Economics and Business Review, Vol. 7 (21), No. 4, 2021: 28-53
DOI: 10.18559/ebr.2021.4.3

Agricultural commodities: An integrated approach to assess the volatility spillover and dynamic connectedness[1]

***Arunendra Mishra*[2], *R Prasanth Kumar*[3]**

Abstract: In this article the dynamic connectedness between the five agricultural commodities is examined by implementing the Diebold and Yılmaz (VAR based) and Time-Varying Parameter Vector Autoregressions (TVP-VAR) measures for understanding the time-varying variance-covariance mechanism using daily data for the period of 2005 to 2019. The findings reveal that at an overall level all the commodity prices are less susceptible to significant volatility shocks from other commodities specifically before the introduction of the pan-India electronic trading portal (eNAM). Cotton prices do not show any variation due to spillover from others for the entire study period. The volatility spillover is visible post eNAM period particularly for the commodity stock prices. Whereas at an overall level the total directional connectedness has gone down in the post eNAM era. The network analysis suggests that the commodity stock prices show a stronger association as compared to market prices. Generally commodity prices show volatility connectedness but with respect to their own market which means strong spillover is missing among both the markets.

Keywords: dynamic connectedness, TVP-VAR, price volatility, volatility spillover, agricultural commodities, network diagrams.

JEL codes: C32, C50, G15.

Introduction

Many investors include agricultural commodities to make their portfolio diversified or as a mixed asset. Agri-commodities are always being valued like equities and there are several studies which show that equity and commodi-

[1] Article received 24 July 2021, accepted 25 October 2021.

[2] Department of Food Business Management and Entrepreneurship, National Institute of Food Technology Entrepreneurship and Management, Sonipat (Delhi NCR) – 131028, India, corresponding author: arunendra.niftem@gmail.com, ORCID: https://orcid.org/0000-0002-6070-1373.

[3] Department of Food Business Management and Entrepreneurship, National Institute of Food Technology Entrepreneurship and Management, Sonipat (Delhi NCR) – 131028, India, prasanth@niftem.ac.in, ORCID: https://orcid.org/0000-0001-5299-7701.

ties markets are integrated (Ahmadi, Behmiri, & Manera, 2016; Nicola, Pace, & Hernandez, 2016; Cabrera & Schulz, 2016; Zhang & Qu, 2015; Wang, Wu, & Yang, 2014; Thukral & Sikka, 2020; Diebold, Liu, & Yilmaz, 2017; Awartani, Aktham, & Cherif, 2016; Nazlioglu, 2011; Fowowe, 2016). Limited literature is available on the relationship of agricultural commodities together with market prices and commodity stock prices. One of the main objectives of this study is to find out and understand the return and volatility spillovers between different market prices and stock prices of the selected agri-commodities.

As Diebold and others (2017) found connectedness as a crucial part of risk measurement and management and mentioned that studying connectedness is really important for the commodities and particularly for the emerging countries since they rely heavily on commodities' production. In simple terms connectedness can be defined as a state of being connected and having a close relationship among two or more entities. In general spillover is an incident/event that occurs because of something else which might be related in context or unrelated. Here spillover effect means a case where one market's prices respond to the shocks coming from other markets. Diebold and others (2017) define the spillover as a "directional connectedness" as if one market responds towards another markets' signals they are interconnected which means spillover and connectedness can be used interchangeably. Caporin, Gupta and Ravazzolo (2021) have defined contagion as a rapid shock spillover that increases cross-market linkages. In general contagion can be expressed as an "unexpected" component of the transmission of shocks. Further (Rigobón, 2019) suggested that contagions are present in the markets every time as are spillovers but contagion tends to be more impactful during the crisis when propagation of shocks intensifies which leads to a macroeconomic event called "shift-contagion". In this study the integration, strength, and direction of association for prices of five agri-commodities of India was investigated:

1. cotton: India is one of the largest producers accounting for about 26% of the world cotton production as well as the third-largest exporter of cotton (COCPC, 2020). Cotton has posted significant positive growth of 68% in exports which is US$ 923 million to US$ 1,550 million between FY20 and FY21 (IBEF, 2021);
2. maize: India ranks 4th in the area and 7th in production if the maize growing countries only are considered. During 1950–1951 India produced 1.73 million metric tons (MT) maize, which increased to 27.8 million MT by 2018–2019 recording close to a sixteen fold increase in production (ICAR, 2020);
3. wheat: India is ranked second in the production of wheat after China having a production share of 103.6 million MT in the year 2019 (IBEF, 2020);
4. barley: one of the four major feed grains (corn, barley, oats and wheat) and used commercially for animal feed, to manufacture malt, which is primarily used in beer production, for seed and human food applications (Tricase, Amicarelli, Lamonaca, & Rana, 2018);

5. soybean: the world's most important seed legume which contributes to approximately 25% of the world's edible oil and about 65% of the global protein concentrate for livestock feeding. In the Indian context the share of soybean is approximately 40% of the total oilseeds and 25% of the edible oils (Agarwal, Billore, Sharma, Dupare, & Srivastava, 2013).

VAR and TVP-VAR methodology was used and the variance decomposition matrix of Diebold and Yilmaz (Diebold & Yilmaz, 2011). By using the network diagrams the direction and strength of association is shown. This study has three major contributions. First the directional and the extent of return/volatility spillovers between the market and stock return/volatility spillovers for agri-commodities is examined. Second the impact of the pan-India electronic trading portal (eNAM) on the price connectedness between the markets and stock return/volatility spillovers for agri-commodities is looked at. Third this study contributes and extends the limited literature specific to return/volatility spillovers for agri-commodities. The price associations before and after the introduction of the pan-India electronic trading portal (eNAM) with the help of network analysis are presented. In addition to that results can be seen in the context of market events and the decisions taken by the government. Measuring the connectedness is of special relevance for policymaking also. It is important to study the relationship between the markets and the commodities as it could be beneficial for investors as well as for the policymakers to understand the spillover of an unexpected event or crisis. (Guhathakurtha, Bhattacharya S.N., & Bhattacharya M., 2020) have mentioned that studying the spillover is more salient in case of a weak institutional framework and particularly when it is difficult to identify and prevent adverse shocks. By giving an example of the global financial crisis 2008 they mentioned that policymakers would like to know which markets are vulnerable to the volatility spillover to and from a specific market. In the context of trade policy (Yan & Deng, 2018) have explained the importance by mentioning that whether it is importing or exporting countries the volume or magnitude of the net effect of domestic product shock is three times as large as the production shock in the foreign country.

This study might be beneficial for overseas investors and individuals because as per the Department for Promotion of Industry and Internal Trade (DPIIT) the food processing industry in India has increasingly attracted Foreign Direct Investment (FDI) where the volume of equity inflow of about US$ 10.24 billion between April 2000 and December 2020. It is attracting major international players like Nestlé who will invest US$ 100.16 million in Gujarat. Another investor has announced US$ 1.19 billion for ethanol production and so on.

Section 1 consists of a review of literature followed by the methodological framework, analysis and connectedness measurements in Section 2, results and discussion in Section 3, and conclusions.

