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Transmission of price shocks and volatility spillovers across major onion markets in India

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Abstract This paper studies the price transmission and volatility spillover effects in the major wholesale onion markets in India. It attempts to determine the extent to which price shocks and volatility are transmitted between markets. The persistence of volatility is high, and sudden supply or climate shocks trigger onion prices. Continual surveillance—especially in strategic markets like Lasalgaon, Pimpalgaon, and Bengaluru—can prevent extreme events by examining the extent of price influences and providing advance price signals. Early warning systems based on 'Big Data' and 'Artificial Intelligence' can help provide advance signals and prevent chaotic events.

Keywords Price transmission, multi-market volatility spillovers, vech

JEL codes Q11, Q13, Q18

The onion has emerged as one of the fastest growing high-value crops in India in recent years. After the potato, the onion is the most produced vegetable, at 22 million tonnes. Fluctuations in production have been slight, particularly after 2002–03 (Saxena and Chand 2017), but onion prices have been extremely volatile across the spatial and temporal dimensions (Sharma et al. 2011; Chengappa et al. 2012; Gummagolmath 2012; Kasturi 2014; Saxena and Chand 2017).

Price spikes became bigger and more frequent after 2009, and prices peaked in 2010, 2013, 2015, 2017 and 2019. The tomato, onion, and potato are the most price-sensitive commodities, but the instability of onion prices—49.3% during 2011–16—makes it the most vulnerable (Saxena et al. 2017). The price elasticity of demand for the onion is 0.1 (NCAER 2012). The demand rigidity is strong; the onion is an integral, almost indispensable, part of Indian diets, and a near-necessity.

The onion is grown in more than one season, and both annual and seasonal trends affect price formation and volatility. Extreme events deter farmers and consumers, and greatly concern policymakers and other stakeholders, particularly because the markets are perceived to be well integrated, and a price shock triggered in a market is transmitted to others with varying speed and intensity. Producers' markets represent the major markets in the major onion-producing states and metropolitan cities represent the major consumers' markets. The extent to which a price shock at a major producer or consumer market affects the price at another market indicates the importance of markets in terms of price transmission. The price transmission needs to be analysed, so that it can be controlled and prevented, and the price instability must be addressed and efforts made to include a more intensive modelling framework.

The degree of transmission of price volatility indicates whether markets are functioning predictably and how price signals are transmitted between markets. This paper examines the transmission of onion prices, considering the price linkages among producers' and consumers' markets; and it also examines the price volatility spillover effects between markets to determine the price volatility transmission.

Data and methodology

Data

The study is based on the price data of onions at selected markets and on the market arrival data. We compiled the data on the production and market arrival of onions from the website of the National Horticultural Research and Development Foundation (NHRDF). We used the vector autoregression (VAR) model to examine the price transmission. We applied the diagonal vector half (vech) model to capture the price volatility spillover between markets.

We selected 12 major wholesale onion markets based on the volume of onion arrivals, and based our analysis on time series weekly data on the prices at these markets from January 2005 to February 2017. Of these 12 markets, 4 were consumers' markets: Delhi, Mumbai, Chennai, and Kolkata. The rest were producers' markets: Lasalgaon, Pimpalgaon, Pune, and Solapur in Maharashtra; Bangalore (now Bengaluru) in Karnataka; Indore in Madhya Pradesh; Patna in Bihar; and Mahuva in Gujarat. For examining the multi-market price volatility spillover effects, we retained the five most important markets based on price transmission analysis and strategic importance. We obtained the price data from the NHRDF website.

Onions are grown in the winter (rabi season) in northern India, and in both summer (kharif) and rabi seasons in the southern and western states: Karnataka, Andhra Pradesh, Tamil Nadu, Maharashtra, and Gujarat (Gummagolmath 2012). Maharashtra produces the most onions in India, contributing about 30% of the production. Karnataka follows, and production is growing in Bihar and Madhya Pradesh (Table 1).

