ISSN: 2456-1452
NAAS Rating (2025): 4.49
Maths 2025; 10(7): 172-181

https://www.mathsjournal.com
Received: 21-06-2025
Accepted: 24-07-2025

Ajay Sharma
Department of Mathematics & Statistics, Chaudhary Charan Singh Haryana Agricultural University (CCS HAU), Hisar, Haryana, India

Joginder Kumar
Department of Statistics, Central University of Haryana, Mahendergarh, Haryana, India

Corresponding Author:
Ajay Sharma
Department of Mathematics & Statistics, Chaudhary Charan Singh Haryana Agricultural University (CCS HAU), Hisar, Haryana, India

Market integration and price dynamics of onions in India

Ajay Sharma and Joginder Kumar

Abstract
Onion is a staple crop in India with significant economic and nutritional value, the market is often characterized by price volatility and spatial disparities due to perishability, regional supply-demand mismatches, and infrastructure gaps. Understanding regional price linkages is vital for ensuring efficient market functioning and farmer welfare. This study investigates the spatial price dynamics of onion across major regional markets in India using advanced multivariate time-series econometric techniques, including the Johansen cointegration test, Granger causality analysis, and Impulse Response Function (IRF). The Johansen Cointegration test confirmed that the selected markets are integrated, and the Granger Causality test was conducted to understand the direction of price transmission among them. The results showed that some selected market pairs had a bidirectional price relationship, while most exhibited unidirectional transmission and a few had no causality association. This indicates that price changes in one market significantly influence others across selected markets and found that Nasik played a major role in transmitting price signals. This research provides valuable insights for policymakers, traders, and supply chain stakeholders by quantifying the extent of market integration and understanding how shocks in one market affect others.

Keywords: Cointegration, ADF, granger causality, impulse response function and price transmission

Introduction

Onion (*Allium cepa L.*) is one of the most widely cultivated and consumed vegetable crops in the world. Known as the "queen of the kitchen," it holds an important place in daily diets because of its flavouring and seasoning properties. Apart from its culinary uses, onion is valued for its nutritional and medicinal properties, as it contains sulphur compounds, flavonoids, and antioxidants that contribute to health benefits. Botanically, onion is a cool-season biennial crop grown as an annual, thriving best in mild temperatures under long-day conditions. It is consumed both in fresh and processed forms, making it an essential part of household diets and global trade.

At the global level, onion ranks as the second most important vegetable crop after tomato in terms of production. It is cultivated in more than 170 countries, highlighting its universal demand. According to FAO statistics, world onion production is estimated at around 100-105 million metric tonnes annually. The leading producers are China, India, Egypt, the United States, Turkey, and Pakistan. Onion is also a key commodity in international trade, with India, China, Egypt, and the Netherlands being major exporters to different parts of the world. Asia dominates onion cultivation, contributing more than two-thirds of global production. China is the largest producer, accounting for nearly one-fourth of the world's output. India follows closely, contributing about one-fifth of global production. Other Asian countries such as Pakistan, Bangladesh, Iran, and Turkey also play significant roles in onion production and consumption. In most Asian countries, onion is considered a staple vegetable and forms an integral part of everyday meals, which explains the high level of demand across the region.

The country is the second-largest producer in the world, with an annual production of about 30-32 million metric tonnes cultivated over nearly 1.6-1.7 million hectares of land. The major onion-producing states include Maharashtra, Madhya Pradesh, Karnataka, Gujarat, Bihar, Rajasthan, and Andhra Pradesh. India is also one of the leading onion exporters, with its major markets being Bangladesh, Malaysia, the United Arab Emirates, Sri Lanka, and Nepal.

However, onion production and marketing in India are highly vulnerable to seasonal fluctuations, storage limitations, and climatic variations, which often result in sharp price volatility. The government frequently intervenes by imposing minimum export prices, export bans, or buffer stock policies to stabilize domestic supply and control inflation. In this context, econometric techniques such as cointegration analysis help assess whether different regional markets are integrated in the long run, indicating common price trends and equilibrium. The Johansen cointegration test revealed long-term equilibrium relationships among major potato markets, suggesting efficient price transmission over time. Furthermore, Granger Causality analysis was employed to identify the direction of short-run causal influences between markets, indicating whether price movements in one market could predict changes in another. Complementing this, the Impulse Response Function (IRF) traced the dynamic effect of a one-time shock in one market on others, revealing the speed and magnitude of price adjustments across regions. Together, these tools offer deep insights into the spatial market integration and price behavior of onion in India, aiding policymakers in formulating market stabilization strategies and improving farmers' income security.