1. Literature review

In the field of financial research the three terms connectedness, contagion and spillover are commonly used (Guhathakurtha et al., 2020). Many studies have explored the connectedness among various sectors but primarily discussed the risk or return in the context of stocks in oils or precious/metal commodities. There is very limited literature available on the relationship of agri-commodity. Some researchers found that there is a relationship among the agri-commodities and other sectors like energy, metal, etc. (Nicola et al., 2016; Koirala, Mishra, D'Antoni, & Mehlhorn, 2015) whereas few did not find any evidence (Fowowe, 2016) and others found an impact but not very significant (Ahmadi et al., 2016; Awartani et al., 2016). The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model was the popular method used by several researchers earlier but later Diebold and Yilmaz provided an index that was based on forecast error variance decomposition using the VAR framework as a measure of returns and volatility spillover. Sim and Zhou (2015) have used the Quantile on Quantile approach to construct estimates to study the interrelationship between the quantiles of oil price shocks and quantiles of the US stock return and concluded that negative oil price shocks have an inverse directional effect on equities. Ji, Bouri, Roubaud and Shahzad (2018) used the dependence-switching CoVaR-copula model to study the risk spillover between energy and agri-commodities and found that systematic risk spillover has an impact during both bullish and bearish markets but more significantly while extreme downward movements are taking place. Reboredo (2018) examined the integration of green bonds and financial markets using the value-at-risk (VaR) values and conditional VaR (CoVaR) and found that green bonds do not show any diversification benefit over financial markets. Hassouneh, Serra, Bojnec and Gil (2016) studied the interdependence between the first and second price of consumer and producer prices using the VECM and MGARCH models and found an inverse relationship between international stock and producer prices. Dahl and Jonsson (2018) has investigated the volatility spillover between seafood markets—EU, Japan and USA—and found the time-varying spillover among the markets. Bonato (2015) examined the integration between soft and grain commodities and also with oil using a Beta GARCH model and found price interactions. Table 1 shows the conclusions of the studies examining the interaction and integration between the different commodities.

Table 1 indicates that connectedness or spillover is not largely explored from the same market multiple commodities perspective. This opportunity was taken to study the integration of prices among multiple commodities and their prices.

Network diagrams are used to show the structural linkages between markets. Wang, Xie and Stanley (2016) have used network analysis based on Pearson correlation and partial correlation. Guhathakurtha and others (2020) also used

Table 1. Summaries of the studies on the connectedness between commodities

Study reference	Methods	Period	Commodity type	Summary
Balli, Naeem, Shahzad, & de Bruin (2019)	VAR, DY2014	2007–2016	energy, precious and industrial metals, and agricultural	connectedness tends to increase during the period of crisis and that the global economic situation influences the connectedness of commodity uncertainty indexes
Ahmadi et al. (2016)	structural VAR	1983–2014	oil, agricultural and metal	the effect of oil shocks on agri-commodities is significant only for short time span
Nicola et al. (2016)	VAR	1970–2013	energy, agricultural, and food	in terms of price returns energy agri-commodities are highly correlated
Cabrera and Schulz (2016)	VECM &MGARCH	2003–2012	energy and agricultural	in the long run prices are in equilibrium but in the short run energy prices do not influence agri-commodities
Zhang and Qu (2015)	ARMA	2004–2014	oil and agricultural	oil price shocks are symmetric on most agri-commodities
Wang, Wu and Yang (2014)	structural VAR	1980–2012	oil and agricultural	impact of oil price shocks depends upon the demand supply of oil, whereas agri-commodities do not show any impact to structural oil shocks
Diebold et al. (2017)	VAR	2011–2016	energy, precious metals, industrial metals, livestock, grains, softs (coffee, cotton, sugar)	energy price shocks are most prominent in other commodities
Awartani et al. (2016)	VAR	2012–2015	oil, equities, euro/dollar exchange rates, precious metals and agricultural	significant volatility transmission from oil to equities but little transmission to agricultural commodities
Nazlioglu (2011)	Toda-Yamamoto linear & Diks-Panchenko nonlinear Granger causality test	1994–2010	oil and agricultural	oil and agri-commodities share nonlinear feedback and show unidirectional nonlinear causality
Fowowe (2016)	structural breaks cointegration test & nonlinear causality test	2003–2014	oil and agricultural	no evidence that agricultural commodity prices respond to oil prices and are neutral to global oil prices
Koirala et al. (2015)	Copula model	2011–2012	energy and agricultural	both the price series are highly correlated
Umar, Gubareva, Naeem and Akhter (2021)	Granger causality test	2002–2020	oil and agricultural	oil and agri-commodities show unidirectional nonlinear causality

ARMA: Autoregressive–moving-average model, VAR: Vector Auto-Regression; GARCH: Generalized Autoregressive Conditional Heteroskedasticity, VECM: Vector Error Correction Model, MGARCH: Multivariate generalized autoregressive conditional heteroscedasticity.

Source: Own elaboration.

network diagrams to show the level of connectedness of the markets. Ciner, Lucey and Yarovaya (2020) have used a different visualization for the co-movement analysis between LME metal markets.

2. Methodology

In this paper there were trials to compute the connectedness measures by the overall measure as Diebold and Yilmaz (2009, 2012). If there is a significant increase of cross-market linkages observed after a shock this is called contagion.

In this article various aspects of connectedness and spillover for the agri-commodity prices in India have been included. The directional connectedness of markets was studied and for this, first, a spillover index used generalized VAR methodology and variance decomposition matrix of Diebold and Yilmaz (2011) was built. TVP-VAR methodology was used. Later this spillover index was used to build the network diagrams which show the direction and strength of connectedness. In this way the volatility spillover among the commodities is used but this method cannot differentiate between contagion and interdependence (Guhathakurtha et al., 2020). The Diebold and Yilmaz (2012) method uses a generalized VAR framework where forecast error variance decompositions are considered to be invariant to the ordering of variables. Largely this method has the following three steps:

1. First, the VAR model using the model variables is estimated; various commodity prices are in the form of time series.
2. After that the forecast-error-variance-decomposition (FEVD) on top of the VAR model has to be calculated.
3. Later the static and dynamic total and also pairwise spillovers from generalized FEVD are calculated.

Starting the analysis with the *pth* order *k* variable VAR model represented by Equation (1):

$$x_t = \sum_{i=1}^{p} \phi_i x_{t-1} + \varepsilon_t \tag{1}$$

Where x_t is a vector of $N \cdot 1$ endogenous variables and ϕ_i are $N \cdot N$ autoregressive coefficient matrices, and ε_t is a vector of error terms that are assumed to be serially uncorrelated (Dahl & Jonsson, 2018).

By using moving average coefficients $x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}$, each variable's forecast error variances can be identified, according to the various market shocks. Following (Diebold et al., 2017) framework and referring to the (Dahl & Jonsson, 2018), the H-step-ahead forecast error variance decomposition is:

$$\theta_{ij}^{g}(H)=\frac{\sigma_{jj}^{-1}\sum_{h=0}^{H-1}\left(e_{i}'A_{h}\sum e_{j}\right)^{2}}{\sum_{h=0}^{H-1}\left(e_{i}'A_{h}\sum A_{h}'e_{j}\right)} \tag{2}$$

Where Σ is the variance matrix for error ε and σ_{ii} is the standard deviation of the error term for the i^{th} element, and e_i is the selection vector, with one as the i^{th} element and zeros otherwise. This produces a spillover index of an $N \cdot N$ matrix, where each element represents the contribution in the forecast error variance from market i to market j (Diebold et al., 2017). The Equation (3) shows the error decomposition normalized by dividing by the row sum (Dahl & Jonsson, 2018):

$$\ddot{\Theta}_{ij}^{g}(H)=\frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N}\theta_{ij}^{g}(H)} \tag{3}$$

which gives total (volatility) spillover index:

$$S^{g}(H)=\frac{\sum_{i,\,j=1,\,i\neq j}^{N}\theta_{ij}^{g}(H)}{\sum_{i,\,j=1}^{N}\theta_{ij}^{g}(H)}\cdot 100=\frac{\sum_{i,\,j=1,\,i\neq j}^{N}\theta_{ij}^{g}(H)}{N}\cdot 100 \tag{4}$$

the directional spillover received by a market:

$$S_{i\leftarrow j}^{g}(H)=\frac{\sum_{j=1,\,i\neq j}^{N}\theta_{ij}^{g}(H)}{\sum_{i,\,j=1}^{N}\theta_{ij}^{g}(H)}\cdot 100=\frac{\sum_{j=1,\,i\neq j}^{N}\theta_{ij}^{g}(H)}{N}\cdot 100 \tag{5}$$

and directional spillover transmitted:

$$S_{j\leftarrow i}^{g}(H)=\frac{\sum_{j=1,\,i\neq j}^{N}\theta_{ji}^{g}(H)}{\sum_{i,\,j=1}^{N}\theta_{ji}^{g}(H)}\cdot 100=\frac{\sum_{j=1,\,i\neq j}^{N}\theta_{ji}^{g}(H)}{N}\cdot 100 \tag{6}$$

