The volatility spillover of potato prices in different markets of India

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Agricultural commodity prices, particularly the prices of perishable commodities, are volatile. The interdependency of market prices of agricultural commodities makes it difficult for accurate modelling. In the present study, two variants of multivariate generalized autoregressive conditional heteroscedastic models, namely DCC and BEKK, have been applied for modelling the price volatility of potato in five major markets in India, i.e. Agra, Delhi, Bengaluru, Mumbai and Ahmedabad. It is observed that the Agra market has the highest price variability, whereas Mumbai has the least. All the studied market prices showed a significant presence of conditional heteroscedasticity. To this end, Volatility Impulse Response Function has been used to assess the impacts of a specific shock on the price volatility spillovers of potatoes among the studied markets. The volatility spillover has been computed for all the markets.

Keywords: Nonlinearity, potato price, spillover, volatility.

THE value of agricultural commodities are influenced by fluctuations in price that arise from various factors including unfavourable weather conditions, natural disasters, shifts in demand and supply, change in agricultural policies and exchange rate volatility. Huge and unforeseen price variations create a scene of unpredictability and increase risks for producers, traders, consumers and the government. Bellemare *et al.*[1] stated agricultural commodity price volatility has been exceptionally high during the last decade when food price volatility reached almost a 30-year high in December 2010. The continuous fluctuations in prices of commodities have attracted interest and attention in the field of economic and financial literacy; it can also be viewed as one of the most important economic events[2]. Commodity prices of generally volatile, and agricultural commodities are primarily known for their continuously volatile nature[3]. Further, volatility of prices has a direct impact on competition by increasing consumer costs[4]. Apergis and Rezitis[5] observed that volatility of price brings up the situation of uncertainty and risk for both producers and consumers. It is established that extreme weather events do have a large impact on volatility. Furthermore, by applying the spillover index, it is possible to calculate the number of volatility spillovers across time. Candila and Farace[6] investigated the presence, size, and persistence of volatility spillovers among five agricultural commodities (corn, sugar, wheat, soybean and bioethanol) and five Latin American (Argentina, Brazil, Chile, Colombia, Peru) stock market indexes. The study also contributed to the analysis that, in general, higher agricultural commodity volatilities may induce economic weakness, mainly in food-exporter countries. In the Indian context, the price volatility of agricultural commodities has been studied extensively. Most studies of price volatility examined the volatility of commodity prices in a specified market. Paul *et al.*[7] studied export price volatility of spices from India. Paul *et al.*[8] examined the price volatility and linkages between domestic and export prices of onion in India. Paul *et al.*[9] studied price volatility in food commodities in India. Paul *et al.*[10] investigated asymmetric price volatility for onion in selected markets of Delhi. Singla *et al.*[11] studied the modelling price volatility in onion hybrid models. Furthermore, a more fragile economy can heavily undermine food security. The concept of volatility impulse response analysis coined by Hafner and Herwartz[12], is built on the methodology of the multivariate GARCH model. The method's main aim is to analyse the conditional variance instead of the conditional mean. This analysis allows visualizing the behaviour of conditional volatility after a historical shock. Sinha *et al.*[13] studied volatility spillover using the multivariate generalized autoregressive conditional heteroscedastic (MGARCH) model for the price of Black Pepper. Paul *et al.*[14] applied different MGARCH models for modelling volatility as well as studying the spillover effect for onion prices in different markets of India.

India occupies the second position on the scale of the largest producers of potatoes globally. India produced around 9.97% of the world's total potato production in 2017 (FAOSTAT). The vast growth in production of potatoes in India can be attributed to expansion in area than improvement in yield per hectare. Agricultural markets are one of the most important global markets not only because they correlate with markets like energy markets, commodities or stock markets, but also because they impact political and social events.