Several studies have explored price integration and volatility in agricultural markets using advanced time-series econometric tools such as cointegration, Granger causality, and impulse response analysis for example, Johansen (1988) [11] developed a multivariate test for multiple cointegrating vectors and the Dickey-Fuller approach. It allows testing of cointegrating vectors and adjustment speeds. This method is widely used for analyzing long-run relationships in non-stationary time series. Hatzigeorgiou *et al.* (2011) [9] analyzed the causal relationship between GDP, energy intensity, and CO_2 emissions in Greece from 1977 to 2007 using Johansen cointegration and Granger causality tests with a multivariate Vector Error Correction Model. The study found both unidirectional and bidirectional causalities among the variables. Belke *et al.* (2011) [4] studied the long-run relationship between energy consumption and real GDP for 25 OECD countries, considering energy prices. They found cointegration between international developments and the variables, indicating that global factors dominate the relationship. The study also showed that energy consumption was price inelastic, with bi-directional causality between energy consumption and economic growth. Saboori *et al.* (2012) [17] examined the relationship between economic growth and CO_2 emissions in Malaysia, using the ARDL method. They found an inverted-U relationship supporting the Environmental Kuznets Curve (EKC) hypothesis. The Granger Causality test revealed no short-run causality but confirmed unidirectional causality from economic growth to CO_2 emissions in the long run. Schaling *et al.* (2014) tested the ‘commodity currency’ hypothesis for the South African Rand using data from 1996 to 2010. They found no cointegration between commodity prices and exchange rates, though a strong unidirectional causality ran from commodity prices to the exchange rate. The relationship was negative and weaker than for other OECD commodity currencies. This suggested that commodity prices influenced the rand, but not vice versa, requiring dynamic risk management strategies. Shrestha *et al.* (2014) [19] studied the tomato market price cointegration in Nepal and found factors like poor infrastructure and marketing inefficiency as barriers. The study found that market integration improved efficiency and competitiveness. Prices in Chitwan and Morang markets were well integrated with Kathmandu. The price adjustment process was faster in the source market. Singh (2014) [20] studied market integration for onion and potato in South Gujarat and found that prices were influenced by arrivals and factors in both local and integrated markets. The study observed moderately high variations in prices and arrivals over the years for both crops. Forson *et al.* (2015) [6] examined the relationship between aid inflows and economic growth in Ghana, accounting for structural breaks and including corruption and trade as control variables. Using a VECM and Toda-Yamamoto approach, the study found a long-run unidirectional causality from EU aid to GDP growth and a short-run causality from trade to GDP. Corruption had no significant effect on growth, its negative impact on development. The findings show the need for anti-corruption measures, Ghana’s 2011 initiative to combat corruption. Bouri *et al.* (2017) [5] investigated the cointegration and nonlinear causality among gold, oil, and the Indian stock market using volatility indices. The study found that these markets were cointegrated and that gold and oil volatilities had a nonlinear and positive effect on the Indian stock market's volatility. There was a two-way inverse causal relationship between the volatilities of gold and oil. These findings were interconnectedness and complex dynamics among global commodities and the Indian financial market. Ahmed and Singla (2017) [1] explored market cointegration and price transmission in selected onion markets using Johansen cointegration, Granger causality, and impulse response 28 functions and revealed that all the market pairs of selected markets were well cointegrated and interdependent. Ozturk (2020) [16] examined the link between Turkey's grain markets and global grain markets using an error correction model. The study found that while wheat, barley, maize, and soybean markets showed weak cointegration, the rice market was not integrated at all. Price changes in the global market had a limited impact on domestic prices in both the short and long term. Adjustments to price shocks were also found to be slow. The study concluded that reducing government intervention and protectionist policies could help better integrate Turkey’s grain markets with international markets. Sapnken *et al.* (2020) [18] analyzed kerosene and LPG consumption trends in Cameroon from 1994 to 2014 using ARDL and Granger causality methods. They found a long-run equilibrium between fuel use, prices, income, and urbanization, with a clear shift from kerosene to LPG. A bidirectional causality between LPG use and income suggests LPG consumption supports economic growth, unlike kerosene. Katoch and Singh (2022) [12] studied the market integration and price causality among major potato markets in West Bengal. Cointegration results show long-run integration, with Burdwan as the price leader through Granger causality. High instability and seasonal variation necessitate a robust marketing system in Burdwan to equalize prices across markets. Mudzunga (2023) [15] examined spatial market integration across major produce markets (Cape Town, Bloemfontein, Durban, and Johannesburg) using price data. Cointegration and Error Correction Model (ECM) results indicated market relationship, with price equilibrium within a month, and well-integrated onion markets. Ajmal *et al.* (2024) [2] emphasized that societal development is closely linked to food, livelihood, nutrition, and healthcare. By analyzing monthly wholesale prices using tools like CAGR, seasonality index, and ARCH-GARCH models, the study revealed volatility in TOP crops (tomato, onion, and potato) in West

Bengal. Out of these, onion exhibited the greatest price fluctuation.

Data Sets

The wholesale prices of onion often go up and down throughout the year in India. This is mainly because of changes in the weather, monsoons, pest problems, and supply and demand issues. The change in prices not only affect the cost of living by raising inflation but also hurt farmers' income and make it harder for people to afford these basic vegetables. The situation is getting worse due to possible El Niño effects and a lack of proper cold storage facilities. Because of this, controlling the fluctuations in prices of onion crops have become an important issue for the government to tackle. So, reliable and accurate volatility forecasting methodology can be effective way out to both the Government as well as farmers. Keeping these points in view, the monthly wholesale price data of onion crops have been collected from Agricultural Marknet. The agricultural produce market committees (APMCs) maintain data on daily, weekly, monthly and yearly basis for prices and arrivals of agricultural commodities. The monthly average wholesale prices of onion crops from Jan-2010 to Dec-2023 for the selected markets have been collected from agriculture marknet (Source: https://agmarknet.gov.in/*)* of India.

Stationarity and Non-stationarity

Time series data are made up of observations taken over time and are considered to come from random processes that follow certain patterns. When working with time series, it is usually assumed that the data are *stationary*. Stationarity means that the average value (mean) and the spread (variance) of the data stay the same over time. Also, the relationship between values at different time points (covariance) should depend only on how far apart the time points are, not on the actual time. In this study, the idea of *weak stationarity* is used, which means the data are considered stationary if the mean, variance, and covariance don't change with time. A time series is called *non-stationary* when it's mean or variance (or both) change over time. One of the main reasons for non-stationarity is the presence of a *unit root*, which indicates a lack of stability in the data over time.

Unit Root

Any data sequence that includes one or more characteristic roots equal to one is known as a *unit root process*. The most basic model that can have a unit root is the AR (1) model (autoregressive model of order one). For example, take the following AR (1) model, which shows how a value in the series depends on its previous value.

$$Y_t = \rho Y_{t-1} + X_t^{\prime}\alpha + e_t \quad (1)$$

Where X_t are optional exogenous regressors which may consist of constant or a constant and trend, ρ and α are parameters to be estimated and the $e_t$denotes a serially uncorrected white noise error term with a mean of zero and a constant variance. If $\rho = 1$, equation (3.3.1) becomes a random walk without drift model, that is, a non-stationary process. When this happens, we face what is known as the unit root problem. This means that, we are faced with a situation of non-stationarity in the series. If, however, ρ <1, then the series Y_t is stationary. The stationarity of the series is important because correlation could persist in non-stationarity time series even if the sample is very large and may result in what is called spurious regression.

Augmented Dickey-Fuller (ADF) Tests

The basic idea behind the ADF unit root test for non-stationary is to simply regress Y_t on its (one period) lagged value Y_{t-1} and find out the estimated ρ is statistically equal to one or not. Equation (1) can be manipulated by subtracting Y_{t-1} from both sides to obtain

$$Y_t - Y_{t-1} = (\rho\text{-}1)\, Y_{t-1} + X_t^{\prime}\delta + e_t \quad (2)$$

$$\Delta Y_t = \alpha Y_{t-1} + X_t^{\prime}\delta + e_t \quad (3)$$

Where $\alpha = \rho$ - 1 and Δ is first difference operator.

