European Economic Letters
ISSN 2323-5233
Vol 14, Issue 4 (2024)
http://eelet.org.uk

# Time-Varying Connectedness and Causality between Energy and Agriculture Futures Markets in India: Evidence from the Russia-Ukraine War

**Neeti Jain (Corresponding Author)**
Research Scholar, Indian Institute of Foreign Trade, Indian Institute of Foreign Trade, B-21 Qutub Institutional Area New Delhi-110016

**Dr Niti Nandini Chatnani**
Professor, Indian Institute of Foreign Trade, Indian Institute of Foreign Trade, B-21 Qutub Institutional Area New Delhi-110016

**Abstract:**
The Russian invasion of Ukraine in February 2022 pressured the prices of essential food and fuel commodities, which were already impacted due to a reduction in crop output because of climatic changes, resulting in high levels of commodity price volatility. A multi-analytical approach is employed to examine the link between energy markets and selected agricultural futures of commodities in India.The empirical results provide insights into the spillover effect of energy markets to agricultural in the Indian economy. During geopolitical instability, agricultural markets exhibit higher interconnectedness with each other and crude oil, however in the long run commodities demonstrates their resilience against transmitted risks from network variables.
***Keywords:*** *Agricultural Futures, Food Security, Energy Markets, TVP-VAR, Spillover*

## 1. Introduction

The uncertainty of the international macroeconomic situation and the search for alternative investment assets impact asset markets and their integration patterns. Russia and Ukraine are the world's leading agricultural commodity producers (OECD, 2022). They are among the top three global exporters of major agricultural commodities such as wheat, barley, maize, rapeseed and rapeseed oil, sunflower seed, and sunflower oil. The ongoing conflict has affected businesses worldwide, caused food shortages, and impacted commodity markets. The volatility of the energy and agricultural markets has important implications for the stability and development of the economy. In times of market crisis, decreased economic activity and accumulated stockpiles of raw and refined commodities lead to market consolidation markets as stockpiling (Corbet et al., 2020; Umar et al., 2021). However, incidences of short supply during turbulence leading to inflated commodity prices have also been observed (Adhikari & Putnam, 2020; Bakas & Triantafyllou, 2020). Against this backdrop, it is crucial to examine the nexus between the agricultural and energy markets in India, especially in an extreme event such as the Russia-Ukraine war. Developing nations, such as India, which depend on local supplies for their population and export revenue, are impacted by sudden price fluctuations in agricultural goods (Manogna & Mishra, 2020).

## 2. Literature Review

Numerous factors contribute to the fluctuation of agricultural prices. Supply determinants include planting decisions, yields, trade policies of exporting countries, input costs, and stock levels. On the demand side, crops serve as food, animal feed, and biofuel inputs. Rising oil prices incentivize biofuel production, increasing demand for agricultural commodities, alongside input cost factors. The agricultural market pricing is influenced by the relationship between energy and commodity markets. Despite the extensive trading in recent years, research on energy markets' impact on agricultural futures is limited. Malhotra and Sharma (2016) concluded that uninformed speculators in oilseed futures markets cause noise and destabilize spot markets. Duc Huynh et al. (2020) found that excessive speculation in futures markets destabilizes spot markets for crude oil, metals, and agricultural commodities.

### 2.1 Interdependency relationship between Agricultural and energy Commodities

Fluctuations in international crude oil prices can significantly affect the supply and demand of agricultural products due to factors like capital speculation, geopolitical conflicts, and changes in the value of the US Dollar (Liu et al., 2018; Manera et al., 2013). Higher energy prices lead to increased processing, transportation, and production costs over time. Wu et al. (2023) used a varying-coefficient interval-valued time series (VC-ITS) model to show that temperature changes dynamically affect crude oil futures but have a static effect on coal futures, while agricultural futures exhibit a negative pass-through effect, highlighting the importance of including climate variables in pricing. Jia et al. (2023) examined the spillover effects of extreme climate events on agricultural and energy futures, emphasizing the need for climate risk in hedging strategies.

Baffes and Haniotis (2010) argue that high crude prices drove the food commodity price boom, with Taghizadeh-Hesary et al. (2019) finding a positive correlation between oil and food prices, while biofuels had a negative correlation. Rehman et al. (2019) and Wu et al. (2011) observed bidirectional volatility spillovers between crude oil and agricultural markets before the crisis, though interdependence may have shifted in recent times. Trujillo-Barrera et al. (2012) identified significant volatility spillover from oil to corn markets, while Gardebroek and Hernandez (2013) found no such spillover. Post-crisis, commodity market dynamics showed signs of price rebound, differing from pre-crisis patterns.

The relationship between energy prices, geopolitical events, capital speculation, and supply-demand situations has been a global concern. COVID-19 affected global oil demand and the cross-correlation between Brent Crude and agricultural futures such as sugar, wheat, and cotton (J. Wang et al., 2020). Price volatility since 2013 has raised concerns about earlier agricultural commodity price declines (Aloui et al., 2023), with Boyd et al. (2018) and Dimpfl et al. (2017) noting that most price volatility in the last 40 years stemmed from macroeconomic and financial shocks. Increased corn-based ethanol production has been a major factor in agricultural price volatility (Bouri & Gupta, 2020; Shen et al., 2017), with speculation exacerbating non-linear price behavior. Raza et al. (2022) suggest that food production shocks in one country often lead to global price increases, highlighting the role of speculation in driving volatility in essential food commodities.