The net spillover is found by subtracting shocks received from shocks transmitted:

$$S_{i}^{g}(H)=S_{j\leftarrow i}^{g}(H)-S_{i\leftarrow j}^{g}(H) \tag{7}$$

This method yields the following parameters:

1. Spillover index: which depicts the indices about the return spillover effects for each market and each commodity.
2. Total spillover index: this is nothing but the average contribution of spillovers from the shocks by all commodities and markets.
3. Directional spillovers: shows the shocks received by *i* vector from all other *j* vectors.
4. Net spillovers: using the directional spillover, it is a difference between stocks transmitted to and transmitted from all commodities.
5. Net pairwise spillovers: it is net spillover but specifically shows the shocks received by *i* vector from all other *j* vectors.

52-week (one-year) rolling window samples were used following (Diebold et al., 2017) the methodology while developing the VAR model. It was found that a few coefficients are unstable as well as the model is sensitive towards the outliers and therefore the TVP-VAR methodology proposed by (Antonakakis, Chatziantoniou, & Gabauer, 2020) was used. It has some advantages over the rolling-window-based VAR. First, it can manage the random set of window size which might reflect flattening the parameters or there is no need to choose an arbitrary rolling window size (Bouri, Demirer, Gabauer, & Gupta, 2021). Second, the meaningful observations were retained. Kalman filter procedure was used. This model takes care of outlier values itself (Youssef, Mokni, & Ajmi, 2020). Referring to the methodology of Korobilis and Yilmaz (2018) TVP-VAR was used instead of a VAR model over a rolling sample window. Antonakakis and others (2020) have mentioned that specifying the arbitrarily set rolling-window size is not required and hence there is no loss of observations. One more reason that TVP-VAR has been preferred is the impulse response analysis results. In VAR model positive shocks to all of the price series (excluding barley) are insignificantly different from zero whereas impulse response analysis shows TVP-VAR model identifies both the positive and negative shocks better than VAR model, although not all relationships are significant. A TVP-VAR model with a lag length of order 4 as per the Bayesian information criterion (BIC) was used (Antonakakis et al., 2020):

$$z_t = B_t z_{t-1} + u_t \; u_t \sim N(O, S_t) \tag{8}$$

$$vec(B_t) = vec(B_{t-1}) + v_t \; v_t \sim N(O, R_t) \tag{9}$$

where z_t and u_t are $k \cdot 1$ dimensional endogenous variables and error term vectors respectively, (B_t) and (S_t) represents a $k \cdot k$ dimensional time-varying VAR coefficient and variance-covariance matrices, $vec(B_t)$ and v_t are $k^2 \cdot 1$ dimensional vectors with R_t defined as a $k^2 \cdot k^2$ dimensional variance-covariance matrix. For connectedness measures it is necessary to transform the TP-VAR to its TVP-VMA representation:

$$z_t = \sum_{i=1}^{p} B_{it} z_{t-i} + u_t = \sum_{j=0}^{\infty} A_{jt} u_{t-j} \tag{10}$$

where A_t demonstrates a $k^2 \cdot k^2$ dimensional time-varying VMA coefficient matrix. The H-step ahead (scaled) generalized forecast error variance decomposition (GFEVD) was computed as:

$$\varnothing^g_{ij,t}(H) = \frac{S^{-1}_{ij,t} \sum_{t=1}^{H-1} (l'_t A_t S_t l_j)^2}{\sum_{j=1}^{k} \sum_{t=1}^{H-1} (l'_t A_t S_t A'_t l_i)} \quad \tilde{\varnothing}^g_{ij,t}(H) = \frac{\varnothing^g_{ij,t}(H)}{\sum_{j=1}^{k} \varnothing^g_{ij,t}(H)} \tag{11}$$

With $\sum_{j=1}^{k} \tilde{\varnothing}^g_{ij,t}(H) = 1$, $\sum_{i,j=1}^{k} \tilde{\varnothing}^g_{ij,t}(H) = k$ and l_j corresponds to a selection vector with unity on the j^{th} position and zero otherwise.

Finally, the (corrected) TCI—which ranges between zero and unity is computed as:

$$C^g_t(H) = \frac{1}{k-1} \sum_{j=1}^{k} 1 - \tilde{\varnothing}^g_{ij,t}(H) \tag{12}$$

This measure can be interpreted as the degree of interconnectedness as well as the market risk. A low (high) TCI value implies that a shock in one variable has on average a low (high) effect on all other variables and hence represents low (high) market interconnectedness (Bouri et al., 2021). Conceptually the Equations (4) to (7) can be used as reference to get the required parameters. For further details please refer to Antonakakis and others' (2020) methodology.

2.1. Data

The first dataset is collected from NCDEX Commodity index data—which is commodity market data from NCDEX (will refer as "Commodity stock Price") and another is from Agmarknet data—which is wholesale market data for eNAM or Agmarknet (will refer as "Market Price"). Both the commodity price time series from the period of 2005 to 2019 and collected daily data for all five commodities: cotton, maize, wheat, barley, and soybean. The criteria for selecting the commodity are (1) commodity is listed in more than one market, (2) the data on volume or quantity of trade for that commodity is available, (3) food grains are selected considering their importance in the food basket, (4) the storable or non-storable categories of the commodities are not considered and (5) the same applies also to "seasonal" and "non-seasonal" commodities. It is assumed that the APMC mandi (a traditional wholesale market place for the farmers) location, the operational cost and the commissions do not impact the commodity prices. However these may influence the decision of farmers for choosing a marketplace for trade. The spillover before and after the introduction of the pan-India electronic trading portal (eNAM) is also considered. It was introduced on 14th April 2016 with an objective of one price in one market in one nation. It is important to consider the eNAM reform as it is one of the major agriculture reforms in India with the primary objective of reducing the price spread between farmer and consumer and by doing this the government tries to increase farm income. The respective time spans are denoted as pre-eNAM and post eNAM. Variables are converted into log returns. The year 2020 data is not used to exclude the impact of the COVID-19 pandemic.

3. Results and discussion

The model is for five commodities: cotton, maize, wheat, barley, and soybean. Table 2 shows the descriptive statistics of the return values. The price series are non-stationary according to the ERS unit root test so the first log difference was used where the formula is $y_t = ln(x_t) - ln(x_{t-1})$. The unconditional variance of the maize is the lowest which means that it has the lowest volatility. As can be seen in Table 2 cotton, barley and soybean are significantly positively skewed, whereas the wheat is significantly negatively skewed. Referring to the ERS unit-root test results all series are stationary in their returns. Table A1 in the Appendix indicates that the unconditional correlations among maize, soybean, and wheat index prices are positive.

Table 2. Descriptive statistics of returns

	Mean	Variance	Skewness	Ex.kurtosis	ERS
Barley MP	0.554	0.15	1.307***	2.376***	–7.118***
Cotton MP	1.032	0.078	0.400***	0.039	–5.091***
Maize MP	0.741	0.048	0.007	1.501***	–6.233***
Soybean MP	0.949	0.077	0.563***	0.965***	–2.869***
Wheat MP	0.95	0.062	–0.154***	1.886***	–6.441***
Barley CIP	0.033	1.27	0.270***	5.537***	–22.662***
Cotton CIP	0.307	160.51	34.289***	1295.938***	–23.776***
Maize CIP	0.039	1.362	6.485***	169.025***	–12.014***
Soybean CIP	0.053	2.966	20.302***	785.260***	–23.395***
Wheat CIP	0.032	0.606	2.261***	40.733***	–20.866***

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$ and ERS unit root test tests for stationarity, MP: market price, CIP: commodity stock price.