In practice, instead of estimating equation (1), we shall estimate equation (3) and test for the null hypothesis $\alpha = 0$ against the alternative of $\alpha \neq 0$. If $\alpha = 0$, then ρ = 1, meaning that we have a unit root problem and the series under consideration is non-stationary. The decision to reject or not to reject the null hypothesis of $\alpha = 0$ is based on the Dickey-Fuller (DF) critical values of the τ (tau) statistic. The DF test based on an assumption that the error terms e_t are uncorrelated.

However, in practice, the error terms in the DF test usually show evidence of serial correlation. To solve this problem, Dickey and Fuller have developed a test known as the ADF test. In the ADF test, the lags of the first difference are included in the regression equation in order to make the error term e_t white noise and the regression equation is presented in the following form:

$$\Delta Y_t = \alpha Y_{t-1} + \sum_{i=1}^{k} \beta_1 \Delta Y_{t-i} + e_t \quad (4)$$

Where k denotes the lag length. In addition to ADF test, we have also used the Phillips - Perron (PP) unit root test

Phillips-Perron (PP) test

Phillips and Perron (1988) introduced an alternative method of controlling for serial correlation when a unit root is tested. The PP method was used to estimate the non-augmented DF test equation (3), and modification was done to the t-ratio of the α coefficient. So, that serial correlation had no effect on the asymptotic distribution of the test statistic. The PP test is based on the statistic:

$$\tilde{t_\alpha} = t_\alpha \left(\frac{\gamma_0}{f_0}\right)^{\frac{1}{2}} - \frac{T(f_0-\gamma_0)(se(\hat{\alpha}))}{2 f_0^{1/2} s} \quad (5)$$

Where, $\hat{\alpha}$ is the estimate and t_α is the t-ratio of α, se ($\hat{\alpha}$) is the coefficient standard error and s is the standard error of the test regression. In addition, γ_0 is a consistent estimate of the error variance in equation (2). The remaining term, f_0 is an estimator of the residual spectrum at frequency zero.

Testing of Cointegration

In case of non-stationarity of the time series, cointegration provides appropriate statistical techniques to investigate if there is a statistically significant relationship between the non-stationary time series. Accordingly, the first steps of our approach include determination of non-stationary nature of the price indices Y_t used for our analysis. In time series econometrics, it is said that price indices are integrated of order one denoted by Y_t ~ I (1) and first difference of price indices are integrated of order zero denoted by ΔY_t ~ I (0).

When price indices are found to be non-stationary in levels but stationary in first difference, cointegration tests may be applied. In this study order of integration of price is tested by using ADF and PP test.

Johansen's Cointegration

To test the presence of cointegration using a single equation (i.e., Engle-Granger approach) becomes a bit restrictive. Let us consider a situation where we have *p*>2 variables in the model and p-1 of them are not weakly exogenous, then the single equation approach can be misleading, particularly if there is more than one cointegration relationship present. Thus, when the number of cointegration vectors is unknown and there is a need to allow all variables in the model to be potentially endogenous, the multivariate Vector Autoregressive (VAR) approach developed by Johansen (1988) is efficient. Johansen's procedure builds cointegrated variables directly on maximum likelihood estimation instead of relying on Ordinary Least squares (OLS) estimation. Johansen derived the maximum likelihood estimates using sequential tests for determining the number of cointegrating vectors. In fact, Johansen's procedure is nothing more than a multivariate generalization of the Dickey-Fuller test.

The Johansen cointegration procedure is based upon an unrestricted vector autoregressive (VAR) model specified in error-correction form as follows:

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \ldots + A_K Y_{t-K} + e_t \quad (6)$$

$$\Delta Y_t = \prod Y_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \, \Delta Y_{t-i} + e_t \quad (7)$$

Where, Y_t includes all p variables (for example prices of various vegetables markets) of the model which are ~ I (1),

Π and Γ_i are parameter matrices to be estimated,

e_t is a vector of random errors which follow a Gaussian white noise.

The Johansen test for cointegration evaluates the rank (r) of the matrix Π. If r = 0, all variables are I (1) and thus not cointegrated. In case 0 < r < p, there exist r cointegrating vectors. In the third case, if r = p all the variables are I (0) and thus stationary, and any combination of stationary variables will be stationary. Π represent the long response matrix and is defined as the product of two matrices: θ and β', of dimension (p × r) and (r × p), respectively. The β matrix contains the long-run coefficients of the cointegrating vectors, θ is known as the adjustment parameter matrix and is similar to an error correction term.

The Johansen cointegration method estimates the Π matrix through an unrestricted VAR and tests whether one can reject the restriction implied by the reduced rank of Π. Two methods of testing for reduced rank of Π are the trace test and the maximum eigen value test, respectively:

$$\lambda_{trace} = -T \sum_{i=r+1}^{n} \ln(1 - \hat{\lambda}_i^{2}) \quad (8)$$

$$\lambda_{max}(r, r+1) = -T ln(1 - \hat{\lambda}_{r+1}) \quad (9)$$

Where, λ_i is the estimated values of the ordered eigen values obtained from the estimated matrix Π and T is the number of the observations after the lag adjustment. The trace statistics test the null hypothesis that the number of distinct cointegrating vectors (r) is less than or equal to r against a general alternative. The maximum eigen value tests the null hypothesis that the number of cointegrating vectors is r against the alternative of r + 1 cointegrating vectors.

Granger Causality Test

The notion of the Granger causality is that if the two variables are integrated of order one, i.e., I (1), then the most accepted way to know the causal relation between them is the Granger causality proposed by Granger, (1969). The present study also performed Granger causality test which explained that the wholesale price in market A causes the price in market B if and only if the past values of market A provide additional information for the forecast of market B. the testing procedure of the Granger Causality involves three steps. In the first step, order of cointegration was tested applying the Augmented Dickey-Fuller test. After confirming the integration, Johansen and Juselius (1990) maximum likelihood approach was used to comprehend the cointegration between the markets. The Johansen cointegration test explained that if cointegration exist among the variables, then Granger causality must also exist either unidirectional or bidirectional. The Granger Causality involves estimation of the simple form of vector autoregressive model (VAR) and is presented as follows:

$$P_t^A = \sum_{i=1}^{m} \alpha_i P_{t-1}^A + \sum_{j=1}^{m} \beta_i l P_{t-j}^B + \mu_{1t} \quad (10)$$

$$P_t^B = \sum_{i=1}^{n} \gamma_i P_{t-i}^{SB} + \sum_{j=1}^{n} \partial_i P_{t-j}^A + \mu_{2t} \quad (11)$$

Where, P_t are the wholesale prices and scripts A and B indicate the two separate markets, t is the time trend, μ_A and μ_B are the error terms of both the model.

