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. 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. Commodity prices of generally volatile, and agricultural commodities are primarily known for their continuously volatile nature. Further, volatility of prices has a direct impact on competition by increasing consumer costs. Apergis and Rezitis 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 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. studied export price volatility of spices from India. Paul et al. examined the price volatility and linkages between domestic and export prices of onion in India. Paul et al. studied price volatility in food commodities in India. Paul et al. investigated asymmetric price volatility for onion in selected markets of Delhi. Singla et al. 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, 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. studied volatility spillover using the multivariate generalized autoregressive conditional heteroscedastic (MGARCH) model for the price of Black Pepper. Paul et al. 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 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)\(^1\) 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

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

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

\[
y_t = \mathbf{H}_t^{1/2} \mathbf{e}_t,
\]

where \(\mathbf{H}_t\) is \(k \times k\) positive-definite matrix of conditional variance, \(k\) the number of series, \(t=1,2,\ldots,n\) observations, and \(\mathbf{e}_t\) 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

\[
\mathbf{H}_t = \mathbf{C} + \mathbf{A} \mathbf{e}_{t-1} \mathbf{e}_{t-1}' \mathbf{A}' + \mathbf{B} \mathbf{H}_{t-1} \mathbf{B}'.
\]

Each element of \(\mathbf{H}_t\) depends on the \(p\) delayed values of the squared \(\mathbf{e}_t\), the cross product of \(\mathbf{e}_t\) and on the \(q\) delayed values of elements from \(\mathbf{H}_t\).

The off-diagonal parameters in matrix \(\mathbf{B}\) represent persistence in volatility in their market. The parameters \(a_{12}\) or \(a_{21}\) represent the cross markets effects, whereas \(a_{11}\) and \(a_{22}\) 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

\[
y_t = \mu(\theta) + \mathbf{e}_t,
\]

where \(\mathbf{e}_t\) 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

\[
\mathbf{H}_t = \mathbf{D}_t \mathbf{R}_t \mathbf{D}_t = \rho_{jj} \sqrt{h_{ii}} h_{jj},
\]

where \(\mathbf{R}_t\) is the \(n \times n\) conditional correlation matrix and the matrices \(\mathbf{D}_t\) and \(\mathbf{R}_t\) are computed as follows

\[
\mathbf{D}_t = \text{diag}(h_{11}^{1/2}, \ldots, h_{nn}^{1/2}),
\]

and \(h_{ii}\) is chosen to be a univariate GARCH(1,1) process; \(\mathbf{R}_t = \text{diag}(Q_t^{1/2}Q_t(\text{diag} \ Q_t))^{1/2}\). \(Q_t = (1-\alpha - \beta) \bar{Q} + \alpha u_{t-1}u_{t-1}' + \beta Q_{t-1}\) refers to a \(n \times n\) symmetric positive definite matrix with \(u_t = \mathbf{e}_t / \sqrt{h_{tt}}\). \(\bar{Q}\) is the \(n \times n\) unconditional variance matrix of \(u_t\) and \(\alpha\) and \(\beta\) are non-negative scalar parameters satisfying \(\alpha + \beta < 1\).

The conditional correlation coefficient \(\rho_{ij}\) between two markets \(i\) and \(j\) is then computed as follows

\[
\rho_{ij} = [(1-\alpha - \beta) \bar{\rho}_{ij} + \alpha \bar{u}_{ij-1}u_{j,t-1}' + \beta q_{ij,t-1}] / \{(1-\alpha - \beta) \bar{\rho}_{ij} + \alpha \bar{u}_{ij-1}^2 + \beta q_{ij,t-1}^2\}',
\]

where \(\rho_{ij}\) refers to the element located in the \(i\)th row and \(j\)th 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\(^{15}\) 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
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.
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 $\alpha$ measures the reaction of conditional volatility to market shocks, and parameter $\beta$ 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 Bengaluru at 0.962 and the minimum value for Agra at 0.099. The value of $\alpha$ is less than $\beta$. The low value of $\alpha$ and the high value of $\beta$ 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 month and the peak response was reached in about the second or third month. Regarding the die-down of the impact of the shock is initially negative for some markets across markets. A key result to be noted is that even if the impact of the shock did not sustain after the second or third month. Regarding the die-down of the impact of the shock is initially negative for some markets across markets.
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 heteroskedasticity 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 VIFR 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.

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    |
| dcdb1     | 0.753    | 0.120          | 6.257   | 0.000    |

\(c, \omega, \alpha, \text{ and } \beta\) denotes respectively, the constant in mean equation, constant in variance, ARCH effect and GARCH effect.