To examine the onion price series for stationarity, we conducted the Augmented Dickey–Fuller test (ADF) (Dickey and Fuller 1979), the Philips–Perron test (Phillips and Perron 1988), and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test (Kwiatkowski et al. 1992). The price series were stationary at level under all options with and without intercept and trend. We used the VAR model to study the price linkages.

Estimating vector autoregression (VAR)

We used the VAR model, a generalization of univariate autoregressive (AR) model, to capture linear dependencies among the multiple time series processes. A VAR model describes the evolution of a set of K

Table 1 Onion production by state and major market

	Production ('000 tonnes)			Major markets (Jan-Dec, 2017, arrival share in %)
	2014–15 (%)	2015–16 (%)	2016–17 (%)	
Major producing states				
Maharashtra	5,362 (28.3)	6,529 (31.2)	6,735 (30.0)	Lasalgaon (2.7), Pimpalgaon (3.0), Solapur (2.9), Pune (2.5)
Madhya Pradesh	2,842 (15.0)	2,848 (13.6)	3,722 (16.6)	Indore (1.4)
Karnataka	3,227 (17.0)	2,696 (12.9)	3,049 (13.6)	Bengaluru (5.4)
Gujarat	1,127 (6.0)	1,356 (6.5)	1,290 (5.8)	Mahuva (3.8)
Bihar	1,247 (6.6)	1,247 (6.0)	1,249 (5.6)	Patna (0.25)
Major consuming markets				
Delhi				2.1
Mumbai				2.2
Kolkata				1.1
Chennai				1.0

Note In Column 2 the figures in parentheses indicate the percentage share in total production; in Column 3 the figures in parentheses indicate the market share in country's onion arrivals.
Source National Horticultural Research and Development Foundation

variables (endogenous variables) over the same sample period ($t = 1, 2, ..., T$) as a linear function of only their past values. The corresponding individual univariate VAR model (with lag 2 in this case) for k (k=12 selected markets) time series sequences are given as

$$y_{1t} = \mu_1 + \phi_{11}^{(1)} y_{1,t-1} + \phi_{12}^{(1)} y_{2,t-1} + ... \phi_{1k}^{(1)} y_{k,t-1} + \phi_{11}^{(2)} y_{1,t-2} + \phi_{12}^{(2)} y_{2,t-2} + ... \phi_{1k}^{(2)} y_{k,t-2} + \varepsilon_{1t}$$

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$$y_{kt} = \mu_k + \phi_{11}^{(1)} y_{1,t-1} + \phi_{12}^{(1)} y_{2,t-1} + ... \phi_{1k}^{(1)} y_{k,t-1} + \phi_{11}^{(2)} y_{1,t-2} + \phi_{12}^{(2)} y_{2,t-2} + ... \phi_{1k}^{(2)} y_{k,t-2} + \varepsilon_{kt}$$

where, y_{it} denotes the market price for i[th] market at time t, μ is constant and ϕ_{it} are VAR coefficients, for each market for two lags (K X K, parameter matrices attached to the lagged values of y_{it}). The results are presented with only a one-week lag. ε_{it} is an error process.

Spillover effects between markets

In price analysis, estimating price volatility transmission is a complex task. There are several ways of specifying the multivariate generalized auto-regressive conditional heteroscedastic (MGARCH) model, and we use a diagonal vech model (Bollerslev et al. 1988) to better understand the conditional variance and covariance matrix, because this model is more flexible when H_t contains more than two variables (Scherrer and Ribarits 2007). The diagonal vech representation is based on the assumptions that the conditional variance depends on squared lagged residuals and the conditional covariance depends on the cross-lagged residuals and lagged covariances of other price series (Harris and Sollis 2003).