The highest producer of potatoes in India is Uttar Pradesh (30.32% of total production), followed by West Bengal (24.91%), Bihar (14.23%), Madhya Pradesh (6.36%), Gujarat (6.22%) and others (24.52%) (Horticultural Statistics at a Glance 2018). The leading states in terms of area under potato are Uttar Pradesh, West Bengal, Bihar, Gujarat and Madhya Pradesh, covering around 94% of the total area. Area coverage under *rabi* potato has increased slightly in India compared to the previous year. The potato production during 2017–18 is estimated to be 5.57% higher compared to the previous year, i.e. 2016–17. Harvesting of the crop is usually dependent on the weather conditions and market prospects. Harvesting is done slightly early if the demand is higher in the market. In short, potato is a staple food such as wheat and rice in India. The total demand for potatoes in India during 2017–18 was estimated to be

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47.15 million tonnes. Besides this, India is also involved in exporting potato and total export during 2017–18 was 395.75 thousand million tonnes (Horticultural Statistics at a Glance). Since potato is one of the staple foods in India, it has high demand throughout the year, and around 80–85% of the produce of *rabi* potato is stored in different cold storages of the major potato growing states. In terms of market arrival, potato arrives in Azadpur (Delhi) market (one of the major potato consuming states) from Uttar Pradesh, Punjab, Himachal Pradesh and Haryana. In the present study, Volatility Impulse Response Function (VIRF)[15] has been used to analyse the impacts of a specific shock on the price volatility spillovers of potatoes among the five major markets, i.e. Agra, Delhi, Bengaluru, Mumbai and Ahmedabad. An empirical comparison of the multivariate GARCH models, namely DCC and BEKK, has been carried out.

To study the volatility of the price of potatoes among different markets, a monthly price data set from January 2005 to April 2021 in five major markets, namely Agra, Delhi, Bengaluru, Mumbai and Ahmedabad, is considered. The daily return (r_t) has been calculated for each market using the formulae

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right), \tag{1}$$

where P_t and P_{t-1} denote the price at time t and $t-1$ respectively.

Multivariate GARCH (MGARCH) models are commonly used to estimate volatility spillovers among different markets. For a multivariate time series, the MGARCH model is given by

$$y_t = H_t^{1/2}\varepsilon_t, \tag{2}$$

where H_t is $k \times k$ positive-definite matrix of conditional variance, k the number of series, $t = 1, 2, \ldots, n$ (observations) and ε_t is the error term. It is with the specification of conditional variance that the MGARCH model changes.

The study uses the BEKK model proposed by Baba, Engle, Kraft and Kroner[16,17]. The BEKK(1,1) model is

$$H_t = CC' + A\varepsilon_{t-1}\varepsilon'_{t-1}A' + BH_{t-1}B'. \tag{3}$$

Each element of H_t depends on the p delayed values of the squared ε_t, the cross product of ε_t and on the q delayed values of elements from H_t.

The off-diagonal parameters in matrix B, b_{12} and b_{21} respectively, measure the dependence of conditional price volatility of the first market to the second market and vice-versa. The parameters b_{11} and b_{22} represent persistence in volatility in their market. The parameters a_{12} or a_{21} represent the cross markets effects, whereas a_{11}, a_{22} represent their own market effects. Therefore, the significant level of each parameter indicates the presence of a strong ARCH or GARCH effect.

The dynamic nature of time-varying correlations has been studied using DCC-GARCH model developed by Engle[2]. The DCC model can be formulated in the following manner

$$y_t = \mu_t(\theta) + \varepsilon_t, \tag{4}$$

where ε_t is a $n \times 1$ vector of zero mean in which innovations are conditional on the information available at time $t-1$. The conditional variance co-variance matrix can be written as

$$H_t = D_t R_t D_t = \rho_{ijt}\sqrt{h_{iit}h_{jjt}}, \tag{5}$$

where R_t is the $n \times n$ conditional correlation matrix and the matrices D_t and R_t are computed as follows

