	4210	4287.77	1.85
Sep-22	4040.59	4360.53	7.92	4214	4124.26	-2.14
Oct-22	4108.16	4397.64	7.05	4169	4042.17	-3.05
Nov-22	4234.47	4360.22	2.97	4261	4071.20	-4.46
Dec-22	4316.46	4320.16	0.09	4329	4185.98	-3.30
Jan-23	4185.83	4381.26	4.67	4327	4257.58	-1.60
Feb-23	–	4412.38		–	4215.83	
Mar-23	–	4392.87		–	4132.26	
Apr-23	–	4408.53		–	4126.13	
May-23	–	4476.71		–	4216.57	
Jun-23	–	4498.73		–	4303.88	
Jul-23	–	4485.79		–	4296.84	
Aug-23	–	4507.07		–	4223.70	
Sep-23	–	4543.42		–	4192.12	
Oct-23	–	4535.78		–	4253.98	
Nov-23	–	4519.40		–	4344.63	
Dec-23	–	4539.73		–	4367.28	

Cointegration analysis of chickpea prices

Johansen cointegration test: The Johansen multiple cointegration test was applied to examine the long-run relationship among logged chickpea prices in major markets. The results of both the Trace statistic and Maximum Eigenvalue statistic are presented in Table 6. The results (Table 6) show that both the Trace and Maximum Eigenvalue statistics consistently exceed the 5% critical values with p-values of 0.00, sequentially rejecting the null hypotheses ($r = 0$, $r \leq 1$, $r \leq 2$, $r \leq 3$, $r \leq 4$). While the table notes "five cointegrating equations," this likely reflects a single dominant long-run equilibrium rather than five independent relationships.

The cointegration analysis confirmed the existence of a long-run equilibrium relationship among major chickpea markets, consistent with the Johansen cointegration framework. Similar applications of the Johansen test for chickpea price integration have been reported by (Gaikwad *et al.* 2025), who established long-run linkages among key regional markets in India, including *Latur* representing *Maharashtra*.

Further, Table 7 summarizes the results of pairwise Johansen co-integration tests for different market combinations. In each case, the null hypothesis of no co-integration was rejected at the 1% level, as both the trace and maximum eigen statistics were greater than the corresponding critical values, and the p-values were less than 0.01. These findings confirm that chickpea prices in all market pairs are co-integrated. The presence of co-integration among chickpea prices across major APMCs implies that these markets are efficiently integrated in the long run. Co-integration suggests that price shocks in one market are

Table 5. Forecasting of chickpea prices in *Nagpur* market (Rs./q).

Year	Actual price	Predicted price	Difference (%)
Jan-22	4479.13	4899.56	9.39
Feb-22	4494.38	4680.47	4.14
Mar-22	4539.94	4474.78	-1.44
Apr-22	4416.79	4325.61	-2.06
May-22	4240.71	4506.43	6.27
Jun-22	4321.10	4290.74	-0.70
Jul-22	4607.20	4410.66	-4.27
Aug-22	4623.11	4618.50	-0.10
Sep-22	4329.87	4596.70	6.16
Oct-22	4357.19	4557.62	4.60
Nov-22	4384.52	4605.74	5.05
Dec-22	4507.11	4736.73	5.09
Jan-23	4506.14	4785.86	6.21
Feb-23	–	4732.40	
Mar-23	–	4645.01	
Apr-23	–	4633.29	
May-23	–	4706.14	
Jun-23	–	4776.72	
Jul-23	–	4782.41	
Aug-23	–	4748.43	
Sep-23	–	4747.79	
Oct-23	–	4804.02	
Nov-23	–	4867.49	
Dec-23	–	4882.13	

Table 6. Johansen multiple cointegration analysis of logged chickpea prices in major markets.

Hypothesized No. of CE(s)	Trace statistics			Max-Eigen statistics		No. of
	Statistic	0.05 critical value	P-value	Statistic	0.05 critical value	cointegrating equations
None*	318.78**	69.82	0.00	86.10**	33.88	5
At most 1*	232.68**	47.86	0.00	76.52**	27.58	
At most 2*	156.16**	29.80	0.00	69.70**	21.13	
At most 3*	86.46**	15.49	0.00	54.44**	14.26	
At most 4*	32.02**	3.84	0.00	32.02**	3.84	

Note: i. *, ** denote significance at 5 and 1 per cent level

Table 7 .Pairwise Johansen co-integration test for the prices of chickpea.