The above mentioned two equations with respect to market A and B can be jointly tested using OLS and then conduct a F-test for the three different expression.

Case I: $[\delta_{11}, \delta_{12}, \delta_{13} \ldots \ldots \ldots . . \delta_n] \neq 0$ and
$[\partial_{21}, \partial_{22,} \partial_{23}, \ldots \ldots . . \partial_n]=0$

Case I indicates the unidirectional causality from P_t^B to P_t^A denoted as $P_t^B \rightarrow P_t^A$

Case II: $[\delta_{11}, \delta_{12}, \delta_{13} \ldots \ldots \ldots . . \delta_n] = 0$ and
$[\partial_{21}, \partial_{22,} \partial_{23}, \ldots \ldots . . \partial_n] \neq 0$

Case II indicates the unidirectional causality from P_t^A to P_t^B denoted as $P_t^A \rightarrow P_t^B$

Case III: $[\delta_{11}, \delta_{12}, \delta_{13} \ldots \ldots \ldots . . \delta_n] \neq 0$ and
$[\partial_{21}, \partial_{22,} \partial_{23}, \ldots \ldots . . \partial_n] \neq 0$

Case III indicates the bidirectional causality from P_t^A to P_t^B denoted as $P_t^A \leftrightarrow P_t^B$

When the sets of market A and B coefficients are statistically significantly, it is said to be feedback, or bilateral causality (Gujarati, 2003) [8]. Unidirectional causality from market A to market B is indicated if the estimated coefficient on the lagged of market B is statistically different from zero and vice versa

Impulse Response Function

The Granger causality test only provides the direction of causality for the specified time period. But it does not show how a shock impacts future values. In contrast, the impulse response function traces how a shock, occurring at a specific time point t_0, moves through the system over time (Kirchgassner *et al.*, 2012) [13]. The Generalized Impulse Response Function (GIRF) was first introduced by (Koop *et al.*, 1996) [14], and since then, several researchers have contributed to advancing both its theoretical framework and practical applications. The existing study also applied the generalized impulse response as given below:

$$IRF_{t+k} = (\mu, P_t, P_{t-1} \ldots\ldots..) = E/P_{t+k}/P_t = P_t + \mu, \quad (12)$$

$$P_{t-1} = P_{t-1} \ldots\ldots.] - E[\frac{P_{t+k}}{P_t} = P_{t,}P_{t-1} = P_{t-1}] \quad (13)$$

Where, IRF_{t+k} = Impulse response Function, lower case letters i.e., p represent realized values, and u is the impulse shock P_{t-1} is the history.

Results and Discussion

Onion is important crop that often shows high fluctuations in prices, affecting both farmers and consumers. This section of the study looks at how onion prices move across different markets, and how they are linked to each other. Tools like Granger causality, cointegration, and impulse response were used to see which markets lead in price changes and how other markets respond. The goal is to understand if onion markets are well connected like tomato markets, and how price changes in one market affect the others.

The descriptive statistics and time series plot of the time series data is given are follows:

Table 1: Descriptive Statistics of monthly wholesale prices (Rs/Qtl) of onion for selected markets

Descriptive Statistics	Haryana	Indore	Delhi	Nasik	Ahmedabad	Bangalore
Mean	1327.93	973.75	1444.17	1254.17	1254.73	1528.34
Median	1280.74	894.25	1277.67	1075.85	1168.75	1382.25
Maximum	2692.63	2049.50	3162.33	3188.94	2516.00	3210.00
Minimum	486.90	334.00	541.00	318.47	456.50	605.00
S. D.	489.95	415.68	664.30	719.97	522.06	668.63
Jarque-Bera (P-value)	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	<0.01

In Table 1, the descriptive statistics of monthly wholesale prices of onion for selected markets have been given for the period January 2010 to December 2023. The highest average price ₹1528.34, ₹1444.17 per quintal was recorded in Bangalore and Delhi respectively. It may be due to large urban population and higher demand for fresh produce and involve more intermediaries (traders, wholesalers). The lower average price of ₹973.75, ₹1254.17 per quintal was recorded in Indore and Nasik respectively, as it is a part of strong onion producing belt or due to reduced transportation and middlemen costs. The minimum price of ₹ 318.47 per quintal and maximum price of ₹3210 per quintal was recorded in Nasik and Bangalore respectively. The wholesale price series of onion were found non-normal (<0.01) as per results of Jarque-Bera test shown in above table.

The time series plot of all the markets are depicted in Figure 1, which clearly indicate the non-stationarity behaviour of an onion price data.

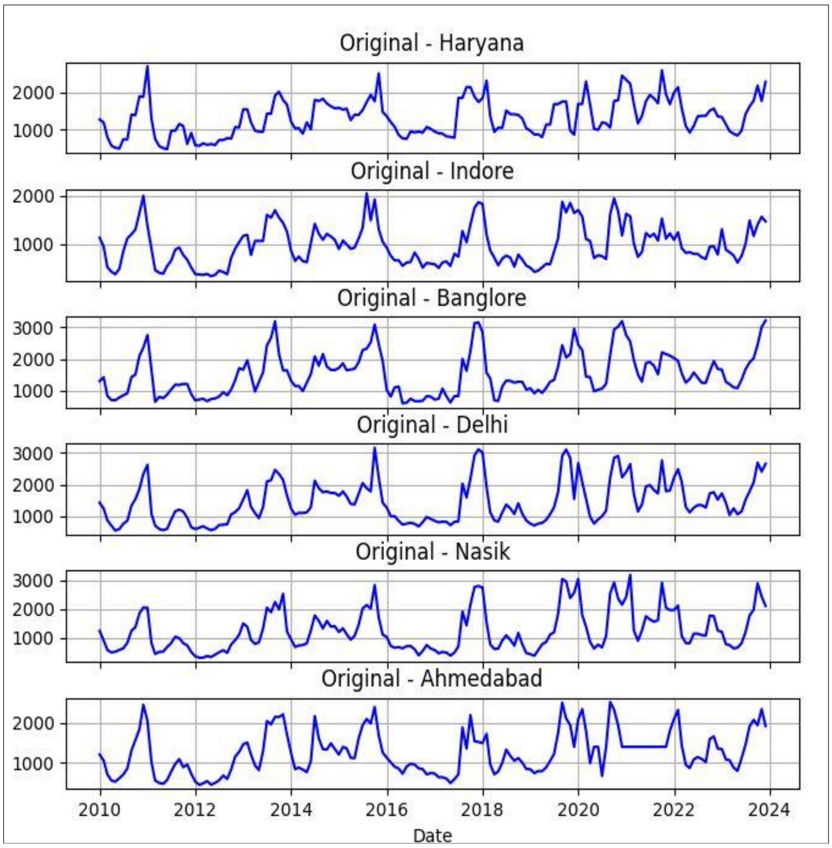

Fig 1: Time series plot of onion wholesale prices of selected markets

Test for Stationarity

To evaluate market integration, the initial step was to test for non-stationarity in the data to determine whether a cointegration method is suitable or not. In this study, the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test were used to evaluate the stationarity of the selected market price series (Table 2).

