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Price Dynamics and Market Integration among Major Tomato Markets in India

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Abstract

The study analyzed the price transmission and spatial integration across tomato-producing (Nashik, Kolar, Madanapalle, and Solan) and consuming (Azadpur, Bangalore, Kolkata, and Chandigarh) markets using monthly price arrival data from 2012 to 2023. Econometric tools such as the Augmented Dickey-Fuller test, Phillips-Perron test, Johansen's cointegration test, Granger causality, and principal component analysis were employed. Monthly price variations were assessed using seasonality indices. Johansen's co-integration test revealed strong integration among the selected markets. The Granger causality analysis identified Bangalore and Kolar as the major transmitters of price information through multiple unidirectional causal relationships, while Kolkata emerged as the most interconnected market by exhibiting several bidirectional relationships. Most markets exhibited a unidirectional or non-price movement relationship, while a few showed bidirectional price movements. A seasonality index greater than one was observed in July, August, and November for all markets, indicating farmers received a higher-than-average price. Principal Component Analysis revealed that only one component had an eigenvalue greater than or equal to one. The findings suggest prioritizing price stabilization measures in major price-transmitting markets while strengthening market coordination through highly interconnected markets.

Keywords: ADF, Co-integration, Market, Price, Tomato

JEL Classification: M31, Q13, Q21, R32

Introduction

Tomato is one of the most important crops in the horticulture sector, with a share of ten per cent in India. It is essential to provide money for growers, employment opportunities, household and nutritional dietary requirements (Rhamya, 2024). Tomato prices in India exhibit significant volatility due to inadequate post-harvest practices, poor marketing, and inadequate processing facilities, resulting in price inflation during July-August and lower prices during December-March, affecting farmers, traders, and consumers.

Agricultural marketing plays a crucial role in transporting commodities from producers to consumers while also helping to stabilize prices. Markets are essential in determining food accessibility and availability. Food accounts for a large portion of the consumption basket in India, so examining agricultural market integration is especially relevant. Chatterjee and Kapur (2016) observed that the extent of price integration varies across different regions. Given concerns about price stability and food security, market integration has become a key issue in recent decades (Akhter, 2016). If markets are well integrated, stabilizing prices in the main market can effectively influence other markets, as price signals are efficiently transmitted across regions. Conversely, if markets are not integrated, it may lead to incorrect price signals, inefficient resource allocation, unequal distribution of marketed surplus, leading to a decline in social welfare.

Tomatoes have been among India's most important protective food crops. India ranks second-largest tomato producer, contributing 11 per cent to the world's tomato output, yet processes less than 1 per cent of its production (Kaundal *et al*., 2024). In India, the area under cultivation and production during 2025-26 is 845 thousand hectares and 227.02 lakh tonnes, respectively (GoI, 2026). The tomato products in India are growing at an estimated 30 per cent

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annually, driven by consumer interest in products such as new ready-to-eat items, ketchup, gravies, pasta sauce, and bulk supplies for food retail chains, including fast-food restaurants and hotels (Subramanian, 2016).

Tomato, being a highly perishable crop, must be sold immediately after harvest, often leading to a decline in prices due to oversupply. This situation often results in reduced planting in the following season, causing price increases. This cycle adversely affects farmers through high postharvest losses and low returns during market oversupply periods. A major challenge for processors is maintaining a steady supply of fresh tomatoes that meet quality standards at a sustainable price. The involvement of intermediaries inflates costs, rarely benefiting farmers from increased production (NABARD, 2023). This, in turn, exacerbates tomato price volatility, causing consumer distress during periods of high prices. In this context, the study was conducted with the objective of studying the integration and price transmission of the tomato crop in these regions and suggest suitable policies regarding the tomato crop.

Data Sources and Methodology

Study Area

The study used secondary data from eight major national markets in India, namely Bangalore, Chandigarh, Kolkata, and Azadpur (Delhi) as consuming markets and Madanapalle, Solan, Kolar, Nashik as producing markets with the focus on the arrival price of tomatoes. The producing markets were chosen for their dominant share in national tomato production and high volume of market arrivals, while the consuming markets were selected because they serve as major wholesale consumption and distribution centres with continued demand. Additionally, the availability of continuous secondary data on arrival prices was a critical criterion for the final selection of all eight markets. The study was based on secondary data. Monthly prices and arrival data from January 2012 to December 2023.