Source: Authors' calculation.

Table 3. Directional spillover table: TVP-VAR model

		Barley MP	Cotton MP	Maize MP	Soybean MP	Wheat MP	Barley CIP	Cotton CIP	Maize CIP	Soybean CIP	Wheat CIP	FROM
Barley MP	Overall	76.24	3.88	1.46	4.44	5.60	3.02	1.48	1.03	1.13	1.71	23.76
	Pre eNAM	75.71	3.19	2.03	4.25	3.81	3.96	2.46	0.94	1.39	2.26	24.29
	Post eNAM	82.00	3.07	1.48	3.45	3.76	0.83	2.15	0.89	0.99	1.36	18.00
Cotton MP	Overall	3.39	80.48	1.80	4.05	3.20	1.85	1.67	0.95	1.34	1.26	19.52
	Pre eNAM	4.21	77.03	1.99	4.08	3.55	2.18	2.37	1.20	1.67	1.71	22.97
	Post eNAM	1.32	79.53	2.25	5.57	4.89	0.72	3.34	0.72	1.26	0.40	20.47
Maize MP	Overall	2.49	2.55	73.84	7.85	6.66	1.67	1.73	1.09	1.23	0.89	26.16
	Pre eNAM	3.75	2.94	71.40	6.80	7.12	1.55	2.55	1.50	1.33	1.06	28.60
	Post eNAM	1.13	2.87	74.19	11.53	4.08	1.14	3.08	0.63	0.75	0.60	25.81
Soybean MP	Overall	3.59	4.35	3.91	71.99	4.01	2.24	2.58	1.78	4.16	1.39	28.01
	Pre eNAM	4.04	4.94	3.52	66.44	6.10	2.33	3.23	2.42	5.34	1.65	33.56
	Post eNAM	1.49	3.71	8.03	78.00	3.11	0.39	1.50	0.58	2.25	0.94	22.00
Wheat MP	Overall	3.58	3.80	6.86	4.99	74.92	1.30	1.63	1.28	0.88	0.76	25.08
	Pre eNAM	4.55	3.34	7.36	3.54	72.84	2.33	2.35	1.39	1.14	1.16	27.16
	Post eNAM	1.66	4.35	4.49	2.20	78.19	0.82	5.73	0.80	0.91	0.85	21.81
Barley CIP	Overall	3.17	1.71	1.08	1.94	1.09	76.31	2.73	3.15	3.63	5.18	23.69
	Pre eNAM	4.06	1.86	0.94	1.83	2.09	69.79	3.99	3.87	5.05	6.53	30.21
	Post eNAM	0.99	1.06	1.91	1.16	0.59	85.52	2.88	1.73	1.33	2.83	14.48

Cotton CIP	Overall	0.43	0.69	0.66	1.01	0.69	1.35	90.97	1.58	1.47	1.15	9.03
	Pre eNAM	0.39	0.46	0.77	1.33	0.37	1.55	90.44	1.90	1.41	1.38	9.56
	Post eNAM	0.60	1.00	0.65	0.52	1.02	0.91	92.48	0.71	1.52	0.58	7.52
Maize CIP	Overall	1.30	1.24	0.69	1.93	1.06	2.91	2.06	76.56	7.37	4.88	23.44
	Pre eNAM	1.69	1.30	0.86	2.36	1.53	3.54	3.06	68.89	10.57	6.19	31.11
	Post eNAM	0.86	1.74	1.49	1.47	0.88	1.84	2.72	85.85	1.03	2.12	14.15
Soybean CIP	Overall	1.60	1.35	0.61	4.59	0.65	3.74	1.91	7.33	74.67	3.55	25.33
	Pre eNAM	2.11	1.29	0.70	5.29	1.04	4.88	2.53	10.30	66.99	4.86	33.01
	Post eNAM	0.98	1.74	0.95	3.21	0.82	1.76	2.68	1.66	85.32	0.88	14.68
Wheat CIP	Overall	2.67	1.59	0.95	2.11	0.85	5.29	1.79	5.32	4.04	75.39	24.61
	Pre eNAM	3.67	1.48	0.81	2.51	1.18	6.50	2.83	6.71	5.52	68.80	31.20
	Post eNAM	1.17	1.41	2.20	1.26	0.93	2.94	2.08	2.22	1.18	84.60	15.40
Directional to others	Overall	22.22	21.17	18.03	32.91	23.82	23.38	17.57	23.51	25.26	20.76	228.64
	Pre eNAM	28.46	20.80	18.97	31.98	26.79	28.83	25.35	30.24	33.44	26.81	271.67
	Post eNAM	10.20	20.96	23.46	30.37	20.09	11.34	26.15	9.94	11.23	10.57	174.33
Directional including own	Overall	98.47	101.64	91.88	104.91	98.73	99.70	108.54	100.07	99.92	96.14	TCI
	Pre eNAM	104.17	97.83	90.37	98.42	99.63	98.61	115.80	99.14	100.42	95.61	TCI
	Post eNAM	92.20	100.50	97.65	108.36	98.28	96.86	118.64	95.79	96.55	95.17	TCI
NET directional connected-ness	Overall	−1.53	1.64	−8.12	4.91	−1.27	−0.30	8.54	0.07	−0.08	−3.86	22.86
	Pre eNAM	4.17	−2.17	−9.63	−1.58	−0.37	−1.39	15.80	−0.86	0.42	−4.39	27.17
	Post eNAM	−7.80	0.50	−2.35	8.36	−1.72	−3.14	18.64	−4.21	−3.45	−4.83	17.43

Notes – MP: market price, CIP: commodity stock price, TCI: total connectedness index.

Source: Authors' calculation.

Table A2 in the Appendix, and Table 3 show the dynamic connectedness using VAR and TVP-VAR respectively. The non-diagonal column sums account for contributions to other markets and row sums account for contributions from others. As it is mentioned in the methodology in order to calculate the net volatility spillover the difference between them should be determined.

The abovementioned values represent directional spillover from a given commodity price series (column-wise) to another (row-wise) and the column "From" shows spillover received by each commodity (row-wise) from all other commodities. Row "To others" represents spillover to all other commodities. The total spillover row is obtained by summing up the column values. The values in each cell for net spillover are obtained as the difference between spillover "To others" and spillover "From others". Table A3 in the Appendix shows the coefficient matrix for the four lags L1 to L4 for all the price series which were tested for the sake of the VAR model stability.

Table A2 in the Appendix is the dynamic connectedness table using VAR which shows that maize and soybean commodity stock prices receive the significant spillover from others followed by wheat. At an overall level market prices are not highly impacted by shocks from others. Cotton prices do not receive any shocks from other commodities for both markets. But if post eNAM behaviour is considered the market price of maize shows 74.93% variation from its own shocks and 25.07% variation due to spillovers from others. Commodity stock prices of all the commodities except cotton show that variation due to spillover from others has dropped significantly post eNAM. It can be seen that directional spillover to other commodities has gone down in post eNAM period. In this period the 24.70% varation in the market price of soybean is due to spillovers to the other commodities which is the highest as compared to other commodities followed by maize with 17.85%.