### 2.1. Global impact of Russia-Ukraine crisis on Commodities

The interaction between the oil and agriculture markets is increasingly crucial as the commodity derivatives market expands. Fernandez-Perez et al. (2016) identified a unidirectional impact of crude oil on agricultural commodity prices, particularly for soybeans, wheat, and corn. Nwoko et al. (2016) observed a significant short-term positive relationship between energy prices and maize, sorghum, and soybean, though rice and wheat were excluded. Mawejje (2016) reported long-term co-integration between agricultural and energy prices, while Nazlioglu and Soytas (2011) found that energy prices do not significantly impact agricultural prices in the short run, and long-term energy price deviations are not transmitted to agricultural prices. Yin and Cao (2024) showed that financialization has increased the speed and magnitude of information flow across commodity markets, including energy and agriculture, while Wei et al. (2023) highlighted how extreme events like financial crises intensify spillovers, stressing the importance of environmental and regulatory factors. Cui and Maghyereh (2024) found significant spillovers in commodity markets during periods of stress, especially in higher-order moments of returns, while Dewan and Dharni (2023) identified herding behavior in the Indian commodity futures market, particularly during market declines, with spillovers to metals and agriculture.

Wei Su et al. (2019) found bidirectional causality between agricultural commodity and oil prices via biofuel and input channels, supporting the vertical market integration model. Taghizadeh-Hesary et al. (2019) observed a strong association between oil and food prices in eight Asian countries, with oil prices explaining the majority of food price variance. Fasanya and Akinbowale (2019) and Zmami and Ben-Salha (2019), using the ARDL technique, confirmed both asymmetric and symmetric relationships between oil and agricultural futures prices, with oil shocks significantly affecting agricultural commodity prices. Wang et al. (2022) analyzed volatility across commodities during the COVID-19 pandemic and the Russia-Ukraine war, finding greater volatility spillovers during the war (35%-85%). Aluminium, platinum, silver, gold, copper, and sugar were net volatility spillover agents, while crude oil was a net transmitter, and soybeans and wheat were net recipients. Mokni and Youssef (2020) concluded that the delayed impacts of oil price shocks on commodity prices are smaller than immediate effects, while Lundberg et al. (2021) found oil and agricultural commodity prices to be counter-cyclical and procyclical using a mixed-domain wavelet approach. Saâdaoui et al. (2022) examined the influence of geopolitical events, such as Brexit, COVID-19, and the Russia-Ukraine war, on essential food commodity prices, finding significant impacts.

### 2.2. Influence of the Russia-Ukraine crisis on Indian Commodities

Kumar et al. (2023) reported a substantial shift in the status of net transmitters and receivers in the wake of the Russia-Ukraine conflict. In the pre-war period, markets such as India, Australia, Korea, Turkey, and the oil market were net transmitters, while the USA, Canada, Brazil, and Mexico were net receivers. However, during the COVID-19 crisis, markets in India, the Republic of Korea, Turkey, and the oil market transitioned from net recipients to net transmitters. Rezitis et al. (2024) examined volatility linkages between energy and agricultural futures, highlighting how external shocks, such as crises, significantly increased cross-correlations and volatility spillovers, particularly during periods of high volatility. Gupta and Pierdzioch (2024) evaluated multi-task forecasting models for agricultural volatility, finding that while these models improved in-sample predictability, they did not offer significant out-of-sample advantages. Iqbal et al. (2023) explored extreme risk spillovers during crises, including COVID-19, revealing that volatility spillovers intensified during extreme events, destabilizing market dynamics. Palazzi et al. (2024) studied the dynamic connectedness between energy and Brazil's cash markets, showing that oil prices strongly influenced Brazilian ethanol prices post-COVID-19, suggesting that energy futures could serve as a hedge against ethanol price fluctuations, especially as Brazil's soybean market gains global significance.

Sarkar and Gupta (2023) calculated a total maximum economic loss of INR 115,562.51 million and a minimum economic loss of INR 92,444.39 million for Indian sectors from the Russia-Ukraine conflict. They noted that India's reliance on Russian and Ukrainian goods, including crude oil and sunflower oil, magnified the economic impact. Rising oil prices during the crisis, which hit a 14-year high, are expected to gradually undermine India's economy. Ukraine, as India's second-largest supplier of sunflower oil, further exacerbated the issue, as Russia and Ukraine together account for 90% of India's sunflower oil imports.

The ongoing Russia-Ukraine conflict has heightened trade uncertainty, particularly in oil and agricultural commodities, with the potential to impact GDP growth, inflation, and energy prices (Deininger et al., 2023). This has led to reduced economic growth and rising inflationary pressures globally. Two key literature gaps drive the need for this study. First, there is a dearth of research on how the Ukraine-Russia war has altered the dynamics of energy and agricultural commodity markets, with most existing research focused on equity and debt markets or developed economies. This study addresses this gap by examining the impact on India, a developing country that relies heavily on both agricultural and energy commodities. Second, as Ukraine and Russia supply one-third of the world's wheat and barley and 70% of global sunflower oil demand, the war's ongoing disruption has limited options for substituting these critical commodities. These agricultural products, produced in India and exported globally, have broad industrial applications, from oil extraction (guar seed) to pharmaceuticals (castor seed, mentha oil) and apparel. The war has led to rising prices and shrinking food reserves globally, with the study using India's futures prices to analyze the short- and long-term impacts of commodity volatility before and after the war. By examining granular data, this study aims to provide a deeper understanding of the spillover effects between oil and agricultural futures prices, focusing on both short- and long-term dynamics.

## 3. Research Methodology

A rolling-window generalized forecast error variance decompositions is used to construct the spillover indices. The approach allows the identification of time-varying patterns. While the static GFEVD classifies the variables of the study into transmitters and receivers, the dynamic GFEVD identifies episodes when the role of transmitters and receivers of spillovers is interrupted or even reversed. The GIRFs will be calculated within the rolling-window approach. It is assumed that volatility is fixed within shorter periods, such as days. However, it varies across more prolonged periods. Volatility is estimated using daily prices. The proxy used is the logarithm of the difference between the current and previous day log price where t refers to a particular moment (day).