We apply the Baba–Engle–Kraft–Kroner (BEKK) (1,1) model (Engle and Kroner 1995) for individual series. The volatility pattern can be assessed by univariate specification of GARCH model of the form

$$h_t = c_0 + a_1\varepsilon^2_{t-1} + ... + a_p\varepsilon^2_{t-p} + b_1h_{t-1} + ... + b_qh_{t-q}$$

where, h_t is conditional variance of error term, p and q are the order of the GARCH model, ε^2_{t-1} are the lagged squared residuals. This can be transferred into a multivariate GARCH model of the resulting variance-covariance matrix H_t as

$$H_t = \begin{bmatrix} h_{11} & h_{12} \\ h_{21} & h_{22} \end{bmatrix} \quad \textit{for i=1,2}$$

Accordingly, the BEKK (1, 1) representation of variance of error term H_t is

$$H_t = C'_0C_0 + A'_{11}\varepsilon_{t-1}\varepsilon'_{t-1}A_{11} + B'_{11}H_{t-1}B_{11}$$

where, A_i and B_i are $n\times n$ parameter matrices and C_0 is a $n\times n$ upper triangular matrix. The parametrization of H_t as a multivariate GARCH, assuming that the information is available up to time t-1 i.e. φ_{t-1}, allows each element of H_t to depend on the q-lagged values of the squares and cross-products of ε_t as well as the p-lagged values of the elements of H_t. The elements of the covariance matrix follow a vector of the autoregressive moving average model (ARMA) in the squares and cross-products of the disturbances. The bivariate BEKK (1,1) model can be written as

$$H_t = C_0'C_0 + \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}' \begin{pmatrix} \varepsilon^2_{1,t-1} & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}\varepsilon_{1,t-1} & \varepsilon^2_{2,t-1} \end{pmatrix} \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} + \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix}' \begin{pmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22,t-1} \end{pmatrix} \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix}$$

The off-diagonal parameters in matrix B, b_{12} and b_{21}, measure the dependence of conditional price volatility between the markets. The parameters b_{11} and b_{22} represent the persistence of own-market volatility. The parameters a_{12} and a_{21} represent the cross-market effects and a_{11} and a_{22} represent the own-market effects. The significance level of each parameter indicates that the autoregressive conditional heteroscedastic (ARCH) effect or the generalized autoregressive conditional heteroscedastic (GARCH) effect is present and strong. The diagonal vech model can be written as

$$\text{vech}(H_t) = C + A\text{vech}(\varepsilon_{t-1}, \varepsilon'_{t-1}) + B\text{vech}(H_{t-1})$$

where vech denotes the vector-half operator. The diagonal elements of the matrix A (α_{ij}, where i=j) measure the influences from past squared shocks (‘innovation’ in the literature) on the current volatility (own-volatility shocks). The non-diagonal elements (α_{ij}, where i ≠ j) determine the cross-product effects of the lagged shocks on the current co-volatility (cross-volatility shocks). Similarly, the diagonal elements of matrix B (α_{ij}, where i=j) determine the influences from the past squared volatilities on the current volatility (own-volatility spillovers), and the non-diagonal elements (α_{ij} where $i \neq j$) measure the cross-product effects of the lagged co-volatilities on the current co-volatility (cross-volatility spillovers).

Onion price transmission

The price transmission between the producers' and consumers' markets shows that a change of one unit in the lagged weekly price of Lasalgaon would change the prices in the following week by 0.45 units in Kolkata, 0.42 units in Mumbai, and 0.39 units in Delhi (Table 2). In terms of consumers' market linkages, Bengaluru prices significantly affect the Chennai market prices, with the highest coefficient value, followed by Mumbai, Pune, Solapur, Patna, and Mahuva. Delhi prices are highly influenced by Lasalgaon, followed by Bengaluru and Solapur. However, the Kolkata market was highly influenced by Lasalgaon and Bengaluru market prices.

The Mumbai and Lasalgaon markets are interdependent (Table 2). The Pimpalgaon and Bengaluru markets influence the Indore, Lasalgaon, Mahuva, and Patna markets, besides their own lagged price changes. A change of one unit in the Pimpalgaon price would change the price in the following week by 0.32 units in Patna, 0.31 units in Indore, and 0.20 units in Lasalgaon (Table 2). The producers' markets at Lasalgaon, Bengaluru, and Solapur are the most influential on consumers' markets, besides their own price influences.