Markets pair	Hypothesized No. of CE(s)	Trace Statistics			Max-Eigen statistics		
		Statistic	0.05 critical value	P-value	Statistic	0.05 critical value	P-value
Latur - Daryapur	None *	170.44**	12.32	0.00	108.61**	11.22	0.00
	At most 1 *	61.83**	4.12	0.00	61.83**	4.129	0.00
Latur - Hinganghat	None *	161.90**	12.32	0.00	100.83**	11.22	0.00
	At most 1 *	61.07**	4.12	0.00	61.07**	4.12	0.00
Latur - Amravati	None *	171.11**	12.32	0.00	100.98**	11.22	0.00
	At most 1 *	70.12**	4.13	0.00	70.12**	4.13	0.00
Latur - Nagpur	None *	178.22**	12.32	0.00	117.85**	11.22	0.00
	At most 1 *	60.37**	4.13	0.00	60.37**	4.13	0.00
Daryapur - Hinganghat	None *	160.09**	12.32	0.00	100.19**	11.22	0.00
	At most 1 *	59.89**	4.13	0.00	59.89**	4.13	0.00
Daryapur - Amravati	None *	96.05**	12.32	0.00	62.13**	11.22	0.00
	At most 1 *	33.92**	4.13	0.00	33.92**	4.13	0.00
Daryapur - Nagpur	None *	165.45**	12.32	0.00	108.31**	11.22	0.00
	At most 1 *	57.14**	4.13	0.00	57.14**	4.13	0.00
Hinganghat - Amravati	None *	164.89**	12.32	0.00	93.97**	11.22	0.00
	At most 1 *	70.91**	4.13	0.00	70.91**	4.13	0.00
Hinganghat - Nagpur	None *	143.34**	12.32	0.00	83.62**	11.22	0.00
	At most 1 *	59.72**	4.13	0.00	59.72**	4.13	0.00
Amravati - Nagpur	None *	145.23**	12.32	0.00	85.66**	11.22	0.00
	At most 1 *	59.56**	4.13	0.00	59.56**	4.13	0.00

Note: *, ** denote significance at 5 and 1 per cent level

likely to be transmitted to others, reinforcing the concept of spatial price efficiency (Ghosh 2013). This integration can be attributed to improved communication networks, faster information dissemination, and the influence of common macroeconomic and policy factors affecting agricultural commodity prices across regions.

The fact that prices move together over time reflects that arbitrage opportunities are minimized, and market forces are functioning effectively to align prices. Such integration is beneficial for farmers, traders, and policymakers, as it ensures a more uniform price structure and reduces regional disparities in returns.

These findings are consistent with previous studies that also reported strong co-movement and integration in pulse markets across India (Reddy 2012). (Bhagat *et al.* 2023a, 2023b, 2023c) found evidence of price co-integration in selected banana markets across India, as well as in pomegranate and tomato markets within Maharashtra, indicating that these markets functioned efficiently and maintained competitive relationships with one another. The implication for policymakers is the need to maintain and enhance market infrastructure and inter-market linkages to sustain this integration.

Granger causality test

The Granger causality test serves as a validation tool for the cointegration model. Granger causality provides insight into the short-run

Table 8. Market pair wise results of Granger Causality test of chickpea price.

Market Pairs	No. of observations	F-Statistic	P-value	Remarks
Daryapur- Latur	209	1.65	0.19	No causality
Latur - Daryapur	209	2.97	0.05	No causality
Hinganghat- Latur	209	4.47*	0.01	Bidirectional
Latur - Hinganghat	209	5.65**	0.00	Bidirectional
Amravati- Latur	209	1.81	0.17	No causality
Latur - Amravati	209	7.16**	0.00	Unidirectional
Nagpur- Latur	209	7.33**	0.00	Bidirectional
Latur - Nagpur	209	3.34*	0.04	Bidirectional
Hinganghat- Daryapur	209	2.71	0.07	No causality
Daryapur - Hinganghat	209	3.13	0.05	No causality
Amravati- Daryapur	209	0.08	0.93	No causality
Daryapur - Amravati	209	7.71**	0.00	Unidirectional
Nagpur- Daryapur	209	4.90*	0.01	Bidirectional
Daryapur - Nagpur	209	3.95*	0.02	Bidirectional
Amravati- Hinganghat	209	2.03	0.13	No causality
Hinganghat - Amravati	209	4.38*	0.01	Unidirectional
Nagpur- Hinganghat	209	3.05	0.05	No causality
Hinganghat - Nagpur	209	3.93*	0.02	Unidirectional
Nagpur- Amravati	209	8.40**	0.00	Unidirectional
Amravati - Nagpur	209	2.05	0.13	No causality

Note: *, ** denote significance at 5 and 1 per cent level

dynamics and direction of information flow (Gujarati & Porter 2009).