### 3.1. VAR Model Estimation

The empirical strategy includes inference from the whole sample and the rolling windows. The following steps are conducted and repeated for each commodity.

$$y_t = \sum_{i=0}^{q} B_i \, y_{t-i} + \varepsilon_t$$

Represented by $y_t$ as N X 1 vector of endogenous variables, $B_i$ as N X N autoregressive coefficient matrices and $\varepsilon_t \sim (0,\Sigma)$ is a vector of independently and identically distributed disturbances.

### 3.2. Moving Average representation of VAR and Total Spillover Index

Second, the total and directional spillover indices are obtained from generalized forecast error variance decompositions of the moving average representation of the VAR model. Variance decompositions allow for parsing forecast error variances of each variable into parts which are attributable to various system shocks. They allow for assessing the fraction of the H-step-ahead error variance in forecasting one variable that is due to shocks to another variable.

$$y_t = \sum_{j=0}^{\infty} A_j \, \varepsilon_{t-j}$$

showing the $N \times N$ coefficient matrices $A_j$ obey the recursion of form $A_j = B_1 A_{t-i} + B_2 A_{j-2} + \ldots B_p A_{j-p}$ with $A_0$ being the N X N identity matrix and $A_j$ =0 for j<0. The H-step-ahead generalized forecast error variance decomposition invariant to the variable ordering is represented as

$$\theta_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' \, A_h \Sigma \, e_j\right)^2}{\sum_{h=0}^{H-1}\left( e_i' \, A_h \Sigma A'_h \, e_j\right)}$$

Where, I,j = 1,2,..,N, Σ = Covariance matrix for error vector Ɛ, $\theta_{ij}$ = j-th diagonal element of Σ, $e_i$ = Selection vector having 1 as the i-th element and 0 (zero) otherwise

Θ[1] is an N X N matrix with $\theta_{ij}(H)$ elements. Every entry contributes variable j to the forecast error variance of variable i. Next, normalization of rows in Θ (H) would be undertaken in order to avoid sums to one under generalized decomposition. Post normalization, total spillover index

$$T\,S\,(H) = \frac{\sum_{i,j=1, i \neq j}^{N} \Theta_{ij}\ (H)}{N} 100\%$$

The total spillover index is indicative of the contribution of volatility shocks among the energy and agricultural futures, considering the total forecast error variance duly.

C is representative of the commodity. The connectedness approach depicts transfer of volatility from variable i to all other variables j and is known as total directional connectedness to others.

$$TO_{ij} = \sum_{n=1}^{k} C_{ij}.nm$$

The directional volatility that can be explained by variable i due to spillover of risk from all other variables j is known as total directional connectedness from others

$$FROM_{ij} = \sum_{m=1}^{k} C_{ji}.nm$$

The deduction of total directional connectedness to others from total directional connectedness from others results in the net total directional connectedness:

$$NET_{ij} = TO_{ij} - FROM_{ij}$$

$NET_{ij}$ illuminates the difference between "TO" and "FROM,". Net transmitter of shocks (risk) to the system is denoted by a positive net value while a net receiver of shocks (risk) from other markets in the system is denoted by a negative net value. $TCI_t$ represents the total connectedness index where $\tilde{\phi}$ is the share of variance

$$TCI_t = \frac{\Sigma_{i,j=1, i \neq j}^{k} \tilde{\Theta}_i^g (H)}{k-1}$$

(8) $NPDC_{ij}$, detects whether variable *j* is driving variable *i* or vice versa. In case, $NPDC_{ij} > 0$ ($NPDC_{ij} < 0$, it showcases that variable *j* is dominating (dominated by) variable *i*. All the above risk spillover and connectedness measures are estimated on a particular 'q' quantile basis. Following Broadstock et al. (2021), it should be borne that the minimum connectedness portfolio (MCoP) approach is utilized. Sharpe Ratio to rank the commodities based on the profitability of the investment against the potential risks.

$$NPDC_{ij}(J) = \frac{\tilde{\phi}_{ji,t}(J) - \tilde{\phi}_{ji,t}(J)}{T} * 100$$

[1] Upper case theta

### 3.3. Data and Descriptive Statistics

The financial time series data, sourced from Bloomberg, spans from 1 October 2020 to 18 July 2023, totaling 716 daily observations. The analysis includes commodities from India's Multi Commodity Exchange (MCX) and National Commodity Exchange (NCDEX). MCX is the primary exchange for precious commodities, metals, and energy derivatives, while NCDEX leads in agricultural derivatives. For contracts like cotton, both exchanges are considered, with selection based on trading volume. The commodities analyzed are crude oil, cotton, and mentha oil (MCX), and castor seed, jeera, guar seed, and turmeric (NCDEX). Commodity returns are calculated as the difference between the current and previous day's prices. Crude oil is categorized as an energy market contract, castor seed, guar seed, and mentha oil as oilseeds, and jeera and cotton as cash crops.

Descriptive statistics, including mean, median, and standard deviation, are shown in Table 1. The returns are left-skewed, with Jarque-Bera tests indicating a non-Gaussian distribution for all commodities, along with significant excess kurtosis. The weighted portmanteau test confirms substantial autocorrelation and ARCH/GARCH errors, justifying the use of TVP-VAR techniques with heteroscedastic variances.

Figure 1 shows the logarithmic values of the time series, which are stationary. Despite the outbreak of war in February 2022, there were no significant changes in commodities like guar seed, cotton, and mentha oil by June 2022. Table 1 presents the descriptive statistics, revealing that crude oil and mentha oil have the highest return averages, while jeera and cotton have the lowest. The skewness statistics confirm an asymmetric price distribution.