Referring to Table 3, in the context of TVP-VAR, it can be observed that an overall level commodity stock price of cotton receives the lowest spillover of 9.03% from others whereas others receive around 25% on average. The cotton commodity stock price has more than 90% variation from its own shocks. The market price of barley during post eNAM shows higher spillover from its own shocks as compared to pre eNAM whereas soybean shows a reverse. In post eNAM variation from its own shocks were smaller as compared to pre eNAM. If the commodity stock prices are discussed all the commodities except cotton show that variation from its own shocks has a higher impact than the variation due to spillover from others. Similarly to the VAR model this model also shows that overall variation due to spillover from others has dropped in post eNAM as compared to pre eNAM. In the post eNAM period the market price of soybean has 30.37% contribution to variation in other commodities which is the highest as compared to others. The analysis reveals that all the commodity prices are less susceptible to significant volatility shocks from other commodities for the entire study period and specifically in the pre eNAM period.

Cotton prices do not show any variation due to spillover from others and variations are mostly from its own shocks for the entire time frame. There is no straightforward interpretation of why cotton prices did not transmit or receive shocks from other commodities. One of the possible reasons could be that India (6.05 Million MT) is one of the largest producers accounting for about 26% of the world's (24.22 Million MT) cotton production as well as the third-largest exporter of cotton. The cotton prices may be more susceptible to international prices rather than domestic prices. It would be interesting to see if a visible spillover exists with respect to importer countries which is beyond the scope of this study. Another reason could be that cotton is a product used largely for industrial consumption whereas other commodities selected in this study are used mostly for household/domestic consumption. Regarding barley Sendhil and others (2018) found the food/home consumption and fodder/animal consumption are among the top reasons for barley cultivation specificly in Haryana, Uttar Pradesh and Rajasthan. It is preferred for fodder/animal consumption since it has more leaves per plant and requires less water/irrigation. For maize, Didar Singh (2014) has mentioned that maize is mostly used by poultry feed industry in India, particularly in the form of broiler feed (50%–60%) and layer feed (25%–35%) processed by poultry farmers themselves. (FICCI, 2018) report on maize consumption pattern shows that feed accounts for about 60% (poultry feed being 47% and livestock feed being 13%) of the maize consumption in India. The food consumption accounts for 20%, with direct consumption being 13% and the processed food industry being 7% only of total maize consumption. Regarding wheat, Singh (2016) mentioned that wheat is staple food for Indians and mainly consumed in the form of homemade 'chapattis' or 'rotis' (unleavened flat bread) using custom-milled 'atta' (whole wheat flour), which is processed at the local level. The same goes for soybean as Agarwal and others (2013) found that 100% of soybean oil being produced and processed in the country is consumed domestically.

There is a spillover effect visible post eNAM, especially for the commodity stock prices. Perhaps eNAM being an electronic selling platform shows the potential to come up with the better prices to the farmer's crop production as compared to the earlier traditional markets or selling methods since eNAM is supposed to mitigate the inefficiencies of traditional selling methods and increase the income of farmers and farm workers. eNAM is introduced to promote uniformity in the agriculture markets by integrating across the markets, removing information asymmetry between buyers and sellers and promoting real time price discovery based on actual demand and supply (Department of Agriculture, 2021). Soybean is most volatile as it receives as well as transmits shocks to other commodities. Soybean is the world's most important seed legume which contributes to approximately 25% of the world's edible oil, about 65% of the global protein concentrate for livestock feeding. In the Indian context the share of soybean is approximately 40% of the total oilseeds and 25%

of the edible oils. Soybean also earns valuable foreign exchange through soya meal but in contrast to cotton, the domestic consumption of edible oils has also gone up sharply. To address this domestic demand other edible oils like palm oil are imported, especially from Malaysia. At an overall level the total directional connectedness has gone down post eNAM. Commodity stock prices show a stronger association as compared to market prices. Commodity prices show volatility connectedness but concerning their own market which means strong spillover is missing among both the markets. To understand the price relationship we should also look at the state-wise commodity price differences. Table 4 shows the market price differences in pre eNAM and post eNAM periods.

Table 4. Market price difference (INR per quintal)

State	Wheat	Maize	Cotton
Gujarat	−17.5	−15.6	–*
Haryana	11.7	2.5	2.1
Madhya Pradesh	−5.5	−19.8	–*
Maharashtra	−6.4	−22.6	−6.8
Telangana	–*	–*	−2.5
Uttar Pradesh	−1.7	−13.9	–*

* Market price differences are not available.

Source: Research Study Report 2020, Ministry of Agriculture and Farmers' Welfare, Government of India.

Commodity stock prices are the prices represented at an overall national level but market prices are more particular to the state or domestic markets. Referring to Table 4 above prices have decreased for all the markets except Haryana. The market prices are more representative of local markets where demand is driven largely by consumption needs as well as the volume of the crop produce whereas commodity stock prices mostly represent the investment or risk mitigation perspective or maybe used in portfolio diversification. Further it is possible that the difference might be because market prices adjusted for transportation cost, vendor commissions, and transaction costs are not available.

Network diagrams—Figures 1–3—depict the connectedness diagrams of total spillover before and after the introduction of the pan-India electronic trading portal (eNAM) and another combining both the periods, respectively. The node colour indicates the total directional connectedness to others: positive (green) or negative (red). The width of the node indicates the strength of spillover. During the pre eNAM period the prices are more associated with their own market. For market prices there is a spillover association but the strength is low. In contrast, commodity stock prices show stronger association

Figure 1. Total directional connectedness to others (pre eNAM)
Source: Authors' calculation.

Figure 2. Total directional connectedness to others (post eNAM)
Source: Authors' calculation.

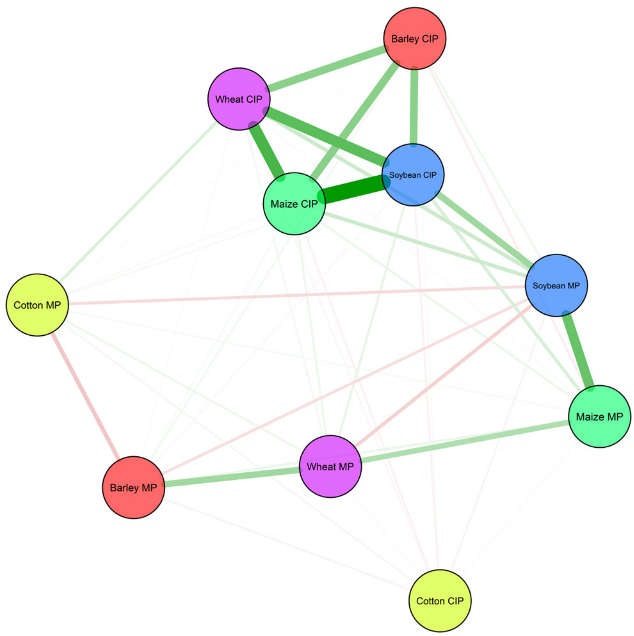

Figure 3. Total directional connectedness (the entire period of the study)
Source: Authors' calculation.

particularly soybean, maize, wheat, and weaken with barley. In the post eNAM scenario there is a strong association visible among soybean and maize market prices which was missing in pre eNAM. Commodity stock prices are also weakly associated in post eNAM era. At an overall level prices show volatility connectedness but with respect to their own market which means integrated spillover is missing between both the markets. Commodity stock prices show a stronger association as compared to market prices. Cotton prices do not show any connectedness with other markets.

The network graphs show that there is a connectedness between maize and soybean. In India, farmers largely follow the intercropping method for these two crops. Later, these are harvested together in September-October, which means the crop life cycles, productions and prices appear in sync for maize and soybean.