Seasonality Index

Monthly seasonal indices (SI) were estimated using the ratio-to-average method. The seasonal index for the *i*th month was calculated as:

$$\mathrm{SI_i} = \frac{\overline{\mathrm{P}}_\mathrm{i}}{\overline{\mathrm{P}}}$$

where SI_i is the seasonal index for the *i*th month, P_i is the average tomato price for the *i*th month across all years, and P is the overall average monthly tomato price during the study period. A seasonal index greater than 1 indicates that prices in a given month are above the overall monthly average, whereas a value below 1 indicates below-average prices.

Seasonal price instability was measured as suggested by (Ali, 2000):

$S_i = I_h - I_i$

S_i= Seasonal indices

I_h = Highest value of seasonal index

I_i = lowest value of the seasonal index

Augmented Dickey-Fuller (ADF) test

A non-stationary time series regression analysis can yield erroneous results (Ghafoor *et al*., 2009). Cointegration is a commonly used method to analyze non-stationary time series that are integrated of the same order, as it allows for the identification of long-term equilibrium relationships between variables. The ADF test is commonly used to identify the order of integration of time series data. It evaluates the null hypothesis that a unit root is present. If the null hypothesis is rejected, the series is considered stationary; otherwise, it is non-stationary (Dickey and Fuller, 1979). The ADF test relies on Ordinary Least Squares estimation. The model involved in the estimation is given below

$$\Delta P_t = \alpha_o + \delta_1 t + \Upsilon P_{t-1} + \sum_{j=1}^{q} \vartheta_j \Delta P_{t-j} + \varepsilon_t$$

Where, P represents the price observed in each market; Δ denotes difference parameter (i.e., $= P_t - P_{t-1}$, $P_{t-1} = P_{t-1} - P_{t-1}$, and P_{n-1}). The Eigen test statistics is used to determine the number of cointegrating vectors, as outlined below as follows:

$$J_{max} = -T \sum_{i=r+1}^{N} ln ln(1 - \lambda_1)$$

$$J_{max} = -T ln(1 - \lambda_{r+1})$$

Where r denotes the number of cointegrated vectors, λ_i is the eigenvalue, and λ_{r+1} is the $(r-1)^{th}$ largest squared eigenvalue derived from the matrix π, and the T represents the effective number of observations. The trace statistics were used to compare the null hypothesis of r cointegrating vectors to the alternative hypothesis of n cointegrating relations. To compare the null hypothesis to the alternative r+1, Max Eigen statistics is performed.

Phillips-Perron (PP) Tests

In the augmented Dickey–Fuller (ADF) proposed by (Dickey and Fuller, 1979), lagged terms including lagged values of the dependent variable are added to the regression to eliminate serial correlation in the residuals. An alternative method for testing for a unit root in the presence of weakly dependent disturbances is provided by the Phillips-Perron (PP) tests developed by (Phillips, 1987) and (Phillips and Perron, 1988). Unlike the ADF approach, which explicitly includes lagged differences in the regression, the PP procedure addresses serial correlation through a nonparametric adjustment based on a consistent estimate of the long-run variance of the error term.

The application of the PP unit root tests is based on the OLS parameter estimate, $\hat{\alpha}$, from the AR(1) (pseudo-) equation

$$x_t = \alpha x_{t-1} + u_t. \quad (1)$$

Using the OLS estimate $\hat{\alpha}$, the PP unit root statistics are then computed as

$$Z_\alpha := T(\hat{\alpha} - 1) - \tfrac{1}{2} (\hat{\lambda}^2 - s^2) (\tfrac{1}{T^2} \Sigma x_{t-1}^2)^{-1} \quad (2)$$

$$Z_t := {}^{S}/\hat{\lambda}\, t_{\hat{\alpha}=1} - \tfrac{1}{2} (\hat{\lambda}^2 - s^2) (\hat{\lambda}^2 {}_{T^2} \Sigma x_{t-1}^2)^{-1/2} \quad (3)$$