Figure 2 illustrates the correlogram with Pearson correlation coefficients, frequency densities, and scatter plots. The scatter plots highlight outliers across all relationship pairs, suggesting the importance of including extreme returns in spillover modeling. At the 1% significance level, all pairwise correlation coefficients significantly differ from zero. Guar seed shows the highest pairwise correlation, while mentha oil exhibits the weakest correlation with other commodities..

**Table 1 :** Descriptive Statistics

| | *Crude Oil* | *Castor Seed* | *Cotton* | *Jeera* | *Guar Seed* | *Mentha Oil* | *Turmeric* |
|---|---|---|---|---|---|---|---|
| *Mean* | 2.269672 | 1.756601 | 1.68301 | 0.270485 | 1.808191 | 2.11966 | 1.819261 |
| *Variance* | 0.378 | 0.54 | 0.434 | 0.008 | 0.424 | 0.391 | 0.417 |
| *Skewness* | -0.134 | -0.101 | -0.205** | -0.004 | -0.150* | -0.127 | -0.182** |
| | -0.141 | -0.265 | -0.025 | -0.962 | -0.099 | -0.163 | -0.046 |
| *Kurtosis* | 2.885*** | 1.190*** | 2.578*** | 5.786*** | 0.995*** | 1.800*** | 1.097*** |
| | 250.116*** | 43.439*** | 203.013*** | 997.528*** | 32.188*** | 98.466*** | 39.827*** |
| *JB* | -1.932* | -1.707* | -19.745*** | -2.693*** | -18.024*** | -1.947* | -2.247** |
| *ERS* | -0.054 | -0.088 | 0 | -0.007 | 0 | -0.052 | -0.025 |
| | 189.004*** | 175.100*** | 141.118*** | 179.230*** | 193.965*** | 205.187*** | 199.719*** |
| *Q(10)* | 120.578*** | 77.641*** | 94.949*** | 159.820*** | 62.463*** | 126.961*** | 101.187*** |

Note: *, **, *** represents the null hypothesis of normality is rejected at the 10%, 5% and 1% level, respectively.

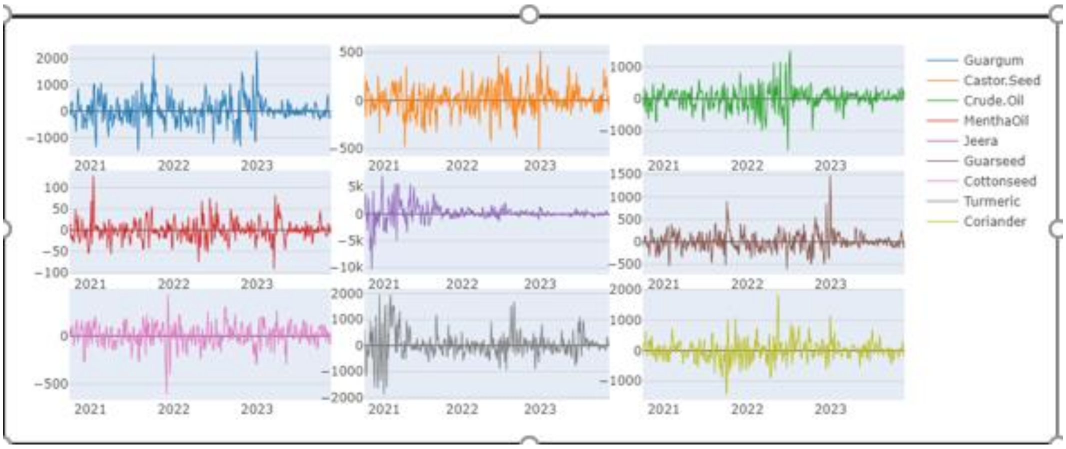



Figure 1: Time series of the energy and agricultural futures contract

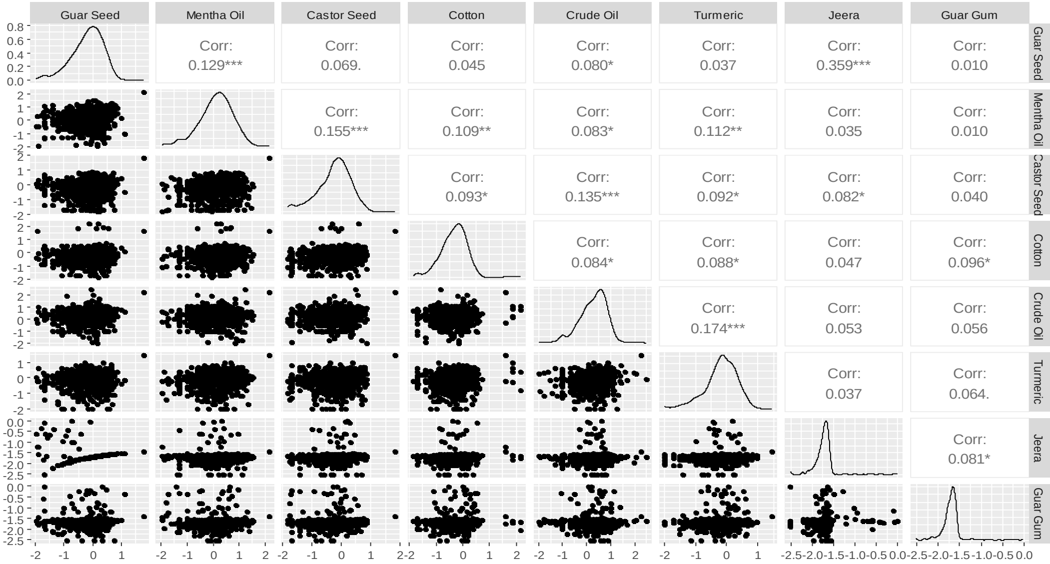



Figure 2: shows the scatter plots, frequency density distributions and pairwise Pearson correlation coefficients of the return series. *** represents statistical significance at the 1% level