Table 2: Results of ADF and PP Tests for Unit root

Series Onion	Stationarity	Augmented Dickey Fuller Test (Schwarz Info Criterion)		Phillip-Perron Test (Bartlett Kernel)	
		t-statistic	P-value	t-statistic	P-value
Haryana	Level	-1.27	0.18	-0.67	0.42
	1st Difference	-13.65	<0.01	-15.88	<0.01
Indore	Level	-1.47	0.13	-1.49	0.12
	1st Difference	-12.69	<0.01	-12.69	<0.01
Delhi	Level	-1.43	0.14	-1.52	0.11
	1st Difference	-11.80	<0.01	-11.76	<0.01
Bangalore	Level	-1.39	0.15	-0.98	0.29
	1st Difference	-10.44	<0.01	-10.36	<0.01
Nasik	Level	-0.62	0.44	-1.98	0.45
	1st Difference	9.45	<0.01	-11.881	<0.01
Ahmedabad	Level	-1.46	0.13	-1.53	0.11
	1st Difference	-11.70	<0.01	-11.70	<0.01

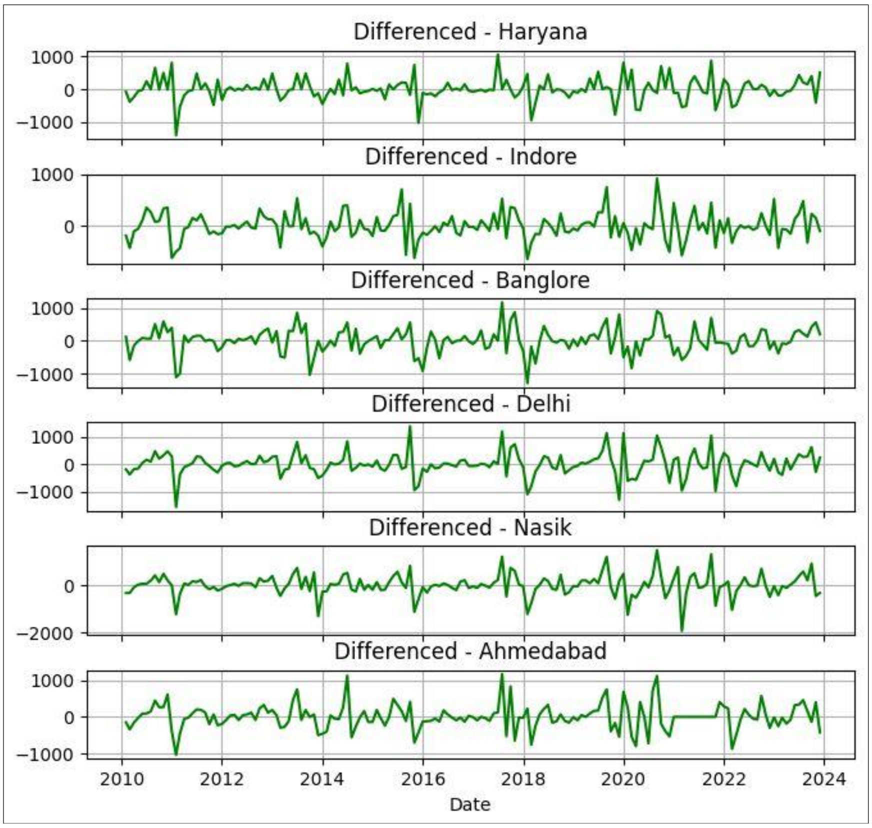

Fig 2: Time series plot of onion wholesale prices after 1st differencing

All selected onion price series were found to be non-stationary at level, according to both Augmented Dickey Fuller (ADF) test and Philips-Perron (PP) test as presented in Table 2. This indicates that the series exhibit statistical properties that change over time, possibly due to random (stochastic) or predictable (deterministic) patterns. However, after first differencing, the series became stationary, as confirmed by both tests. This transformation indicates that the data is suitable for cointegration analysis. The stationarity of differenced data is shown in Figure 2.

Johansen's Cointegration Test

The results of Johansen's Maximum Likelihood approach using both the Maximum Eigenvalue and Trace statistics are presented in Table 3. The Johansen procedure was applied to analyse cointegration among selected onion markets in India through a three-step process. First, the appropriate lag length was determined using the Schwarz Information Criterion (SIC). Second, the order of integration was confirmed through the Augmented Dickey-Fuller (ADF) test. In the third step, the Trace test and Maximum Eigenvalue test based on the Vector Autoregressive (VAR) model were applied to determine the presence of cointegrating vectors among the selected markets. The initial null hypothesis for both tests, which posits no cointegration ($r = 0$), was tested against the alternative hypothesis of at least one cointegrating relationship ($r \leq 1$). Both the Trace and Max Eigenvalue statistics rejected the null hypothesis, as their test values exceeded the 5% critical values, and the corresponding P-values were less than 0.05. This indicates the presence of one or more cointegrating equations in the VAR system.

Subsequently, the null hypotheses from r≤1 to r≥6, were also rejected for the Trace test, implying the existence of up to six cointegrating equations among the onion markets. The Max Eigenvalue test similarly identified six cointegrating vectors, reinforcing the evidence of strong market integration. These findings suggest that, despite being geographically dispersed and spatially segmented, the selected onion markets are well integrated, and price signals are effectively transmitted across markets, ensuring market efficiency. These results align with earlier studies by Kar *et al.* (2014) and Baeg and Singla (2014) [3], have also reported strong long-run price linkages in Indian agricultural markets.