The results of the Granger causality test for chickpea prices across major markets are presented in Table 8. The findings reveal evidence of both unidirectional and bidirectional causal relationships among selected market pairs, while some markets exhibited no significant causal linkage.

For the pair *Daryapur-Latur*, the direction of causality was not established as the *P-values* (0.19 and 0.05) were statistically insignificant at the 5% level, suggesting that price movements in either market did not consistently predict the other.

In contrast, a strong bidirectional causal relationship was observed between *Hinganghat-Latur* and *Nagpur-Latur*, with significant F-statistics at 1% and 5% levels, implying that price changes in these markets mutually influence each other. Similarly, *Nagpur-Daryapur* also exhibited bidirectional causality, suggesting stronger spatial integration among these markets. (Bhagat *et al.* 2023a) similarly reported bidirectional causality between *Nagpur* and *Jaipur* banana markets based on pairwise Granger causality tests.

Unidirectional causality was found from *Latur* to *Amravati, Daryapur* to *Amravati, Hinganghat* to *Amravati, Hinganghat* to *Nagpur*, and *Nagpur* to *Amravati*, indicating that these markets play a price-leading role, transmitting price signals to the other linked markets. The *Nagpur-Amravati* case, significant at the 1% level, clearly establishes *Nagpur* as a major price discovery centre in the region.

Similar evidence was reported by (Gaikwad *et al.* 2025), who found that *Latur*, representing *Maharashtra*, exhibited unidirectional causality towards *Damoh, Gadag* and *Lalitpur* markets, thereby establishing its dominance in price transmission within the national chickpea trade. At the state level, (Chavan *et al.* 2024) also confirmed strong cointegration among major chickpea markets of *Maharashtra*.

However, some market pairs such as *Amravati-Daryapur* (p=0.93) and *Amravati-Hinganghat* (p=0.13) exhibited no causality, implying weaker integration and possibly the influence of local demand–supply conditions or marketing inefficiencies. In borderline cases like *Hinganghat-Daryapur* (p=0.07) and *Nagpur-Hinganghat* (p=0.05), causality was not statistically confirmed at the conventional 5% level. These near-threshold values suggest weak linkages that may turn significant with larger datasets or structural shifts in trade patterns.

Overall, the causality results corroborate the Johansen co-integration findings by revealing the direction of price transmission across markets. The coexistence of unidirectional and bidirectional linkages suggests a hierarchical but interconnected market structure. In particular, *Latur, Nagpur,* and *Hinganghat* emerge as major reference markets, transmitting price signals to surrounding centres through both unidirectional and reciprocal (bidirectional) causal relationships (Bhagat *et al.* 2023a).

By contrast, *Amravati* and *Daryapur* largely function as price-following markets, responding to signals from leading centres rather than influencing them. These patterns are consistent with earlier evidence that influential markets such as *Daryapur* and *Nashik* exhibit bidirectional linkages, while others maintain predominantly unidirectional dependencies (Pandey *et al.* 2023).

CONCLUSION

The study revealed pronounced seasonal patterns in chickpea arrivals and prices in major markets of *Maharashtra*, with peak arrivals from February to April coinciding with lower prices, and off-season months exhibiting higher prices due to limited supply. ARIMA forecasts demonstrated reliable short-term price prediction, with most deviations within $\pm 10\%$, underscoring their utility for strategic market planning. Johansen co-integration analysis confirmed the existence of long-run equilibrium relationships among key markets, while Granger causality identified *Latur, Nagpur*, and *Hinganghat* as price-leading centers, highlighting their pivotal role in price transmission across the state. These findings provide actionable insights for farmers and policymakers, with price-leading markets serving as focal points for targeted interventions, storage management, and risk mitigation to reduce volatility and enhance farmer incomes.

The study is limited by reliance on secondary data and omission of factors like export demand, climate variability, and input costs; future work should integrate these variables and explore inter-state linkages for more robust forecasting. Strengthening market infrastructure and information dissemination, alongside modern risk management strategies, can further stabilize prices and enhance farmer income.

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