where $t_{\hat{\alpha}=1} := s^{-1}(\hat{\alpha} - 1)(\Sigma x_{t-1}^2)^{1/2}$ and $s^2 := T^{-1} \Sigma \hat{u}_t^2$ and are estimators of the short- and long-run variances of $\{u_t\}$, respectively. Perron and Serena, (1996) proposed two alternative procedures for estimating the long-run variance. One of these is a nonparametric kernel estimator, which derives the long-run variance estimate from the sample autocovariance structure of the data, $= s^2_{WA}$, with $s^2_{WA} := \Sigma\, \omega(h/m)\, \hat{\gamma}_h$, where $\hat{\gamma}_h := T^{-1} \Sigma \hat{u}_t \hat{u}_{t+|h|}$, where $\hat{u}_t$ are the OLS residuals from regressing x_t on x_{t-1}, with kernel function $\omega(\cdot)$ satisfying the general conditions reported in Jansson (2002, Assumption A3) and the bandwidth parameter $m \in (0, \infty)$ satisfying $1/m + m^2/T \to 0$ as $T \to \infty$ (which corresponds to Assumption A4 of Jansson, 2002). Secondly, a parametric autoregressive spectral density (ASD) estimator, $\hat{\lambda}^2 = s^2_{AR}$, of the form suggested by Berk (1974), where $s^2_{AR} := s^2_k / (1 - \Sigma \hat{\alpha}_i)^2$, and $s^2_k := T^{-1} \Sigma \hat{\varepsilon}^2_{k,t}$, are computed using the estimates from the ADF-type regression:

$$\Delta x_t = \hat{\rho} x_{t-1} + \Sigma_{j=1}^{k} \hat{\alpha}_j \Delta x_{t-j} + \hat{\varepsilon}_{k,t} \quad (4)$$

for $k \geqslant 2$.

Johansen's Cointegration Tests

The cointegration test evaluates whether a set of non-stationary time series maintains a long-term equilibrium relationship. In this study, Johansen's cointegration test was applied to assess the long-term predictability between different markets using the maximum likelihood approach. This method considers an n-dimensional vector integrated at the first order and determine a vector autoregressive model. The model was later refined by (Johansen and Juselius, 1990) by introducing an error correction mechanism, represented as follows:

$$X_t = c + \sum_{i=1}^{k} \prod\nolimits_t X_{t-1} + \varepsilon_t$$

$$\Delta X_t = \mu + \textstyle\sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-1} + \prod_i X_{t-k} + \varepsilon_t$$

Where X_t is an n x 1 vector of the first order, is a deterministic component that may include an intercept term, a linear trend term, or both. Π_i an n x r matrix of parameters α and β. The vector c is constant, D is the first difference operator, and k is the optimal lag length based on the Hannan-Quinn criterion. The term ε_t is a random error that indicates the stationarity of linear combinations of X_t.

Granger Causality Test

The markets' co-integration test was performed using Johansen's test. Thereafter Granger causality test was used to assess the order and direction of causal relationships among variables in an equilibrium. The following tests were used to determine whether market q_2 Granger causes market or vice-versa was checked using:

$$q_{it} = c + \sum_{j=1}^{n} (\phi q_{it-j} + \delta_j q_{2t-j}) + \varepsilon_t$$

Granger causality was carried out using a simple test of the joint significance of the β_k coefficient i.e., H_0: $\beta_1 = \beta_2 = \ldots \beta_n = 0$

Principal Component Analysis

Principal Component Analysis (PCA) is a technique used to recognize patterns in raw data and represent them in a manner that emphasizes similarities and differences. It achieves this by forming linear combinations of the original variables to create an index that captures the maximum variance within multivariate data. In practice, this estimation is commonly performed using the data matrix's singular value decomposition (SVD) (Shlens, 2005). PCA was performed using the pca command in Stata 15.1, which computes principal components based on the correlation matrix of the price series. Kaiser's criterion (eigenvalue ≥ 1) was used to determine the number of components to retain.

Given a dataset containing n observations and p variables, it can be represented as an n×pn/times pn×p data matrix X, Principal Component Analysis (PCA) aims to convert the original variables into a new set of k variables known as principal components. These components are designed to capture the most significant variations within the data. Each principal components are formulated as a linear combination of the original variables as follows

PC1 = b11 * x1 + b12 * x2 + ... + b1p * xp
PC2 = b21 * x1 + b22 * x2 + ... + b2p * xp
PCk = bk1 * x1 + bk2 * x2 + ... + bkp * xp

Where, bij represents the weight of the variable xj on the principal component PCi, and xj is the jth variable in the data matrix X. The principal components are ordered such that the first component PC1 receives the most significant variation in the data, the second component PC2 the second most significant variation, and so on. The reduced dimensionality of the dataset is indicated by the number of principal components, represented by k.