Table 3: Johansen Cointegration in selected onion markets

H_0	H_1	Trace Statistic			Max-Eigen Statistic		
		Trace Statistic	0.05 Critical Value	P-value	Max-Eigen Statistic	0.05 Critical Value	P-value
r=0	r≥1	183.85*	95.75	<0.01	54.32*	40.07	0.01
r≤1	r≥2	129.53*	69.81	<0.01	45.62*	33.87	<0.01
r≤2	r≥3	83.91*	47.85	<0.01	30.52*	27.58	<0.01
r≤3	r≥4	53.38*	29.79	<0.01	25.93*	21.13	<0.01
r≤4	r≥5	27.44*	15.49	<0.01	16.38*	14.26	0.02
r≤5	r≥6	11.06*	3.84	<0.01	11.06*	3.84	<0.01

Note: * denotes rejection of null hypothesis at 5% level of significance

For the further study, we paired each market, resulting in fifteen bi-variate systems *viz*. Haryana-Ahmedabad, Haryana-Bangalore, Haryana-Delhi, Haryana-Indore, Haryana-Nasik, Ahmedabad-Bangalore, Ahmedabad-Delhi, Ahmedabad-Indore, Ahmedabad-Nasik, Bangalore-Delhi, Bangalore-Indore, Bangalore-Nasik, Delhi-Indore, Delhi-Nasik and Indore-Nasik. Since the data series are integrated at the same order, cointegrating techniques can be used to determine whether a stable long- run relationship exists between each pair. The results of Johansen's cointegration tests for each pair markets are presented in Table 4, using the trace statistic and maximum eigen value statistic.

Table 4: Results of Bi- variate Johansen's cointegration rank test for onion markets

	λ_{trace} Statistic	P-value	λ_{Max} Statistic	P-value
Haryana - Ahmedabad				
H_0: r=0 vs H_1: r≥1	129.14*	<0.01	74.82*	<0.01
H_0: r≤1 vs H_1: r≥2	54.31*	<0.01	54.31*	<0.01
Haryana - Bangalore				
H_0: r=0 vs H_1: r≥1	126.31*	<0.01	80.69*	<0.01
H_0: r≤1 vs H_1: r≥2	45.62*	<0.01	45.62*	<0.01
Haryana - Delhi				
H_0: r=0 vs H_1: r≥1	121.99*	<0.01	76.29*	<0.01
H_0: r≤1 vs H_1: r≥2	45.69*	<0.01	45.69*	<0.01
Haryana - Indore				
H_0: r=0 vs H_1: r≥1	114.08*	<0.01	72.62*	<0.01
H_0: r≤1 vs H_1: r≥2	41.46*	<0.01	41.46*	<0.01
Haryana - Nasik				
H_0: r=0 vs H_1: r≥1	120.16*	<0.01	79.35*	<0.01
H_0: r≤1 vs H_1: r≥2	40.81*	<0.01	40.81*	<0.01
Ahmedabad - Bangalore				
H_0: r=0 vs H_1: r≥1	115.47*	<0.01	67.94*	<0.01
H_0: r≤1 vs H_1: r≥2	47.53*	<0.01	47.53*	<0.01
Ahmedabad - Delhi				
H_0: r=0 vs H_1: r≥1	119.95	<0.01	70.37*	<0.01
H_0: r≤1 vs H_1: r≥2	49.58*	<0.01	49.53*	<0.01
Ahmedabad - Indore				
H_0: r=0 vs H_1: r≥1	127.34*	<0.01	81.18*	<0.01
H_0: r≤1 vs H_1: r≥2	46.15*	<0.01	46.15*	<0.01
Ahmedabad - Nasik				
H_0: r=0 vs H_1: r≥1	119.00*	<0.01	75.46*	<0.01
H_0: r≤1 vs H_1: r≥2	43.53*	<0.01	43.53*	<0.01
Bangalore - Delhi				
H_0: r=0 vs H_1: r≥1	125.72*	<0.01	78.42*	<0.01
H_0: r≤1 vs H_1: r≥2	47.30*	<0.01	47.30*	<0.01
Bangalore - Indore				
H_0: r=0 vs H_1: r≥1	110.84*	<0.01	67.92*	<0.01
H_0: r≤1 vs H_1: r≥2	42.92*	<0.01	42.92*	<0.01
Bangalore - Nasik				
H_0: r=0 vs H_1: r≥1	115.52*	<0.01	66.85*	<0.01
H_0: r≤1 vs H_1: r≥2	48.66*	<0.01	48.66*	<0.01
Delhi - Indore				
H_0: r=0 vs H_1: r≥1	109.68*	<0.01	62.93*	<0.01
H_0: r≤1 vs H_1: r≥2	46.74*	<0.01	46.74*	<0.01
Delhi - Nasik				

H_0: r=0 vs H_1: r≥1 H_0: r≤1 vs H_1: r≥2	122.20* 46.90*	<0.01 <0.01	75.30* 46.90*	<0.01 <0.01
Indore - Nasik				
H_0: r=0 vs H_1: r≥1 H_0: r≤1 vs H_1: r≥2	106.15* 46.01*	<0.01 <0.01	60.13* 46.01*	<0.01 <0.01

Note: * denotes rejection of null hypothesis at 5% level of significance

The trace statistic and maximum eigen value statistic have led to the same conclusion that all the fifteen markets pairs are co-integrated. In other words, we can say that all the six selected onion markets are well integrated and price signals are transferred from one market to the other to ensure efficiency. Thus, Johansen's cointegration tests have shown even though the selected onion markets in India are geographically isolated and spatially segmented, they are well-connected in terms of price of onion, demonstrating that the selected onion markets have long-run price linkage across them. This means that, selected onion markets price in India move closely together in the long-run. This also indicates that the onion marketing is an open market of which the forces of demand and supply are the determinant of the various market prices hence ensuring high efficiencies between spatial markets.

Granger Causality Test among the Selected Onion Markets: The causal relationship among the selected onion market prices was analysed using the Granger causality approach. This method identifies the direction of price transmission between various markets and provides insights into spatial arbitrage, which involves the physical movement of goods to balance out price disparities (Ghafoor *et al.*, 2009) [7]. The results of Granger's causality are shown in Table 5, which shows that all the five F- statistics for the causality tests of monthly wholesale prices of onion in India market are statistically significant. The null hypothesis of no Granger's causality was rejected for all selected markets of onion crop.