## 4. Results

This section analyzes the transmission and reception of volatility shocks among the commodities studied. The dynamic total connectedness is 35.72% in the pre-period and 39.78% in the post-period, reflecting an increase in interconnectedness post-COVID-19 and amid the ongoing geopolitical uncertainty. Pre-period fluctuations range from -17.15 to 18.93, while post-period fluctuations vary from -12.18 to 22.16. The post-period saw heightened volatility, especially between turmeric and cumin, driven by disruptions in energy and agricultural resource mobility due to the war. These disruptions led to price increases and heightened volatility.

The dynamic net directional connectedness quantifies volatility transmission, indicating whether a commodity acts as a transmitter or receiver of shocks. A positive value signals a volatility transmitter. Crude oil, for example, exhibits negative directional connectedness post-period, reflecting its diminished role as a volatility transmitter after the war's onset. Table 2 presents the Average Total Connectedness index for both periods, showing that 35.72% of variance was explained by internal volatility in the pre-period, with external factors accounting for 64.28%. Post-war, the index rose to 39.78%, signaling an increase in volatility transmission.

Figure 3 shows dynamic net pairwise directional connectedness, highlighting the relationship between oil and agricultural commodities. The y-axis represents the pairwise connectedness index, where negative values indicate contagion from one market to another, and positive values indicate the reverse. In the pre-period, guar gum and coriander had significant short-term impacts on system volatility, while turmeric and cumin were major long-term transmitters. In contrast, guarseed and cottonseed were primarily short- and long-term recipients.

Post-war, the volatility transmission dynamics shifted. Turmeric became the primary volatility source, while coriander acted as both a short-term receiver and transmitter. The long-term connections between commodities weakened. The volatility spillover between crude oil and agricultural commodities remained weak, except for mentha oil and castor seed, which showed stronger responses to oil price fluctuations.

Volatility spillovers from crude oil to agricultural markets were generally smaller than vice versa. However, agricultural markets exhibited greater volatility spillovers to crude oil, signaling that disruptions in agricultural markets had a more significant impact on oil prices than the other way around. The net pairwise connectedness also turned negative for most pairs after the event, indicating that energy markets had less influence on agricultural markets post-war.

The high-frequency analysis (Figure 4) shows that market shocks are processed quickly, with short-term spillovers dominating. Shocks from 6 to 90 days ago had little impact on current interconnectedness, suggesting that recent events, especially geopolitical uncertainty, were the primary drivers of volatility transmission.

This analysis provides valuable insights for stakeholders navigating global commodity markets. The results indicate that during periods of geopolitical instability, agricultural markets become more interconnected, particularly with crude oil, as supply chain disruptions drive price increases. While volatility spillovers were more pronounced in agricultural markets, crude oil's disconnect from these markets underscores its role as a safe haven asset. Mentha oil and cotton, in particular, demonstrated resilience against external risks.

European Economic Letters
ISSN 2323-5233
Vol 14, Issue 4 (2024)
http://eelet.org.uk

**Table 2:** Average Dynamic connectedness table

Panel A : Pre Russia Ukraine Crisis

| | Coriander | Turmeric | Cottonseed | Guarseed | Cumin | MenthaOil | Crude.Oil | Castor.Seed | Guargum | FROM |
|---|---|---|---|---|---|---|---|---|---|---|
| Coriander | 64.14 | 1.05 | 3.5 | 4.8 | 9.14 | 4.76 | 5.66 | 3 | 3.94 | 35.86 |
| Turmeric | 3.22 | 69.95 | 4.45 | 3.96 | 3.92 | 2.04 | 4.56 | 4.14 | 3.75 | 30.05 |
| Cottonseed | 3.61 | 1.73 | 71.18 | 5.02 | 2.81 | 1.09 | 5.77 | 3.8 | 4.99 | 28.82 |
| Guarseed | 4.56 | 2.05 | 4.73 | 62.36 | 5.94 | 1.49 | 5.92 | 8.42 | 4.52 | 37.64 |
| Jeera | 7.94 | 2.5 | 3.84 | 3.93 | 65.56 | 2.06 | 5.64 | 4.42 | 4.09 | 34.44 |
| MenthaOil | 3.78 | 0.58 | 1.94 | 1.79 | 6.33 | 77 | 5.4 | 1.45 | 1.71 | 23 |
| Crude.Oil | 3.41 | 1.62 | 4.43 | 4.53 | 2.85 | 1.31 | 73.7 | 4.08 | 4.07 | 26.3 |
| Castor.Seed | 2.74 | 1.5 | 6.87 | 8.99 | 3.08 | 1.07 | 4.84 | 66.18 | 4.74 | 33.82 |
| Guargum | 3.49 | 1.85 | 6.95 | 6.86 | 3.36 | 2.76 | 7.44 | 3.14 | 64.16 | 35.84 |
| TO | 32.75 | 12.9 | 36.71 | 39.88 | 37.43 | 16.59 | 45.23 | 32.46 | 31.83 | 285.77 |
| Inc.Own | 96.89 | 82.85 | 107.89 | 102.24 | 102.99 | 93.59 | 118.93 | 98.64 | 95.98 | cTCI/TCI |
| Net | -3.11 | -17.15 | 7.89 | 2.24 | 2.99 | -6.41 | 18.93 | -1.36 | -4.02 | 35.72/31.75 |
| NPDC | 2 | 0 | 5 | 6 | 4 | 3 | 8 | 4 | 4 | |