Results and Discussion

The descriptive statistics of tomato prices across the eight selected markets show considerable variation in price levels over the study period. Among all markets, Kolkata recorded the highest average price of Rs. 2,542.48 per quintal, followed by Bangalore (Rs. 1,704.55) and Madanapalle (Rs. 1,599.41), while Kolar (Rs. 1,170.22) and Nashik (Rs. 1,178.01) reported the lowest average prices, indicating relatively higher prices in major consuming markets over producing markets. The standard deviation was highest in Madanapalle (Rs. 1,391.47) and Bangalore (Rs. 1,302.28), indicating greater price volatility in these markets, whereas

Table 1: Descriptive statistics of prices and arrivals for various markets

Statistical Measures	Bangalore	Chandigarh	Kolkata	Madanapalle	Kolar	Solan	Nashik	Azadpur
Average price (Rs./Quintal)	1704.55	1463.19	2542.48	1599.41	1170.22	1595.11	1178.01	1475.15
Kurtosis	7.21	11.79	0.51	23.97	15.76	6.65	16.58	9.04
Skewness	2.23	2.62	0.95	4.09	3.08	1.87	3.18	2.26
Standard Deviation	1302.28	768.47	1297.39	1391.47	835.86	742.04	765.54	841.52
Jarque BeraTest	18.82	52.39	4.93	253.26	100.30	13.65	112.41	28.50

Kolar (Rs. 742.04) and Solan (Rs. 765.54) exhibited relatively more stable prices. All markets showed positive skewness values, ranging from 0.95 in Kolkata to 4.09 in Madanapalle. Similarly, high kurtosis values, particularly in Madanapalle (23.97), Nashik (16.58), and Kolar (15.76), indicate distributions with heavier tails and a greater likelihood of extreme price observations than would be expected under a normal distribution. The Jarque-Bera test statistics indicates that the price distributions in all selected markets deviate from normality, with the highest value observed in Madanapalle (253.26), Nashik (112.41), and Kolar (100.30). These results, together with the high skewness and kurtosis values, suggested the presence of asymmetric distributions and frequent extreme price observations across the markets

Seasonality Indices

The seasonal indices (SI) presented in Table 2 present distinct and consistent patterns of price seasonality in tomato markets. Prices remain markedly subdued during (January through April), with SI values consistently below unity across nearly all markets. For instance, Kolkata showed SI values as low as 0.49 in February and 0.50 in March, while Nashik and Chandigarh similarly exhibited indices in the range of 0.58-0.80 during this period, indicating that tomato prices during these months fall well below the annual average. A notable change occurred from May onward, as prices begin to rise sharply across most markets, till July, which emerged as the peak-price month across all eight markets. SI values in July range from a relatively moderate 1.06 in Solan to a high of 1.89 in Nashik, with Madanapalle (1.67), Kolar (1.66), Kolkata (1.60), Chandigarh (1.61), and Azadpur (1.62) all showing seasonal peaks, indicating less supply caused by the summer heat and monsoon-induced crop damage and transportation disruptions. Solan, however, shows a higher price in September (SI = 1.93). Following the July peak, prices generally moderate during August and September in most markets, though they remain above or near unity in several locations, before declining again toward year-end. November and December showed moderate indices in markets such as Chandigarh (1.34 and 0.92), Kolkata (1.28 and 0.94), and Azadpur (1.27 and 0.91).

Table 2: Instability and seasonality of Tomato prices in selected markets

Months	Bangalore	Chandigarh	Kolkata	Madanapalle	Kolar	Solan	Nashik	Azadpur (Delhi)
	SI	SI	SI	SI	SI	SI	SI	SI
Jan	0.91	0.80	0.64	0.69	0.88	0.86	0.62	0.75
Feb	0.60	0.72	0.49	0.57	0.61	0.82	0.58	0.67
Mar	0.59	0.70	0.50	0.65	0.56	0.83	0.70	0.70
April	0.74	0.69	0.58	0.74	0.68	0.91	0.70	0.69
May	1.26	0.59	1.00	1.16	1.17	0.67	0.95	0.50
June	1.35	0.99	1.19	1.32	1.21	0.73	1.37	0.78
July	1.46	1.61	1.60	1.67	1.66	1.06	1.89	1.62
Aug	1.01	1.35	1.27	1.23	1.20	1.04	1.45	1.42
Sept	0.72	1.11	1.14	0.89	0.96	1.93	0.86	1.26
Oct	0.97	1.20	1.29	0.89	0.96	0.99	0.87	1.31
Nov	1.21	1.34	1.28	1.14	1.03	1.15	1.07	1.27
Dec	1.16	0.92	0.94	0.96	0.95	0.96	0.84	0.91