Multi-market volatility spillover effects

Agricultural commodity markets are integrated, and it is important that stakeholders and participants understand how price shocks and volatility are transmitted across markets. Considerable research has been carried out, and these studies are based on standard cointegration, causality, and the impulse response function. Recent studies hold that hybrid techniques are needed to examine price transmission.

We use the VAR to study cross-market volatility spillover between the Lasalgaon, Pimpalgaon, Bengaluru, Delhi, and Indore markets based on the transmission of price signals (Table 3). Pimpalgaon and Lasalgaon are the most important primary markets for the rabi onion crop. Bengaluru dominates in the supply of kharif onion and transmits signals accordingly. Madhya Pradesh contributes 14.07% of the onion production; therefore, we selected Indore. Delhi is a major consumers' market.

The conditional variances (Figure 1) and conditional covariances (Figure 2) are not constant over time. In

Table 2 Price transmission across markets: VAR coefficients with one-week lagged prices

	Consumers' Markets				Producers' markets							
	Chennai	Delhi	Kolkata	Mumbai	Bengaluru	Indore	Lasalgaon	Mahuva	Patna	Pimpalgaon	Pune	Solapur
Dependent Consumers' markets												
Chennai	0.47			0.2	0.35			0.13	0.16		0.17	0.17
Delhi	*	0.63			0.23		0.39		*			0.15
Kolkata			0.37	0.18	0.40		0.45		*			0.23
Mumbai	*			0.75	0.18		0.42					0.19
Dependent Producers' markets												
Bengaluru				0.26	0.89		0.17					
Indore	*				0.25	0.51			*	0.31		0.12
Lasalgaon	*				0.30		0.75	*	*	0.20		0.15
Mahuva	*				0.32			0.52	*	0.16		
Patna	*				0.26		0.41		0.38	0.32	*	
Pimpalgaon	*				0.32		0.22	*	*	0.66	0.14	0.19
Pune	*			0.2		*	0.35				0.98	
Solapur	*				0.17	*	0.19		*			0.95

The table includes only significant VAR coefficients at 5% level of significance.
*indicates negative VAR coefficient. The shaded cells indicate the non-significant coefficients.

Table 3 Prices at onion markets

	Bengaluru	Delhi	Indore	Lasalgaon	Pimpalgaon
Mean (INR per quintal)	1,114	1,103	856	1,030	993
Maximum (INR per quintal)	4,075	5,066	4,130	5,040	5,023
Minimum (INR per quintal)	209	325	138	138	155
Std. Deviation	720	765	675	845	828
Skewness	1.7	2.2	2.1	2.2	2.4
Kurtosis	5.9	8.8	8.2	8.8	9.8
Jarque-Bera	539.7	1,404.6	1,160.9	1,404.9	1,813.2
Probability	0.00	0.00	0.00	0.00	0.00