Table 5: Pair-wise Granger causality in selected onion markets

Null Hypothesis	F-statistic	P-value	Granger	Direction
Indore does not Granger Cause Haryana Haryana does not Granger Cause Indore	23.90* 3.06*	<0.01 0.04	Yes Yes	Bi-Directional
Delhi does not Granger Cause Haryana Haryana does not Granger Cause Delhi	15.22* 1.84	<0.01 0.16	Yes No	Uni-Directional
Bangalore does not Granger Cause Haryana Haryana does not Granger Cause Bangalore	15.04* 5.27*	<0.01 0.05	Yes Yes	Bi-Directional
Ahmedabad does not Granger Cause Haryana Haryana does not Granger Cause Ahmedabad	22.01* 5.36*	<0.01 0.05	Yes Yes	Bi-Directional
Nasik does not Granger Cause Haryana Haryana does not Granger Cause Nasik	30.74* 0.58	<0.01 0.55	Yes No	Uni-Directional
Delhi does not Granger Cause Indore Indore does not Granger Cause Delhi	3.02 6.67*	0.51 0.01	No Yes	Uni-Directional
Bangalore does not Granger Cause Indore Indore does not Granger Cause Bangalore	2.90 6.40*	0.57 0.02	No Yes	Uni-Directional
Ahmedabad does not Granger Cause Indore Indore does not Granger Cause Ahmedabad	5.19* 9.25*	0.06 0.02	Yes Yes	Bi-Directional
Nasik does not Granger Cause Indore Indore does not Granger Cause Nasik	13.81* 2.06	<0.01 0.13	Yes No	Uni-Directional
Bangalore does not Granger Cause Delhi Delhi does not Granger Cause Bangalore	7.56* 7.68*	<0.01 <0.01	Yes Yes	Bi-Directional
Ahmedabad does not Granger Cause Delhi Delhi does not Granger Cause Ahmedabad	5.43* 2.15	0.05 0.11	Yes No	Uni-Directional
Nasik does not Granger Cause Delhi Delhi does not Granger Cause Nasik	18.08* 2.23	<0.01 0.11	Yes No	Uni-Directional
Ahmedabad does not Granger Cause Bangalore Bangalore does not Granger Cause Ahmedabad	6.27* 6.48*	0.02 0.02	Yes Yes	Bi-Directional
Nasik does not Granger Cause Bangalore Bangalore does not Granger Cause Nasik	17.13* 0.53	<0.01 0.58	Yes No	Uni-Directional
Nasik does not Granger Cause Ahmedabad Ahmedabad does not Granger Cause Nasik	13.51* 1.21	<0.01 0.29	Yes No	Uni-Directional

Note: *denotes rejection of null hypothesis at the 5% level of significance

The lags of the dependent variable used to obtain white-noise residuals using the Schwarz Information Criterion (SIC)

The results of Granger's Causality revealed that unidirectional causality was found between market pairs; Delhi-Haryana, Nasik-Haryana, Indore-Delhi, Indore-Bangalore, Nasik-Indore, Ahmedabad-Delhi, Nasik-Bangalore, Nasik-Ahmedabad and Nasik Delhi and exists Bi-directional causality between Haryana-Ahmedabad, Haryana- Indore, Haryana-Bangalore, Ahmedabad-Indore, Bangalore-Delhi and Ahmedabad-Bangalore for monthly wholesale markets.

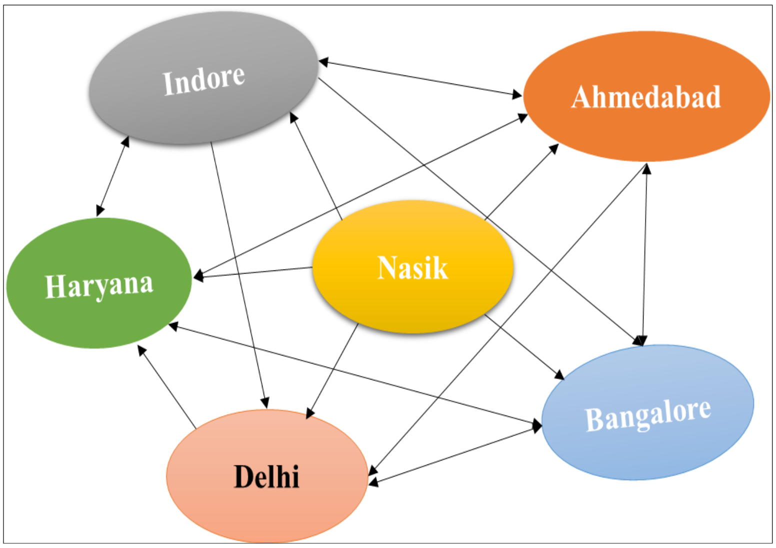

Fig 3: Granger Causality direction between selected markets pairs of onion

Figure 3, shows the Granger causality direction between selected market pairs for onion. The diagram highlights that Nasik acts as a central market with potential influence on several other markets, indicating its key role in price transmission. Markets like Haryana**,** Delhi**,** and Bangalore are closely connected, showing interdependencies, while Indore and Ahmedabad also demonstrate relevant linkages. This implies that Nasik may be a significant price-leading market in the onion supply chain. Bi-directional Granger causality was observed between Haryana-Ahmedabad, Haryana-Indore, Haryana-Bangalore, Ahmedabad-Indore, Bangalore-Delhi and Ahmedabad-Bangalore, despite the lack of geographic proximity, can be attributed to factors beyond spatial distance. In India, agricultural markets have become increasingly integrated through improved logistics, cold storage and digital trading platforms like the electronic National Agriculture Market (eNAM), enabling efficient price signal transmission across distant markets.