SI= Seasonality index

Table 3: ADF and PP test to check the stationarity of the data

Markets	Augmented Dickey-Fuller (ADF)		Phillips-Perron (PP)
	Level	1st difference	Level
Bangalore	-5.88***	-6.68***	-6.37***
Chandigarh	-5.473**	-7.46***	-6.42***
Kolkata	-1.26 (0.65)	-7.95***	-4.78***
Azadpur	-5.74***	-7.12***	-6.41***
Madanapalle	-7.56***	-6.46***	-8.30***
Kolar	-8.62***	-5.25***	-5.86***
Solan	-4.79***	-6.30***	-6.59***
Nashik	-2.32 (0.17)	-4.93***	-5.87***

*Note: *** and ** indicate significance levels at 1% and 5% respectively*

Shrestha *et al*., (2014) also found a high price fluctuation in the tomato price during June-October and a low price during January-April each year. Similarly, Guleria *et al*., (2022) found that farmers received above-average prices from August to November. Further, (Kaur *et al*., 2021; Sidhu *et al*., 2010) observed that the markets exhibited higher seasonal indices during July, August, September, and November.

Augmented Dickey-Fuller test (ADF)

It is essential to analyse whether the variables are stationary to avoid inaccurate results and to verify their co-integration. Hence, order of integration verification is required, as co-integration is not possible when variables exhibit a unit root. This was assessed using stationarity tests.

The ADF test was applied to determine whether the price series was stationary. The ADF results indicate that Bangalore, Chandigarh, Azadpur, Madanapalle, Kolar and Solan were stationary at the level, whereas Kolkata and Nashik became stationary after first differencing (Table 3). The Phillips–Perron test confirmed these findings. This was validated by performing the Phillips-Perron test, which confirms that the data were stationary and not affected by unit root issues. Therefore, the co-integration analysis can proceed.

Johansen co-integration test

The Johansen co-integration test was used to determine the level of integration among tomato markets (Table 4). The unrestricted co-integration rank test shows that all the equations are co-integrated in trace statistics, and the presence of at least three co-integrating equations in maximum Eigen value at 1 per cent and 5 per cent level of significance, respectively, indicating that tomato prices in the market had long-run equilibrium, indicating the consistency of price linkages across markets, i.e., Bangalore, Chandigarh, Kolkata, Azadpur, Madanapalle, Solan, Kolar, and Nashik. The presence of long-run equilibrium relations or cointegration between markets was also observed by (Vasanthi *et al*., 2017).

Granger Causality test

The pairwise Granger causality analysis at lag 2 reveals a heterogeneous pattern of price transmission among the selected markets (Table 5).

The result indicates that while several markets exhibited unidirectional price transmission, Nashik did not show any

Table 4: Unrestricted Cointegration Rank Test

Null hypothesis	Eigen value	Trace statistics	5% Critical value	Max-Eigen statistics	5% Critical value
None	0.49	273.95***	159.53	92.45***	52.36
At most 1	0.29	181.50***	125.62	47.86**	46.23
At most 2	0.27	133.64***	95.75	42.86**	40.08
At most 3	0.19	90.78**	69.82	30.01	33.88
At most 4	0.16	60.77***	47.86	24.07	27.58
At most 5	0.14	36.71***	29.80	21.15**	21.13
At most 6	0.06	15.55**	15.49	8.44	14.26
At most 7	0.05	7.13***	3.84	7.13**	3.84

*Note: *** and ** denotes rejection of the hypothesis at 1% and 5% respectively*

Table 5: Results of pairwise granger causality

Lag=2	Bangalore	Chandigarh	Kolkata	Madanapalle	Azadpur	Kolar	Solan	Nashik
Bangalore	X	→	→	→	→	X	→	→
Chandigarh	X	X	↔	X	X	X	→	→
Kolkata	X	↔	X	→	↔	↔	↔	→
Azadpur	X	X	↔	X	X	X	→	→
Madanapalle	X	→	X	X	→	X	→	→
Kolar	X	→	↔	→	→	X	→	→
Solan	→	X	→	X	X	X	X	X
Nashik	X	X	X	X	X	X	X	X

Note: ↔ = Bidirectional, → = Uni-directional, X = no relationship

causal relationship with the selected markets, suggesting weak short-run market integration. Bangalore and Kolar emerged as the major transmitters of price information by exerting unidirectional influence on the largest number of markets. In contrast, Kolkata exhibited multiple bidirectional causal relationships with Chandigarh, Azadpur, Kolar, and Solan, highlighting its role as the most interconnected market and an important centre for reciprocal price discovery.