Conclusions

In this paper the connectedness for the five commodities has been studied: cotton, maize, wheat, soybean and barley by using daily data for the period of fifteen years. Regarding the commodity stock prices, the analysis reveals that all the commodities are less vulnerable to variation due to spillover from others, and variations are primarily from their shocks. This type of relationship is more visible in the pre eNAM period. Cotton prices do not show any variation due to spillover from others for the entire period and variations are mostly from its own shocks. There is a spillover effect visible during post eNAM period especially for the commodity stock prices. Soybean is most volatile as it receives as well as transmits shocks to other commodities. At an overall level the total directional connectedness has gone down in post eNAM era. Commodity stock prices show stronger association as compared to market prices. Commodity prices show volatility connectedness but with respect to their own market which means strong spillover is missing among both the markets.

As a limitation the five most traded commodities have been considered. It would be beneficial if the scope were to be expanded to more commodities. Also, there are several other models available which can be used to evaluate the results or can be extended to have a holistic analysis for the analysis period.

For future studies there is a scope to examine the volatility spillover using more commodities and in the context of global prices. An index for each commodity to standardize the effect and compare it with other markets could be established—the same commodity as well as against different commodities. Regarding the methodology it would be possible use TVP-SV (Time-Varying Parameter Vector autoregression with Stochastic Volatility) model to study the time related volatility further.

Appendix

Table A1. Unconditional correlations matrix (pairwise Pearson correlations)

	Barley MP	Cotton MP	Maize MP	Soybean MP	Wheat MP	Barley CIP	Cotton CIP	Maize CIP	Soybean CIP	Wheat CIP
Barley MP	1.000	–0.103	0.038	–0.058	0.176	0.025	–0.021	0.012	–0.012	0.010
Cotton MP	–0.103	1.000	0.017	–0.064	0.031	0.007	0.022	0.012	0.018	0.065
Maize MP	0.038	0.017	1.000	0.280	0.148	–0.031	0.009	0.035	0.071	0.011
Soybean MP	–0.058	–0.064	0.280	1.000	–0.082	0.030	–0.020	0.092	0.178	0.092
Wheat MP	0.176	0.031	0.148	–0.082	1.000	0.006	–0.007	0.032	0.040	0.023
Barley CIP	0.025	0.007	–0.031	0.030	0.006	1.000	0.011	0.219	0.217	0.217
Cotton CIP	–0.021	0.022	0.009	–0.020	–0.007	0.011	1.000	–0.023	–0.024	–0.014
Maize CIP	0.012	0.012	0.035	0.092	0.032	0.219	–0.023	1.000	0.476	0.341
Soybean CIP	–0.012	0.018	0.071	0.178	0.040	0.217	–0.024	0.476	1.000	0.305
Wheat CIP	0.010	0.065	0.011	0.092	0.023	0.217	–0.014	0.341	0.305	1.000

Notes – MP: market price, CIP: commodity stock price.

Source: Authors' calculation.

Table A2. Directional spillover table—VAR Model

		Barley MP	Cotton MP	Maize MP	Soybean MP	Wheat MP	Barley CIP	Cotton CIP	Maize CIP	Soybean CIP	Wheat CIP	FROM
Barley MP	Overall	95.03	1.22	0.47	0.38	2.43	0.36	0.04	0.04	0.02	0.01	4.97
	Pre eNAM	94.45	1.48	0.59	0.60	2.22	0.51	0.09	0.05	0.00	0.01	5.55
	Post eNAM	97.59	0.45	0.12	0.24	0.89	0.03	0.10	0.12	0.37	0.09	2.41
Cotton MP	Overall	0.56	97.52	0.25	0.67	0.41	0.03	0.07	0.05	0.14	0.29	2.48
	Pre eNAM	0.75	95.76	0.43	1.89	0.48	0.04	0.10	0.06	0.18	0.31	4.24
	Post eNAM	0.16	95.71	0.02	0.87	2.27	0.10	0.00	0.29	0.43	0.15	4.29
Maize MP	Overall	0.37	0.27	85.52	8.13	4.91	0.13	0.02	0.18	0.45	0.02	14.48
	Pre eNAM	0.46	0.58	87.96	4.25	5.71	0.11	0.01	0.36	0.51	0.05	12.04
	Post eNAM	0.11	0.58	74.93	19.82	3.56	0.65	0.02	0.01	0.28	0.03	25.07
Soybean MP	Overall	0.16	0.39	4.76	89.61	0.25	0.23	0.09	0.78	3.05	0.67	10.39
	Pre eNAM	0.19	1.52	2.67	87.27	1.40	0.50	0.11	1.36	3.85	1.13	12.73
	Post eNAM	0.09	1.01	11.12	85.65	0.25	0.08	0.04	0.10	1.59	0.06	14.35
Wheat MP	Overall	2.59	0.60	5.65	1.00	89.71	0.07	0.04	0.09	0.15	0.10	10.29
	Pre eNAM	2.18	0.75	6.49	0.23	89.64	0.13	0.04	0.14	0.23	0.17	10.36
	Post eNAM	1.06	0.89	4.64	0.07	91.72	0.12	1.04	0.19	0.20	0.06	8.28
Barley CIP	Overall	0.04	0.01	0.15	0.14	0.02	87.29	0.03	4.10	4.03	4.19	12.71
	Pre eNAM	0.06	0.02	0.17	0.28	0.04	84.14	0.04	5.03	4.88	5.35	15.86
	Post eNAM	0.05	0.12	0.92	0.09	0.03	96.59	0.28	1.02	0.21	0.69	3.41

Cotton CIP	Overall	0.07	0.07	0.42	0.05	0.13	0.01	99.11	0.05	0.06	0.03	0.89
	Pre eNAM	0.16	0.09	0.61	0.06	0.29	0.02	98.62	0.05	0.05	0.04	1.38
	Post eNAM	0.75	0.04	0.01	0.00	1.31	0.27	96.43	0.12	1.04	0.04	3.57
Maize CIP	Overall	0.01	0.03	0.10	1.29	0.08	3.44	0.04	70.67	16.14	8.21	29.33
	Pre eNAM	0.01	0.06	0.17	1.92	0.10	3.97	0.04	63.97	19.24	10.52	36.03
	Post eNAM	0.12	0.07	0.12	0.27	0.28	0.65	0.09	97.51	0.19	0.71	2.49
Soybean CIP	Overall	0.01	0.05	0.35	4.37	0.12	3.26	0.07	15.86	69.44	6.48	30.56
	Pre eNAM	0.02	0.13	0.36	4.81	0.16	3.76	0.06	19.09	63.46	8.15	36.54
	Post eNAM	0.50	0.68	0.33	3.10	0.64	0.19	0.71	0.08	93.42	0.35	6.58
Wheat CIP	Overall	0.04	0.34	0.03	1.24	0.06	3.73	0.02	9.10	7.28	78.17	21.83
	Pre eNAM	0.02	0.25	0.02	1.79	0.09	4.57	0.02	11.87	9.25	72.12	27.88
	Post eNAM	0.09	1.36	0.57	0.24	0.02	0.69	0.03	0.68	0.50	95.81	4.19
Directional to others	Overall	3.85	2.97	12.16	17.27	8.41	11.26	0.42	30.26	31.33	20.01	137.95
	Pre eNAM	3.84	4.88	11.51	15.83	10.49	13.59	0.51	38.01	38.20	25.73	162.61
	Post eNAM	2.93	5.20	17.85	24.70	9.26	2.78	2.33	2.60	4.79	2.20	74.63
Directional including own	Overall	98.87	100.50	97.68	106.88	98.12	98.55	99.53	100.93	100.77	98.18	TCI
	Pre eNAM	98.29	100.64	99.47	103.10	100.13	97.73	99.14	101.98	101.65	97.85	TCI
	Post eNAM	100.52	100.92	92.78	110.35	100.97	99.37	98.76	100.11	98.21	98.02	TCI
NET directional connected-ness	Overall	−1.13	0.50	−2.32	6.88	−1.88	−1.45	−0.47	0.93	0.77	−1.82	13.79
	Pre eNAM	−1.71	0.64	−0.53	3.10	0.13	−2.27	−0.86	1.98	1.65	−2.15	16.26
	Post eNAM	0.52	0.92	−7.22	10.35	0.97	−0.63	−1.24	0.11	−1.79	−1.98	7.46

Notes – MP: market price, CIP: commodity stock price, TCI: total connectedness index.