$$D_t = \mathrm{diag}(h_{iit}^{1/2}, \ldots, h_{nnt}^{1/2}), \tag{6}$$

h_{iit} is chosen to be a univariate GARCH(1,1) process; $R_t = (\mathrm{diag}\,Q_t)^{-1/2}Q_t(\mathrm{diag}\,Q_t)^{-1/2}$, $Q_t = (1-\alpha-\beta)\bar{Q} + \alpha u_{t-1}u'_{t-1} + \beta Q_{t-1}$ refers to a $n \times n$ symmetric positive definite matrix with $u_{it} = \varepsilon_{it}/\sqrt{h_{iit}}$, $\bar{Q}$ is the $n \times n$ unconditional variance matrix of u_t and α and β are non-negative scalar parameters satisfying $\alpha + \beta < 1$.

The conditional correlation coefficient ρ_{ij} between two markets i and j is then computed as follows

$$\begin{aligned}\rho_{ij} = {} & [(1-\alpha-\beta)\bar{q}_{ij} + \alpha u_{i,t-1}u_{j,t-1} + \beta q_{ij,t-1}]/ \\ & [((1-\alpha-\beta)\bar{q}_{ii} + \alpha u_{i,t-1}^2 + \beta q_{ii,t-1})^{1/2} \\ & \times ((1-\alpha-\beta)\bar{q}_{jj} + \alpha u_{j,t-1}^2 + \beta q_{jj,t-1})^{1/2}],\end{aligned} \tag{7}$$

where ρ_{ij} refers to the element located in the ith row and jth column of the symmetric positive definite matrix Q_t.

The VIRF describe the impact of an independent shock on the volatility of the variables. The nature of independence of the given shock from other previous shocks allows the construction of VIRF from historical data. However, in a multivariate setup, it is hard to assume that shocks are independent if they all occur simultaneously. In such cases, Cholesky decomposition is used for the orthogonalization of residuals. For the present investigation, the methodology by Hafner and Herwartz[12] has been followed to compute the VIRF.

The pattern of potato prices in different markets is displayed in Figure 1. It can be visualized that the prices vary a lot over time, leading to volatility. Results obtained for descriptive statistics are reported in Table 1. A perusal of Table 1 reveals that the mean monthly price of potatoes is maximum in Bengaluru, i.e. INR 1139.58/quintal, and

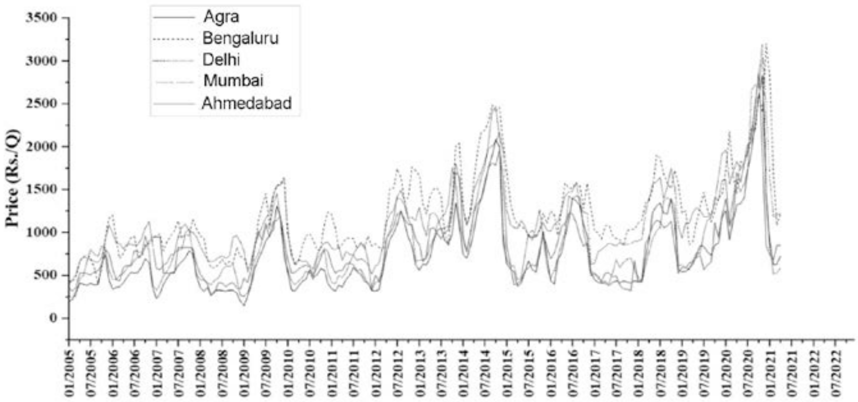

Figure 1. The time plot of potato prices in studied markets.

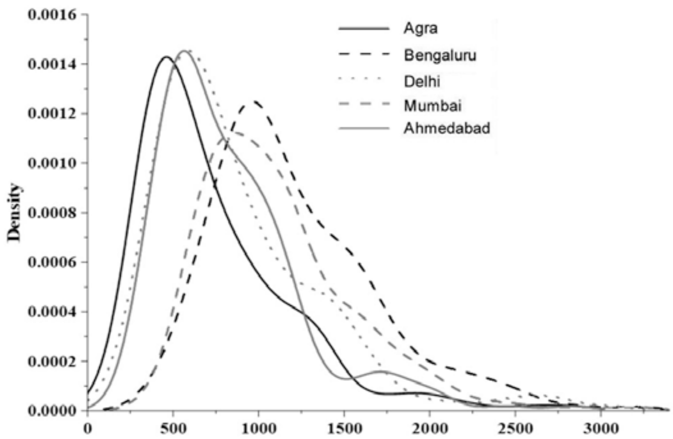

Figure 2. Kernel density function of market price of potato.