Panel B : Post Russia Ukraine Crisis

| | Coriander | Turmeric | Cottonseed | Guarseed | Cumin | MenthaOil | Crude.Oil | Castor.Seed | Guargum | FROM |
|---|---|---|---|---|---|---|---|---|---|---|
| Coriander | 62.69 | 5.86 | 2.26 | 5.28 | 11.81 | 3.54 | 2.08 | 3.04 | 3.44 | 37.31 |
| Turmeric | 12.95 | 57.08 | 4.18 | 3.91 | 10.24 | 2.63 | 2.28 | 3.44 | 3.3 | 42.92 |
| Cottonseed | 4.83 | 3.52 | 66.75 | 4.96 | 6.13 | 3.95 | 3.22 | 3.44 | 3.19 | 33.25 |
| Guarseed | 7.19 | 2.63 | 2.96 | 65.32 | 7.53 | 3.19 | 2.4 | 4.85 | 3.93 | 34.68 |
| Jeera | 12.22 | 5.07 | 1.86 | 4.63 | 61.75 | 4.09 | 2.86 | 3.8 | 3.71 | 38.25 |
| MenthaOil | 5.2 | 3.62 | 2.63 | 2.24 | 6.9 | 68.83 | 4.96 | 2.64 | 2.99 | 31.17 |
| Crude.Oil | 4.9 | 3.48 | 2.59 | 3.16 | 4.52 | 3.69 | 70.26 | 4.28 | 3.12 | 29.74 |
| Castor.Seed | 5.95 | 4.68 | 2.65 | 6.05 | 6.59 | 3.38 | 4.09 | 62.97 | 3.64 | 37.03 |
| Guargum | 6.22 | 4.11 | 1.94 | 4.35 | 5.47 | 3.61 | 3.39 | 4.79 | 66.12 | 33.88 |
| TO | 59.48 | 32.98 | 21.07 | 34.58 | 59.18 | 28.07 | 25.28 | 30.28 | 27.32 | 318.24 |
| Inc.Own | 122.16 | 90.05 | 87.82 | 99.9 | 120.93 | 96.9 | 95.54 | 93.26 | 93.44 | cTCI/TCI |
| Net | 22.16 | -9.95 | -12.18 | -0.1 | 20.93 | -3.1 | -4.46 | -6.74 | -6.56 | 39.78/35.36 |
| NPDC | 8 | 4 | 1 | 5 | 7 | 4 | 3 | 3 | 1 | |

Figure 3 : Net pairwise directional connectedness.Notes: The black area illustrates the dynamic net pairwise directional connectedness while the short-term and long-term dynamic net pairwise directional connectedness are illustrated in pink and green, respectively.

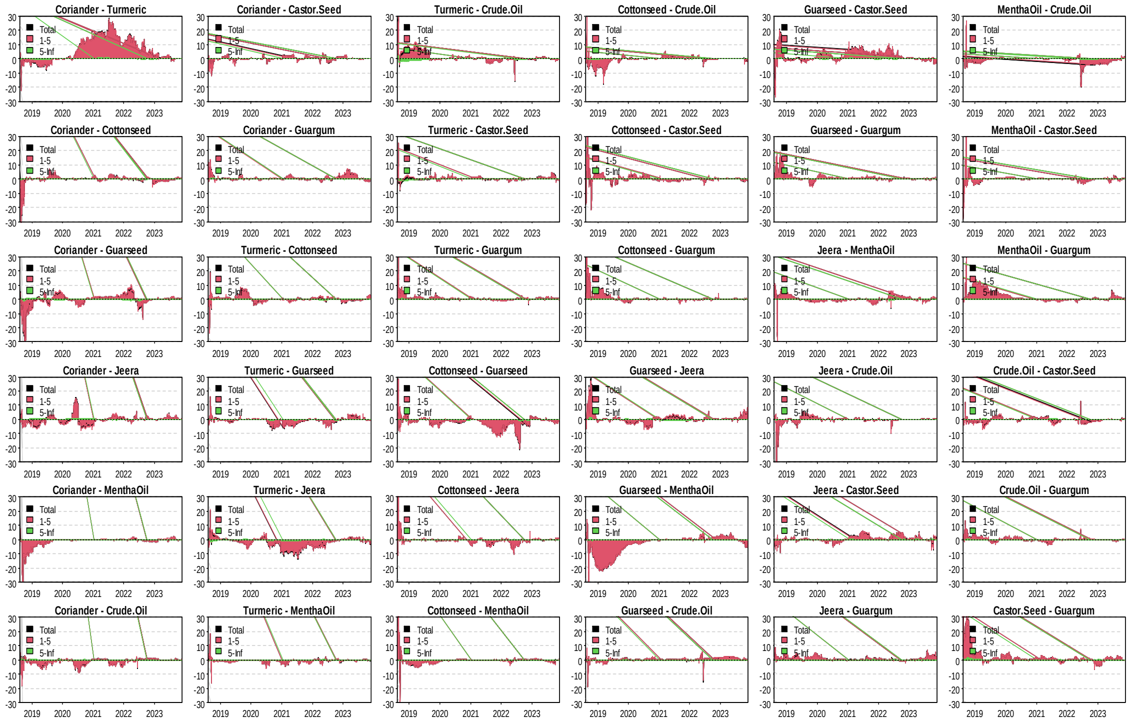
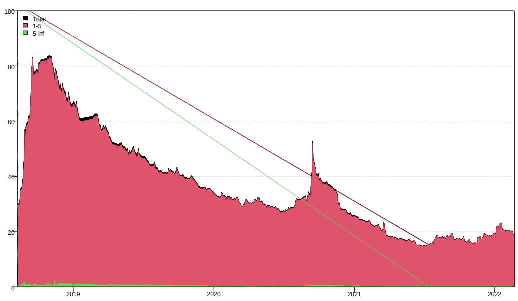
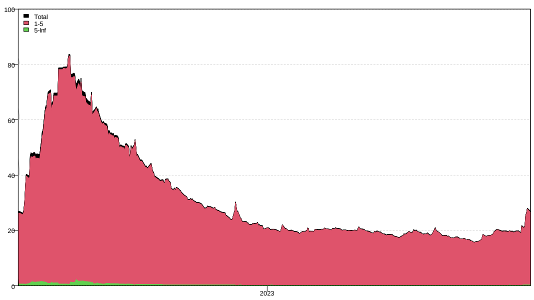