Impulse Response Function

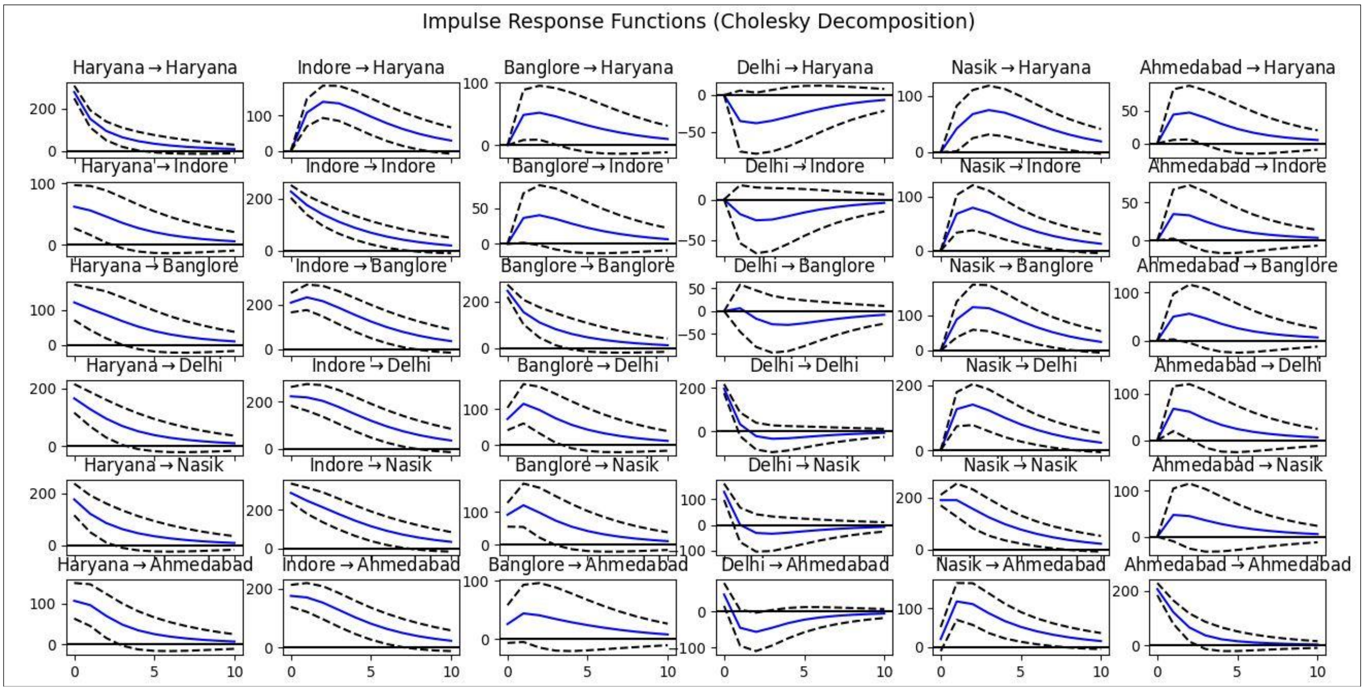

Fig 4: Impulse response function for selected markets of onion

The most effective way to interpret the implications of the models regarding price transmission patterns, causality, and market adjustments is by examining the time path of prices following external shocks, known as the impulse response function. The impulse response function illustrates how a one-unit or one standard deviation shock to a variable influences the current and future values of all endogenous variables within the system over a defined time frame. It captures how the dependent variables (endogenous variables) respond when a disturbance is introduced into the error term. The findings from the impulse response analysis, as presented in Figure 4, reveals the magnitude and duration of the impact that a standard deviation shock in one onion market has on the prices in all connected markets, observed over a span of ten months.

Conclusion

In the present study, the Johansen Cointegration, Granger Causality and Impulse Response Function have been used to forecast the volatility of prices onion crops in India. The cointegration analysis of onion crop revealed a long-term equilibrium relationship among selected markets, indicating that despite short-term fluctuations, prices tend to move together over time. For, onion crop, the presence of cointegration suggests that shocks in one market are likely to impact others. The Johansen cointegration test confirmed multiple co-integrating vectors, reinforcing inter-market connectivity. For example, the Nasik market showed a major influence on price movements across regions.

References

1. Ahmed M, Singla N. Market integration and price transmission in major onion markets of India. Econ Aff. 2017;62(3):405-417.
2. Ajmal S, Rohith S, Unniravisankar P, Nabay A. Price dynamics of tomato, onion and potato (TOP) in India. Asian J Agric Ext Econ Sociol. 2024;42:134-143.
3. Beag FA, Singla N. Cointegration, causality and impulse response analysis in major apple markets of India. Agric Econ Res Rev. 2014;27(2):289-298.
4. Belke A, Dobnik F, Dreger C. Energy consumption and economic growth: New insights into the cointegration relationship. Energy Econ. 2011;33(5):782-789.
5. Bouri E, Jain A, Biswal PC, Roubaud D. Cointegration and nonlinear causality amongst gold, oil, and the Indian stock market: Evidence from implied volatility indices. Resour Policy. 2017;52:201-206.
6. Forson JA, Buracom P, Baah-Ennumh T, Chen G, Carsamer E. Corruption, EU aid inflows and economic growth in Ghana: Cointegration and causality analysis. Contemp Econ. 2015;9(3):299-318.
7. Ghafoor A, Mustafa K, Mushtaq K. Cointegration and causality: An application to major mango markets in Pakistan. Lahore J Econ. 2009;14(1):85-113.
8. Gujarati DN, Porter DC. Basic econometrics. 4th ed. New York: McGraw-Hill; 2003.
9. Hatzigeorgiou E, Polatidis H, Haralambopoulos D. CO_2 emissions, GDP and energy intensity: A multivariate cointegration and causality analysis for Greece, 1977-2007. Appl Energy. 2011;88(4):1377-1385.
10. Johansen S. Statistical analysis of cointegration vectors. J Econ Dyn Control. 1988;12(2-3):231-254.
11. Kar A, Atteri RB, Kumar P. Marketing infrastructure in Himachal Pradesh and integration of Indian apple markets. Indian J Agric Mark. 2004;18(3):243-261.
12. Katoch S, Singh R. Cointegration and causality analysis in major potato markets of West Bengal. Indian J Agric Mark. 2022;36(1):169-180.
13. Kirchgässner G, Wolters J, Hassler U. Introduction to modern time series analysis. Berlin: Springer; 2012.
14. Koop G, Pesaran MH, Potter SM. Impulse response analysis in nonlinear multivariate models. J Econom. 1996;74(1):119-147.
15. Mudzunga N. Analysing onion market integration in major South African fresh produce markets, 2009-2019 [dissertation]. Thohoyandou: University of Venda; 2023.
16. Ozturk O. Market integration and spatial price transmission in grain markets of Turkey. Appl Econ. 2020;52(18):1936-1948.
17. Saboori B, Sulaiman J, Mohd S. Economic growth and CO_2 emissions in Malaysia: A cointegration analysis of the environmental Kuznets curve. Energy Policy. 2012;51:184-191.
18. Sapnken FE, Tamba JG, Ndjakomo SE, Koffi FD. Oil products consumption and economic growth in Cameroon households: An assessment using ARDL cointegration and Granger causality analysis. Int J Energy Econ Policy. 2020;10(6):510-523.
19. Shrestha RB, Huang WC, Ghimire R. Market price cointegration of tomato: Effects to Nepalese farmers. Int J Food Agric Econ. 2014;2(2):87-96.
20. Singh N. A study of integration of markets for onion and potato in South Gujarat. Int Res J Agric Econ Stat. 2014;5(2):241-244.