Table 1. Descriptive statistics

Markets	Mean	Median	Maximum	Minimum	Standard deviation	CV
Agra	671.19	548.00	2086.00	147.00	367.13	54.70
Ahmedabad	763.06	661.00	1965.00	271.00	335.40	43.95
Bengaluru	1139.58	1037.00	2480.00	414.00	417.46	36.63
Delhi	797.75	695.00	2467.00	245.00	399.66	50.10
Mumbai	1029.38	953.00	2167.00	394.00	351.20	34.12

Table 2. Unit root test results

	ADF test		PP test	
Markets	*t* stat	*p*-value	*t* stat	*p*-value
Agra	–5.04	0.00	–3.85	0.00
Ahmedabad	–4.57	0.00	–3.68	0.01
Bengaluru	–3.40	0.01	–3.06	0.03
Delhi	–5.57	0.00	–4.19	0.00
Mumbai	–4.45	0.00	–3.58	0.01

minimum in Agra at INR 671.19/quintal. Similarly, the maximum price of potatoes was observed in Bengaluru at INR 2480/quintal, followed by Delhi. The coefficient variation (CV), as depicted in Table 1, indicates that Agra markets have the highest variation in price, followed by the Delhi market. Since the price of potatoes is highly fluctuating in all the markets with marginal differences in standard deviation values, it can be concluded that all markets are subject to high shocks. The kernel density estimates, as depicted in Figure 2, clearly indicate a significant departure from normality.

The study applied various unit root tests such as the Augmented Dickey-Fuller (ADF) test and Phillips–Perron (PP) test to check data stationarity. The results of the unit root tests are reported in Table 2. It may be seen that all the log return series are stationary at level.

The results of the estimated MGARCH–BEKK model for the log return series of the monthly price of potatoes