Figure 4: Dynamic total connectedness.

Notes: The black area illustrates the dynamic total connectedness while the short-term and long-term dynamic total connectedness are illustrated in pink and green, respectively. Dotted lines correspond to frequency connectedness (Baruník and Křehlík, 2018) and time connectedness TCI (Diebold and Yılmaz, 2012) using a 200 days rolling-window VAR.





Panel A: Pre Russia Ukraine Crisis

Panel B: Post Russia Ukraine Crisis

## 5. Policy Implications

Evaluating the dynamic linkage between commodity markets is crucial for investors, value chain participants, and consumers, as it reflects the broader health of the Indian economy (Malhotra et al., 2023). Following the 2008 and 2011 food crises, there has been increased scrutiny of agricultural commodity derivative markets. The relationship between oil and agricultural markets is complex, with agricultural volatility not solely driven by energy markets, as empirical evidence suggests. As commodity markets recovered from the global downturn, agricultural futures saw price surges in late 2021, raising concerns about food insecurity similar to previous crises. Market volatility was largely due to intrinsic factors, with the study indicating that long-term spillover effects increased during economic recovery.

Uncertainty in commodity markets can lead to overproduction or underproduction, impacting farmers and consumers. Importing countries are particularly vulnerable to food shortages when exporting nations raise export taxes, disproportionately affecting economically disadvantaged populations. Strategists can use these findings to improve sustainability in the energy and agricultural sectors. Additionally, the results contribute to a better understanding of shock transmission in commodity futures markets, helping both institutional and individual investors develop strategies to mitigate negative spillovers. Although traded volumes are low compared to production, futures markets empower farmers and Farmer Producer Organizations (FPOs) with improved negotiating power. These insights may also be applicable to other countries facing uncertainty and food insecurity.

## 6. Conclusion

India is characterized by income use patterns focused on daily food purchases. The Ukraine conflict could exacerbate existing vulnerabilities. The war's impact extends beyond wheat and sunflower oil imports from Russia and Ukraine, creating a global multi-commodity crisis across food, social, economic, and political sectors. Price increases reflected changes in the global environment over time. There is a transient relationship between variables responsible for joint price movements among unrelated agricultural commodities. Results confirm that connectedness between commodities rises during extreme regimes. Crude oil futures transmit volatility within the framework, but the effects are short-lived. Crude oil also significantly receives volatility shocks from agricultural markets, indicating agricultural market volatility is not solely due to crude oil price behavior.

Agricultural commodities are crucial as production inputs, potentially inducing inflationary pressures. The study revisits volatility connectedness between oil and agricultural markets. Empirical results show increasing co-movement among unrelated asset classes, with long-term risk mitigation. These findings support long-term policy on trading agricultural commodities in derivatives markets. Analysis suggests investors should assess risk and return based on the tenure of investments in oil and agricultural commodities, particularly for those heavily exposed to these markets. For instance, crude oil market investors can hedge risks during extreme booms and busts with agricultural markets, aiding in portfolio management and loss minimization.

During the analysis window, there was reduced industrial demand for crude oil and agricultural commodities. Commodity futures prices surged due to the Russia-Ukraine conflict, indicating a low impact of the conflict while, the actual impact exceeded the calculated value. Future research can explore factors such as substitute prices and demand-supply equilibrium to measure impacts. Research on more commodities across global exchanges can help understand the price discovery mechanism during unprecedented geopolitical crises.