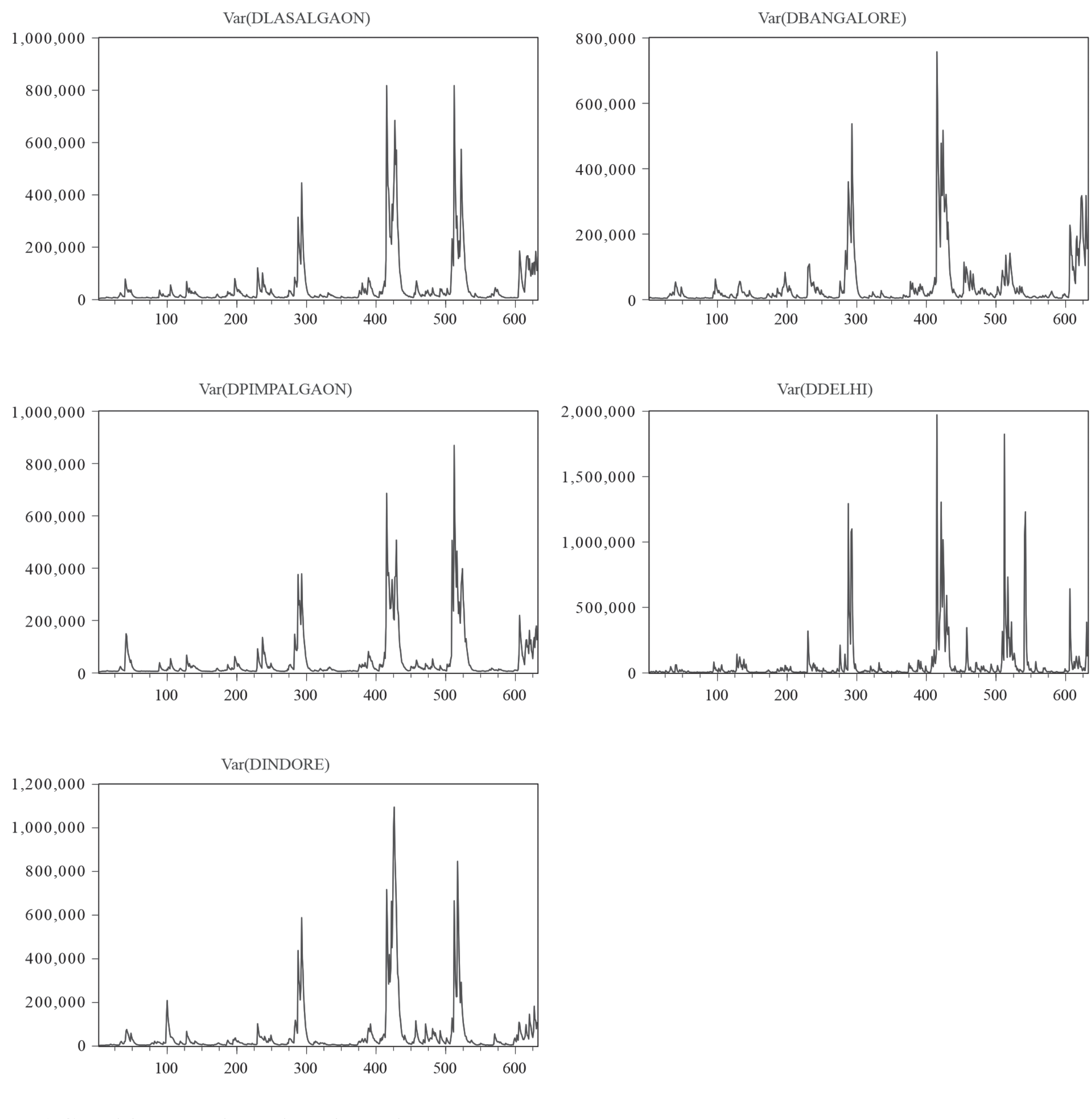

Figure 1 Conditional variance in onion prices

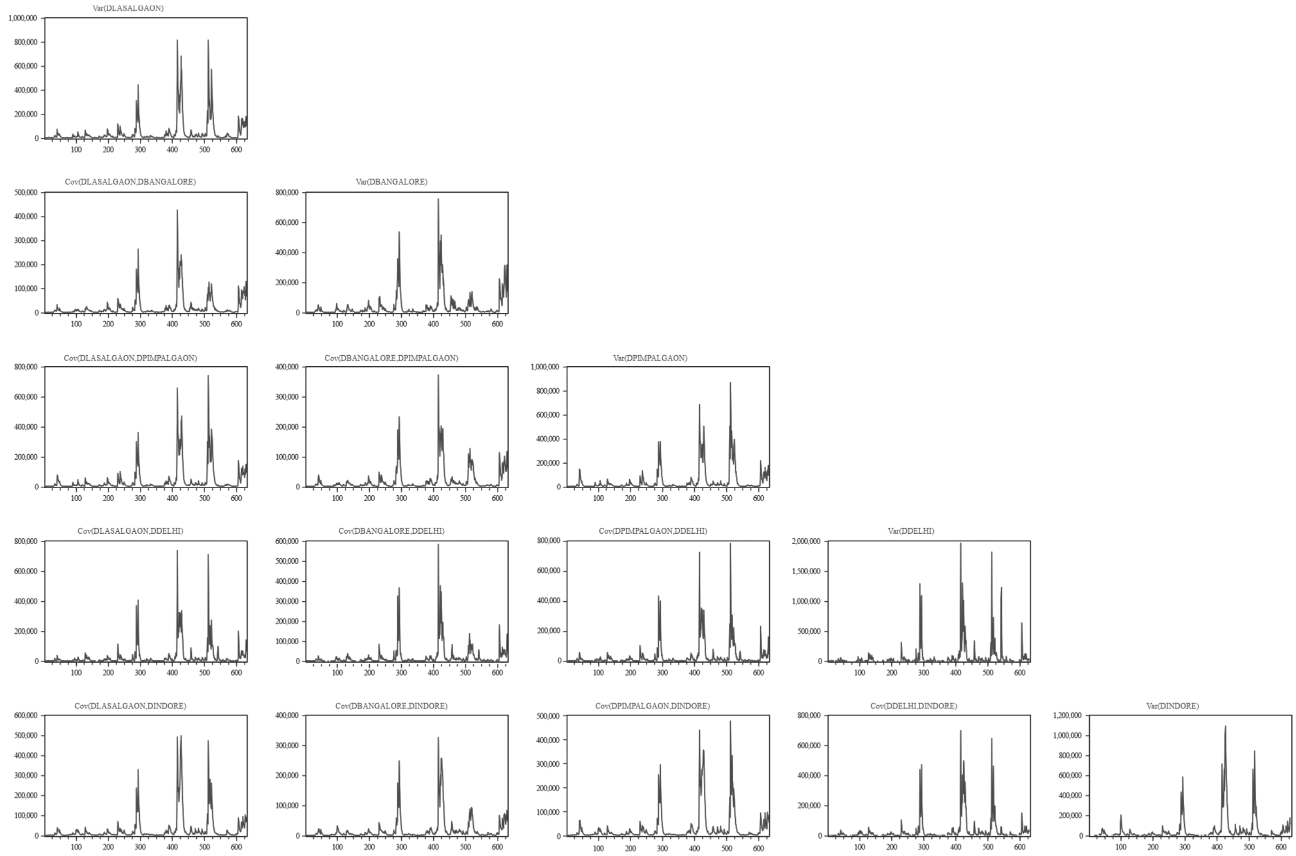

Figure 2 Conditional covariance in onion prices

terms of price volatility, the markets are interdependent; price volatility shocks arise from own-market price volatility and cross-volatility shocks from other markets. The results are presented in Table 4. The matrix of alphas (α) reflects the ARCH effect of price shocks. The own-volatility shocks in selected markets (a_{11}, a_{22}, a_{33}, a_{44} and a_{55}) are significant. The ARCH effect in price fluctuations was the strongest in Delhi ($a_{44=}$ 0.584) and weakest in Indore ($a_{55=}$ 0.286); the previous shocks in Delhi will impact its own price volatility stronger than the shocks arising from the other four markets.

The estimated cross-volatility coefficients, a_{ij} ($i \neq j$)—the price shocks in the markets—influence the price volatility in other markets, but the own-volatility shocks, a_{ij} ($i=j$), are generally greater than the cross-volatility shocks. Past volatility shocks in particular markets have a larger impact on their own price volatility rather than past volatility shocks arising from other markets. The market-specific shocks in lagged terms (ARCH effects) significantly contribute to the price volatility in a given market in a recursive way. The degree of pair-wise cross-volatility price shocks is the weakest (0.091) between Bengaluru and Indore and the strongest (0.276) between Pimpalgaon and Lasalgaon.