Source: Author's calculation.

Table A3. Coefficient matrix

	Barley MP	Cotton MP	Maize MP	Soybean MP	Wheat MP	Barley CIP	Cotton CIP	Maize CIP	Soybean CIP	Wheat CIP
L1.Barley CIP	0.209	0.027	–0.045	0.033	–0.01	0.096	0.069	0.028	0.015	0.024
L1.Barley MP	–0.631	0	0.011	–0.005	0.013	0.002	0.037	–0.003	–0.013	–0.001
L1.Cotton CIP	0	0.006	0	0.005	0	0.004	0.001	0.001	0.004	0
L1.Cotton MP	–0.003	–0.505	0.005	–0.041	–0.009	–0.009	–0.063	0.003	–0.002	–0.007
L1.Maize CIP	0.025	0.092	0.109	–0.041	–0.035	–0.027	–0.049	0.037	–0.056	–0.004
L1.Maize MP	–0.012	0.007	–0.649	0.027	0.019	0.027	0.072	0.009	–0.032	–0.003
L1.Soybean CIP	0.069	–0.016	–0.028	0.432	0.018	0.001	–0.045	0	0.035	0.001
L1.Soybean MP	–0.027	0.062	0.123	–0.397	0.071	–0.005	0.094	0.001	0.04	0.01
L1.Wheat CIP	–0.057	0.113	–0.091	0.009	0.09	0.062	0.094	–0.026	0.035	0.009
L1.Wheat MP	0.054	–0.019	0.044	0.046	–0.483	0	–0.326	0.007	–0.027	–0.016
L2.Barley CIP	0.192	–0.027	0.014	0.034	–0.005	0.007	–0.035	0.024	0.03	–0.001
L2.Barley MP	–0.425	0.015	0.016	–0.005	0.01	–0.009	0.049	–0.004	–0.014	–0.009
L2.Cotton CIP	0.003	0	0.006	0.005	0.003	0	0.002	–0.003	0.004	–0.001
L2.Cotton MP	0.024	–0.21	0.043	0.006	0.008	–0.025	–0.046	0	–0.011	–0.001
L2.Maize CIP	–0.054	0.049	0.126	0.043	0.027	–0.023	0.035	0.012	–0.001	–0.023
L2.Maize MP	0.009	–0.031	–0.428	–0.012	0.029	0.024	0.162	0.018	–0.011	–0.001
L2.Soybean CIP	0.046	0.049	–0.021	0.258	0.013	0.016	0.092	0.006	–0.044	0.016
L2.Soybean MP	–0.046	–0.015	0.02	–0.284	–0.031	–0.011	–0.178	–0.003	0.03	–0.009

L2.Wheat CIP	0.173	–0.001	0.06	0.075	0.208	0.028	–0.019	0.007	0.022	0.021
L2.Wheat MP	0.085	–0.061	–0.028	–0.087	–0.298	0.032	0.076	0.016	–0.001	0.003
L3.Barley CIP	0.281	0.029	–0.045	–0.004	0.009	0.015	–0.046	0.015	0.033	0.02
L3.Barley MP	–0.326	–0.013	–0.007	–0.01	0.005	–0.004	0.033	–0.004	–0.012	0
L3.Cotton CIP	0.008	0.006	–0.001	0.004	0.003	0.004	0.005	–0.004	0.001	0.001
L3.Cotton MP	–0.032	–0.103	0.004	0.02	0.023	–0.012	–0.059	–0.005	–0.002	0.004
L3.Maize CIP	–0.023	0.072	0.08	0.007	0.065	0.009	–0.006	0.047	–0.015	0.011
L3.Maize MP	–0.037	–0.056	–0.277	–0.07	–0.013	0.002	0.055	0.002	–0.047	–0.007
L3.Soybean CIP	–0.015	0	0.001	0.142	–0.006	–0.01	0.142	–0.033	–0.033	–0.024
L3.Soybean MP	0.002	0.053	0.014	–0.125	–0.008	0.014	–0.144	0.008	0.04	0
L3.Wheat CIP	0.014	–0.008	0.065	0.033	0.172	0.009	–0.069	0.058	0.005	0.063
L3.Wheat MP	0.122	0.029	0.008	–0.03	–0.135	–0.007	0.124	0.005	–0.013	–0.009
L4.Barley CIP	0.088	–0.042	0.014	0.077	–0.027	–0.049	0.054	–0.001	0.015	0.023
L4.Barley MP	–0.178	–0.026	–0.016	–0.006	0.003	0.009	0.021	–0.004	–0.015	0.004
L4.Cotton CIP	0.002	0.001	–0.001	–0.006	0	0	–0.005	–0.002	–0.006	–0.001
L4.Cotton MP	–0.011	–0.018	0.004	0.021	0.024	–0.003	–0.124	0.009	0.012	–0.002
L4.Maize CIP	0.108	0.042	0.145	0.015	0.04	0.005	0.126	0.026	0.017	0.009
L4.Maize MP	–0.013	0.021	–0.169	–0.105	–0.048	–0.001	0.023	–0.003	–0.053	–0.013
L4.Soybean CIP	0.009	–0.093	–0.041	0.07	–0.004	0.001	0.087	–0.025	–0.023	–0.019
L4.Soybean MP	–0.051	0.095	0.014	–0.05	–0.003	0.006	–0.077	0.016	0.05	0.01
L4.Wheat CIP	0.003	–0.002	0.004	0.042	0.085	0.023	–0.132	0.018	0.019	0.001
L4.Wheat MP	0.068	0.099	0.019	0.031	–0.028	0.042	0.079	0.017	0.019	–0.007

Notes – MP: market price, CIP: commodity stock price.

Source: Author's calculation.

References

Agarwal, D. K., Billore, S. D., Sharma, A. N., Dupare, B. U., & Srivastava, S. K. (2013, October). Soybean: Introduction, improvement, and utilization in India—problems and prospects. *Agricultural Research*, *2*, 293–300. https://doi.org/10.1007/s40003-013-0088-0

Ahmadi, M., Behmiri, N. B., & Manera, M. (2016, September). How is volatility in commodity markets linked to oil price shocks?. *Energy Economics*, *59*, 11–23. https://doi.org/10.1016/j.eneco.2016.07.006

Antonakakis, N., Chatziantoniou, I., & Gabauer, D. (2020, April). Refined measures of dynamic connectedness based on time-varying parameter vector autoregressions. *Journal of Risk and Financial Management*, *13*, 84. https://doi.org/10.3390/jrfm13040084

Awartani, B., Aktham, M., & Cherif, G. (2016, December). The connectedness between crude oil and financial markets: Evidence from implied volatility indices. *Journal of Commodity Markets*, *4*, 56–69. https://doi.org/10.1016/j.jcomm.2016.11.002

Balli, F., Naeem, M. A., Shahzad, S. J., & de Bruin, A. (2019, June). Spillover network of commodity uncertainties. *Energy Economics*, *81*, 914–927. https://doi.org/10.1016/j.eneco.2019.06.001

Bonato, M. (2015). Realized correlations, betas and volatility spillover in the commodity market: What has changed?. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2571217

Bouri, E., Demirer, R., Gabauer, D., & Gupta, R. (2021, April). Financial market connectedness: The role of investors' happiness. *Finance Research Letters*, 102075. https://doi.org/10.1016/j.frl.2021.102075

Cabrera, B. L., & Schulz, F. (2016, February). Volatility linkages between energy and agricultural commodity prices. *Energy Economics*, *54*, 190–203. https://doi.org/10.1016/j.eneco.2015.11.018