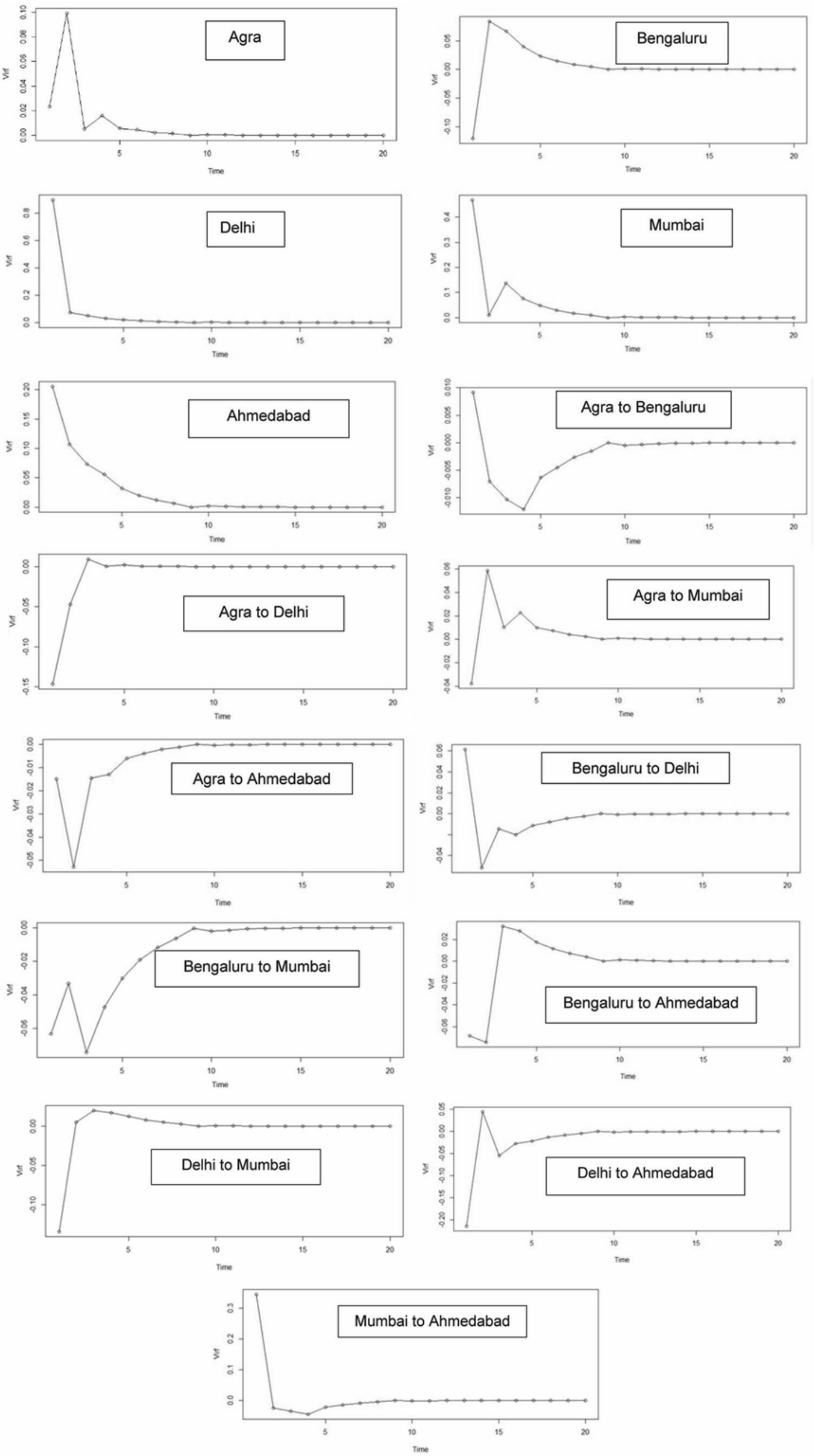

Figure 3. VIRF of different markets.

Table 3. Results of BEKK (1,1) model

	Agra	Bengaluru	Delhi	Mumbai	Ahmedabad
Constant (C)					
Agra	0.157	–0.035	0.151	0.081	0.075
Bengaluru	0.000	0.022	–0.096	0.050	0.061
Delhi	0.000	0.000	0.072	0.031	0.073
Mumbai	0.000	0.000	0.000	–0.014	–0.010
Ahmedabad	0.000	0.000	0.000	0.000	–0.034
ARCH coefficients (A)					
Agra	0.218	0.226	0.165	0.279	0.267
Bengaluru	0.047	0.097	–0.276	–0.119	–0.022
Delhi	0.328	0.029	0.134	0.129	–0.216
Mumbai	–0.413	0.230	–0.169	–0.165	–0.198
Ahmedabad	0.094	–0.076	0.251	0.034	0.368
GARCH coefficients (B)					
Agra	0.552	–0.254	0.125	–0.261	0.573
Bengaluru	–0.465	–0.810	–0.463	–0.315	–0.712
Delhi	–0.256	0.291	–0.102	0.256	–0.391
Mumbai	0.533	0.404	0.341	–0.086	–0.281
Ahmedabad	0.028	0.347	0.309	0.232	0.304
Standard error of coefficient of constant					
Agra	0.028	0.031	0.026	0.015	0.028
Bengaluru	0.000	0.030	0.031	0.018	0.018
Delhi	0.000	0.000	0.038	0.014	0.050
Mumbai	0.000	0.000	0.000	0.012	0.185
Ahmedabad	0.000	0.000	0.000	0.000	0.048
Standard error of ARCH coefficients					
Agra	0.107	0.157	0.212	0.030	0.112
Bengaluru	0.098	0.112	0.134	0.061	0.104
Delhi	0.210	0.127	0.271	0.069	0.115
Mumbai	0.192	0.185	0.237	0.058	0.171
Ahmedabad	0.099	0.073	0.083	0.051	0.091
Standard error of GARCH coefficients					
Agra	0.207	0.261	0.205	0.097	0.327
Bengaluru	0.215	0.107	0.182	0.127	0.206
Delhi	0.295	0.343	0.288	0.136	0.372
Mumbai	0.103	0.254	0.189	0.143	0.650
Ahmedabad	0.206	0.152	0.199	0.082	0.302