Principal component analysis (PCA)

The PCA model is applied to analyse the possible relationship between the selected markets. It examined whether all eight markets actually move together as a single system, or are they driven by separate, independent forces. PCA answers this by looking at patterns of co-movement across all eight-price series at once. The Principal Component Analysis revealed that the price movements across all eight tomato markets, both producing and consuming markets, are governed by a single dominant common factor (Table 6). With an eigenvalue of 6.05, the first principal component alone explained 76 per cent of the total price variation, and since no other component met Kaiser's criterion of eigenvalue ≥ 1, only this one component was retained for analysis. The near-uniform and positive loadings of all eight markets on this component (ranging from 0.32 to 0.38) indicated that tomato prices across Bangalore, Chandigarh, Kolkata, Azadpur, Madanapalle, Kolar, and Solan move unidirectionly, driven by a shared national price signal rather than isolated regional dynamics. The relatively higher loadings of Kolkata (0.38), Kolar (0.37), and Azadpur (0.37) further showed their role as the primary drivers of this common price movement. Collectively, the PCA results corroborate the findings of the Johansen cointegration and Granger causality tests, confirming that the selected tomato markets are well integrated and that a single price-determining force centred on the key wholesale market governs price behaviour across the entire market system. Although Nashik did not exhibit any significant short-run Granger causal relationship with the other markets, its positive loading on the first principal component and its inclusion in the cointegrated system suggest that it remains integrated with the selected markets

Table 6: Results of principal component analysis

Variable	Comp1	Comp2	Comp3	Comp4	Comp5	Comp6	Comp7	Comp8
Bangalore	0.36	0.36	-0.41	0.11	-0.07	0.32	0.27	-0.61
Chandigarh	0.34	-0.47	0.48	-0.07	-0.01	0.50	0.31	0.02
Kolkata	0.38	0.01	0.09	-0.01	-0.61	-0.53	0.42	0.15
Azadpur (Delhi)	0.37	-0.34	0.12	0.13	-0.16	-0.20	-0.68	-0.43
Madanapalle	0.32	0.53	0.55	0.28	0.45	-0.18	0.01	0.03
Kolar	0.37	0.33	-0.17	-0.09	-0.27	0.39	-0.41	0.57
Solan	0.34	-0.38	-0.47	0.48	0.41	-0.14	0.12	0.31
Nashik	0.34	-0.03	-0.14	-0.81	0.40	-0.22	0.01	-0.02
Eigen values	6.05	0.69	0.38	0.36	0.23	0.15	0.09	0.05
Proportion of variation explained	0.76	0.09	0.05	0.05	0.03	0.02	0.01	0.01
Cumulative variation explained				0.76				
Total no of observations				144				

in the long run.

Conclusions and Policy Implications

The study analysed price transmission and spatial integration among eight major tomato markets in India. Seasonality analysis showed prices peaked in July-August, indicating seasonal vulnerability. The ADF and Phillips-Perron tests confirmed stationarity, while Johansen's cointegration test revealed strong long-run equilibrium relationships among all selected markets. The Granger causality analysis identified Bangalore and Kolar as the principal transmitters of price information, while Kolkata emerged as the most interconnected market through multiple bidirectional causal relationships. Moreover, the PCA confirmed that a single component with an eigenvalue of 6.05 explained 76 per cent of total price variation, with all markets loading positively. These findings suggested that price stabilization policies should prioritize Bangalore and Kolar, as they are the major transmitters of price information to other markets. Simultaneously, strengthening market intelligence and price monitoring through Kolkata, the most interconnected market, would improve price discovery and information flow. Investments in cold chain infrastructure and improved market linkages, particularly for Nashik and Madanapalle, are essential to enhance market integration. In addition, promoting tomato processing units and strengthening digital market information systems would help reduce seasonal price volatility and improve farmers' returns.

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