Caporin, M., Gupta, R., & Ravazzolo, F. (2021, January). Contagion between real estate and financial markets: A Bayesian quantile-on-quantile approach. *The North American Journal of Economics and Finance*, *55*, 101347. https://doi.org/10.1016/j.najef.2020.101347

Ciner, C., Lucey, B., & Yarovaya, L. (2020, March). Spillovers, integration and causality in LME non-ferrous metal markets. *Journal of Commodity Markets*, *17*, 100079. https://doi.org/10.1016/j.jcomm.2018.10.001

COCPC. (2020). *National cotton scenario*. The Cotton Corporation of India Ltd. Retrieved from https://cotcorp.org.in/national_cotton.aspx

Dahl, R. E., & Jonsson, E. (2018, December). Volatility spillover in seafood markets. *Journal of Commodity Markets*, *12*, 44–59. https://doi.org/10.1016/j.jcomm.2017.12.005

Department of Agriculture. (2021). *e-NAM Overview*. Retrieved October 20, 2021 from https://www.enam.gov.in/web/

Didar Singh, A. (2014). *India Maize Summit 2014*. FICCI. Retrieved from https://ficci.in/spdocument/20386/India-Maize-2014_v2.pdf

Diebold, F., & Yilmaz, K. (2009, August). Measuring financial asset return and volatility spillovers, with application to global equity markets. *The Economic Journal*, *119*, 158–171.

Diebold, F., & Yilmaz, K. (2011, October). *On the network topology of variance decompositions: Measuring the connectedness of financial firms*. (Working Paper No. 17490). Cambridge, MA: National Bureau of Economic Research. https://doi.org/10.3386/w17490

Diebold, F., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, *28*, 57–66.

Diebold, F., Liu, L., & Yilmaz, K. (2017, August). *Commodity connectedness*. (Working Papers No. 23685). Cambridge, MA: National Bureau of Economic Research. https://doi.org/10.3386/w23685

FICCI. (2018). *Vision 2022*. Retrieved from https://ficci.in/spdocument/22966/India-Maize-Summit.pdf

Fowowe, B. (2016, June). Do oil prices drive agricultural commodity prices? Evidence from South Africa. *Energy*, *104*, 149–157. https://doi.org/10.1016/j.energy.2016.03.101

Guhathakurtha, K., Bhattacharya, S. N., & Bhattacharya, M. (2020, November). A network analysis of the Asia-Pacific and other developed stock markets: Pre and post global financial crisis. *Applied Finance Letters*, *9*, 112–131. https://doi.org/10.24135/afl.v9i2.283

Hassouneh, I., Serra, T., Bojnec, Š., & Gil, J. M. (2016, December). Modelling price transmission and volatility spillover in the Slovenian wheat market. *Applied Economics*, *49*, 4116–4126. https://doi.org/10.1080/00036846.2016.1276273

IBEF. (2020, May). *Wheat production may cross 113 million tonnes: Skymet*. India Brand Equity Foundation, Ministry of Commerce & Industry, Government of India. Retrieved from https://www.ibef.org/news/wheat-production-may-cross-113-million-tonnes-skymet

IBEF. (2021, July). *Indian agriculture and allied industries report*. Indian Agriculture Industry Analysis. Retrieved from https://www.ibef.org/industry/agriculture-presentation

ICAR. (2020). *India maize scenario*. ICAR-Indian Institute of Maize Research. Retrieved from https://iimr.icar.gov.in/india-maze-scenario/

Ji, Q., Bouri, E., Roubaud, D., & Shahzad, S. J. (2018, September). Risk spillover between energy and agricultural commodity markets: A dependence-switching CoVaR-copula model. *Energy Economics*, *75*, 14–27. https://doi.org/10.1016/j.eneco.2018.08.015

Koirala, K. H., Mishra, A. K., D'Antoni, J. M., & Mehlhorn, J. E. (2015, March). Energy prices and agricultural commodity prices: Testing correlation using copulas method. *Energy*, *81*, 430–436. https://doi.org/10.1016/j.energy.2014.12.055

Korobilis, D., & Yilmaz, K. (2018). Measuring dynamic connectedness with large Bayesian VAR models. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3099725

Nazlioglu, S. (2011, May). World oil and agricultural commodity prices: Evidence from nonlinear causality. *Energy Policy*, *39*, 2935–2943. https://doi.org/10.1016/j.enpol.2011.03.001

Nicola, F., Pace, P. D., & Hernandez, M. A. (2016, June). Co-movement of major energy, agricultural, and food commodity price returns: A time-series assessment. *Energy Economics*, *57*, 28–41. https://doi.org/10.1016/j.eneco.2016.04.012

Reboredo, J. C. (2018, August). Green bond and financial markets: Co-movement, diversification and price spillover effects. *Energy Economics*, *74*, 38–50. https://doi.org/10.1016/j.eneco.2018.05.030

Rigobón, R. (2019). Contagion, spillover, and interdependence. *Economica*, *19*, 69–99. https://doi.org/10.1353/eco.2019.0002

Sendhil, R., Singh, R., Kumar, A., Chand, R., Pandey, J. K., Singh, R., … Verma, R. P. (2018). Adoption level, yield and constraints in Indian barley (Hordeum vulgare) cultivation: Insights from baseline data for identifying livelihood prospects. *Indian Journal of Agricultural Sciences*, *88*, 1233–1240.

Sim, N., & Zhou, H. (2015, June). Oil prices, US stock return, and the dependence between their quantiles. *Journal of Banking & Finance*, *55*, 1–8. https://doi.org/10.1016/j.jbankfin.2015.01.013

Singh, S. K. (2016). *India grain and feed annual*. Retrieved from https://apps.fas.usda.gov/newgainapi/api/report/downloadreportbyfilename?filename=GrainandFeed Annual_NewDelhi_India_2-26-2016.pdf

Thukral, S., & Sikka, R. (2020, November). Liquidity in Asian financial markets: Crowding out or spillover effect. *Applied Finance Letters*, *9*, 90–102. https://doi.org/10.24135/afl.v9i2.251

Tricase, C., Amicarelli, V., Lamonaca, E., & Rana, R. L. (2018). Economic analysis of the barley market and related uses. In Z. Tadele (Ed.), *Grasses as food and feed*. IntechOpen. https://doi.org/10.5772/intechopen.78967

Umar, Z., Gubareva, M., Naeem, M., & Akhter, A. (2021, February). Return and volatility transmission between oil price shocks and agricultural commodities. *PLOS ONE*, *16*. https://doi.org/10.1371/journal.pone.0246886

Wang, G.-J., Xie, C., & Stanley, H. E. (2016, October). Correlation structure and evolution of world stock markets: Evidence from Pearson and partial correlation-based networks. *Computational Economics*, *51*, 607–635. https://doi.org/10.1007/s10614-016-9627-7

Wang, Y., Wu, C., & Yang, L. (2014, July). Oil price shocks and agricultural commodity prices. *Energy Economics*, *44*, 22–35. https://doi.org/10.1016/j.eneco.2014.03.016

Yan, W., & Deng, G. (2018, April). Origin of production shocks, agricultural price spikes and trade policy. *The Manchester School*, *87*, 81–102. https://doi.org/10.1111/manc.12219

Youssef, M., Mokni, K., & Ajmi, A. N. (2020, August). *Dynamic connectedness between stock markets in the presence of COVID-19 pandemic: Does economic policy uncertainty matter?*. https://doi.org/10.21203/rs.3.rs-61157/v1

Zhang, C., & Qu, X. (2015). The effect of global oil price shocks on China's agricultural commodities. *Energy Economics*, *51*, 354–364. https://doi.org/10.1016/j.eneco.2015.07.012