for five cities, namely Agra, Bengaluru, Delhi, Mumbai and Ahmedabad, are presented in Table 3. In Table 3, the ARCH effect of own market and cross markets are represented by matrix A, whereas the GARCH effect of own market and cross markets are represented by matrix B.

Table 4 reports the results of the DCC model. Here the parameter α measures the reaction of conditional volatility to market shocks, and parameter β measures the persistence of conditional volatility irrespective of anything happening in the market. The condition that $0 < \alpha + \beta < 1$ are all satisfied, for all the five markets. The maximum value occurred for Agra at 0.962 and the minimum value for Bengaluru at 0.695. In all the markets, the value of α is less than β. The low value of α and the high value of β indicates the importance of long-run persistence compared to short-run persistence. A close analysis of *dcca1* and *dccb1* showed that both the coefficients are statistically significant and indicate that system of series as a whole makes sense to fit the DCC model.

The VIRF depends on the initial volatility H_t given to the system. The value of initial volatility can be either the volatility state at the time the shock incurred or any other date chosen from the sample period. Figure 3 shows the volatility impulse responses. The impact of the shock appears not only in the expected conditional variances but also in the expected conditional covariances. The impact of the shock on expected conditional variances in all the cities can be evaluated from the first month itself.

The initial impact of the shock on expected conditional covariances between all the cities was noticeable at the initial shock and the peak response was reached in about the second or third month. Regarding the die-down of the impact of the shock on expected conditional covariances, it can be seen that the impact of shock did not sustain after ten months in all the cities. The continuous fluctuations in the initial months confirm that volatility transmission across markets is usually attributed to news and cross-market hedging, which dynamically changes expectations across markets. A key result to be noted is that even if the impact of the shock is initially negative for some markets in terms of both variances and covariances, the duration was very short.

Table 4. Results of DCC model

Parameter	Estimate	Standard error	t value	Pr (>|t|)
Agra				
c	0.007	0.034	0.202	0.840
ω	0.000	0.008	0.007	0.995
α	0.163	0.069	2.354	0.015
β	0.799	0.008	97.450	0.000
Bengaluru				
c	0.004	0.012	0.354	0.724
ω	0.009	0.005	1.753	0.080
α	0.142	0.064	2.225	0.026
β	0.553	0.211	2.628	0.009
Delhi				
c	0.005	0.016	0.286	0.775
ω	0.000	0.002	0.049	0.961
α	0.215	0.034	6.288	0.000
β	0.594	0.001	502.113	0.000
Mumbai				
c	0.006	0.011	0.537	0.591
ω	0.000	0.000	0.063	0.950
α	0.236	0.025	9.489	0.000
β	0.599	0.002	346.643	0.000
Ahmedabad				
c	0.005	0.014	0.352	0.725
ω	0.000	0.001	0.146	0.883
α	0.149	0.019	7.995	0.000
β	0.758	0.001	615.584	0.000
dcca1	0.042	0.017	2.494	0.013
dccb1	0.753	0.120	6.257	0.000

c, ω, α and β denotes respectively, the constant in mean equation, constant in variance, ARCH effect and GARCH effect.