The coefficient betas (β) reflected the GARCH effects of onion price volatility spillovers; a market's current price volatility depends on its own and other markets' past volatility. All the diagonal elements were significant, indicating the strong GARCH effects in the price fluctuations in all five markets. The value of the own-volatility spillover effect was the lowest (β_{44}= 0.464) in Delhi and the highest (β_{55}= 0.702). in Indore. The past volatility at Indore will impact its own future price volatility more than the past volatility at the other four markets. The β_{ij} coefficients (where $i \neq j$ for all i and j) are significant and non-zero, and these prove that the volatility spillovers across these well integrated markets are high and positive.

The estimated lagged cross-volatility spillover persistence between Indore (dependent market) and the

Table 4 Parameter estimation for the diagonal vech (1, 1) equation

Parameters	Markets	Lasalgaon (i_1)	Bengaluru (i_2)	Pimpalgaon (i_3)	Delhi (i_4)	Indore (i_5)
C	Lasalgaon (j_1)	4,304				
	Bengaluru (j_2)	2,781	2,565			
	Pimpalgaon (j_3)	3,720	2,724	3,574		
	Delhi (j_4)	2,607	1,790	2,604	3,361	
	Indore (j_5)	2,205	1,265	2,142	1,684	1,854
α	Lasalgaon (j_1)	0.324				
	Bengaluru (j_2)	0.199	0.333			
	Pimpalgaon (j_3)	0.276	0.167	0.289		
	Delhi (j_4)	0.228	0.242	0.234	0.584	
	Indore (j_5)	0.194	0.091	0.189	0.187	0.286
β	Lasalgaon (j_1)	0.567				
	Bengaluru (j_2)	0.602	0.614			
	Pimpalgaon (j_3)	0.598	0.595	0.605		
	Delhi (j_4)	0.582	0.617	0.579	0.464	
	Indore (j_5)	0.678	0.755	0.679	0.680	0.702
$\alpha+\beta$	Lasalgaon (j_1)	0.891				
	Bengaluru (j_2)	0.801	0.947			
	Pimpalgaon (j_3)	0.874	0.762	0.894		
	Delhi (j_4)	0.81	0.858	0.813	1.048	
	Indore (j_5)	0.872	0.847	0.869	0.867	0.988

All parameters significant at 5% level.

four other markets is 0.678 (Lasalgaon), 0.755 (Bengaluru), 0.679 (Pimpalgaon), and (0.68) Delhi. That shows the persistence of volatility spillover from the four markets to Indore. The cross-volatility spillover persistence for Delhi is 0.582 (stemming from Lasalgaon), 0.617 (Bengaluru), and 0.579 (Pimpalgaon). This establishes the importance and influence of the Lasalgaon and Bengaluru markets.

The sum of ARCH and GARCH coefficients ($a_{ii}+\beta_{ii}$) are 0.891 for Lasalgaon, 0.947 for Bengaluru, 0.894 for Pimpalgaon, 1.048 for Delhi, and 0.988 for Indore. The values of these coefficients are close to unity, supporting the assumptions that the covariance is stationary and that volatility persists.

Conclusions

This study examines the price shocks and the price volatility spillover effects in the major onion markets of India. Maharashtra is the leading onion-producing state; its markets dominate supply and distribution and strongly influence other markets. Lasalgaon and Bengaluru are the most influential producers' markets. Bengaluru prices significantly affect Chennai market prices, with the highest coefficient value; prices at Chennai are influenced also by Mumbai, Pune, Solapur, Patna, and Mahuva. Delhi prices are influenced by Lasalgaon, with a high magnitude, and by Bengaluru and Solapur.

Market prices are highly volatile; own-volatility shocks are generally larger than cross-volatility shocks. Sudden supply or climate shocks trigger onion prices. Continual surveillance—especially in strategic markets like Lasalgaon, Pimpalgaon, and Bengaluru—can prevent extreme events by examining the extent of price influences and providing advance price signals. Early warning systems based on Big Data and artificial intelligence can help provide advance signals and prevent chaotic events.

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