The present study investigated the effect of volatility spillovers in monthly potatoes price in five different markets, Agra, Ahmedabad, Bengaluru, Delhi and Mumbai, from January 2005 to April 2021. The empirical results support the presence of ARCH and GARCH effects in all the markets. Accordingly, to accommodate the conditional heteroscedasticity and inter-dependence of studied markets, MGARCH models, namely BEKK and DCC, have been applied. It is observed that price volatility is not only dependent on its own market's past volatility but also depends on cross-market volatility. Finally, the application of VIRF demonstrated volatility spillover of all the studied markets and showed the impacts of impulse responses on expected conditional variances and expected conditional covariances. To this end, one can conclude that changes in the volatility of one market will often trigger reactions in other markets.

1. Bellemare, M. F., Barrett, C. B. and Just, D. R., The welfare impacts of commodity price volatility: evidence from rural Ethiopia. *Am. J. Agric. Econ.*, 2013, **95**, 877–899.
2. Engle, R. F., Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica*, 1982, 987–1007.
3. Newbery, D. M., The theory of food price stabilisation. *Econ. J.*, 1989, **99**(398), 1065–1082.
4. Zheng, Y., Kinnucan, H. W. and Thompson, H., News and volatility of food prices. *Appl. Econ.*, 2008, **40**, 1629–1635.
5. Apergis, N. and Rezitis, A., Food price volatility and macroeconomic factors: evidence from GARCH and GARCH-X estimates. *J. Agric. Appl. Econ.*, 2011, **43**, 95–110.
6. Candila, V. and Farace, S., On the volatility spillover between agricultural commodities and Latin American stock markets. *Risks*, 2018, **6**, 116.
7. Paul, R. K., Prajeshnu and Himadri, G., GARCH nonlinear time series analysis for modelling and forecasting of India's volatile spices export data. *J. Indian Soc. Agric. Stat.*, 2009, **63**, 123–131.
8. Paul, R. K., Saxena, R., Chaurasia, S. and Rana, S., Examining export volatility, structural breaks in price volatility and linkages between domestic and export prices of onion in India. *Agric. Econ. Res. Rev.*, 2015, **28**, 101–116.
9. Paul, R. K., Bhardwaj, S. P., Singh, D. R., Kumar, A., Arya, P. and Singh, K. N., Price volatility in food commodities in India – an empirical investigation. *Int. J. Agric. Stat. Sci.*, 2015, **11**(2), 395–401.
10. Paul, R. K., Rana, S. and Saxena, R., Effectiveness of price forecasting techniques for capturing asymmetric volatility for onion in selected markets of Delhi. *Indian J. Agric. Sci.*, 2016, **86**, 303–309.
11. Singla, S., Paul, R. K. and Shekhar, S., Modelling price volatility in onion using wavelet based hybrid models. *Indian J. Econ. Dev.*, 2021, **17**, 256–265.
12. Hafner, C. and Herwartz, H., *Time-Varying Market Price of Risk in the CAPM*, Humboldt-Universität zu Berlin, Wirtschaftswissenschaftliche Fakultät, 1999.
13. Sinha, K. *et al.*, Volatility spillover using multivariate GARCH model: an application in futures and spot market price of black pepper. *J. Indian Soc. Agric. Stat.*, 2017, **71**(1), 21–28.
14. Paul, R. K., Das, T., Panwar, S., Paul, A. K. and Bhar, L. M., Volatility and spillover in onion prices in major markets of Karnataka, India. *Indian J. Agric. Market.*, 2019, **33**, 65–76.
15. Koop, G., Pesaran, M. H. and Potter, S. M., Impulse response analysis in nonlinear multivariate models. *J. Econ.*, 1996, **74**, 119–147.
16. Baba, Y., Engle, R. F., Kraft, D. F. and Kroner, K. F., Multivariate simultaneous generalized ARCH. Manuscript, Department of Economics, University of California, San Diego, 1990.
17. Engle, R. F. and Kroner, K. F., Multivariate simultaneous generalized ARCH. *Econ Theory*, 1995, **11**, 122–150.

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