**References:**

1. Adhikari, R., & Putnam, K. J. (2020). Comovement in the commodity futures markets: An analysis of the energy, grains, and livestock sectors. *Journal of Commodity Markets*, *18*.
2. Aloui, R., Ben Jabeur, S., Rezgui, H., & Ben Arfi, W. (2023). Geopolitical risk and commodity future returns: Fresh insights from dynamic copula conditional value-at-risk approach. *Resources Policy*, *85*.
3. Baffes, J., & Haniotis, T. (2010). Placing the 2006/08 Commodity Price Boom into Perspective. *World Bank Discussion Papers*, *5371*(July).
4. Bakas, D., & Triantafyllou, A. (2020). Commodity price volatility and the economic uncertainty of pandemics. *Economics Letters*, *193*.
5. Bouri, E., & Gupta, R. (2020). *Jumps in energy and non-energy commodities*.
6. Boyd, N. E., Harris, J. H., & Li, B. (2018). An update on speculation and financialization in commodity markets. In *Journal of Commodity Markets* (Vol. 10, pp. 91–104). Elsevier B.V.
7. Broadstock, D. C., Chan, K., Cheng, L. T. W., & Wang, X. (2021). The role of ESG performance during times of financial crisis: Evidence from COVID-19 in China. *Finance Research Letters*, *38*.
8. Cui, L., & Maghyereh, A. (2024). Geopolitical risks and systemic stress in commodity markets: Spillovers during periods of stress. Journal of Commodity Markets, 28, 1-18.
9. Deininger, K., Ali, D. A., Kussul, N., Shelestov, A., Lemoine, G., & Yailimova, H. (2023). Quantifying war-induced crop losses in Ukraine in near real time to strengthen local and global food security. *Food Policy*, *115*, 102418.
10. Dewan, M., & Dharni, R. (2023). Herding behavior in the Indian commodity futures market: Evidence from market declines. *Global Economic Review*, 52(3), 245-261.
11. Dimpfl, T., Flad, M., & Jung, R. C. (2017). Price discovery in agricultural commodity markets in the presence of futures speculation. *Journal of Commodity Markets*, *5*, 50–62. https://doi.org/10.1016/j.jcomm.2017.01.002
12. Duc Huynh, T. L., Burggraf, T., & Nasir, M. A. (2020). Financialisation of natural resources & instability caused by risk transfer in commodity markets. *Resources Policy*, *66*. https://doi.org/10.1016/j.resourpol.2020.101620
13. Fasanya, I., & Akinbowale, S. (2019). Modelling the return and volatility spillovers of crude oil and food prices in Nigeria. *Energy*, *169*, 186–205.
14. Fernandez-Perez, A., Frijns, B., & Tourani-Rad, A. (2016). Contemporaneous interactions among fuel, biofuel and agricultural commodities. *Energy Economics*, *58*, 1–10.

15. Gardebroek, C., & Hernandez, M. A. (2013). Do energy prices stimulate food price volatility? Examining volatility transmission between US oil, ethanol and corn markets. *Energy Economics*, *40*.
16. Gupta, R., & Pierdzioch, C. (2024). Multi-task forecasting of agricultural commodity price volatility: In-sample and out-of-sample predictability. *Journal of Forecasting*, 43(1), 72-89.
17. Iqbal, M., Ali, S., & Hussain, A. (2023). Extreme risk spillovers during crises: Evidence from the COVID-19 pandemic and beyond. *Journal of Risk and Financial Management*, 16(8), 214-229.
18. Jia, S., Liu, F., & Zhou, X. (2023). Climate change and commodity futures: A GARCH-Copula approach to tail-risk spillovers. *Energy Economics*, 111, 105964.
19. Kumar, S., Jain, R., Narain, Balli, F., & Billah, M. (2023). Interconnectivity and investment strategies among commodity prices, cryptocurrencies, and G-20 capital markets: A comparative analysis during COVID-19 and Russian-Ukraine war. *International Review of Economics and Finance*, *88*, 547–593.
20. Kumar Soni, T. (2014). Cointegration, linear and nonlinear causality. *Journal of Agribusiness in Developing and Emerging Economies*, *4*(2), 157–171.
21. Liu, Y., Han, L., & Yin, L. (2018). Does news uncertainty matter for commodity futures markets? Heterogeneity in energy and non-energy sectors. *Journal of Futures Markets*, *38*(10), 1246–1261.
22. Lundberg, C., Skolrud, T., Adrangi, B., & Chatrath, A. (2021). Oil Price Pass through to Agricultural Commodities†. *American Journal of Agricultural Economics*, *103*(2), 721–742.
23. Malhotra, M., & Sharma, D. K. (2016). Volatility Dynamics in Oil and Oilseeds Spot and Futures Market in India. *Vikalpa*, *41*(2), 132–148.
24. Manera, M., Nicolini, M., & Vignati, I. (2013). Financial speculation in energy and agriculture futures markets: A multivariate garch approach. *Energy Journal*, *34*(3).
25. Mawejje, J. (2016). Food prices, energy and climate shocks in Uganda. *Agricultural and Food Economics*, *4*(1).
26. Mokni, K., & Youssef, M. (2020). Empirical analysis of the cross-interdependence between crude oil and agricultural commodity markets. *Review of Financial Economics*, *38*(4), 635–654.
27. Nazlioglu, S., Erdem, C., & Soytas, U. (2013). Volatility spillover between oil and agricultural commodity markets. *Energy Economics*, *36*.
28. Nwoko, I. C., Aye, G. C., & Asogwa, B. C. (2016). Effect of oil price on Nigeria's food price volatility. *Cogent Food & Agriculture*, *2*(1).
29. Palazzi, M., Costa, M., & Guimarães, C. (2024). Dynamic connectedness between energy markets and Brazil's cash markets: The post-COVID-19 era. *Energy Economics*, 108, 105878.
30. Plourde, A., & Watkins, G. C. (1998). Crude oil prices between 1985 and 1994: How volatile in relation to other commodities? *Resource and Energy Economics*, *20*(3).
31. Raza, S. A., Guesmi, K., Belaid, F., & Shah, N. (2022). Time-frequency causality and connectedness between oil price shocks and the world food prices. *Research in International Business and Finance*, *62*. https://doi.org/10.1016/j.ribaf.2022.101730
32. Rehman, M. U., Bouri, E., Eraslan, V., & Kumar, S. (2019). Energy and non-energy commodities: An asymmetric approach towards portfolio diversification in the commodity market. *Resources Policy*, *63*(July), 101456.
33. Rezitis, A., Drosos, S., & Tsionas, E. (2024). Volatility linkages between energy and agricultural futures: The impact of external shocks. *Journal of International Financial Markets, Institutions and Money*, 73, 101350.
34. Saâdaoui, F., Ben Jabeur, S., & Goodell, J. W. (2022). Causality of geopolitical risk on food prices: Considering the Russo–Ukrainian conflict. *Finance Research Letters*, *49*.
35. Sarkar, B. D., & Gupta, L. (2023). Analyzing the impact of Russia-Ukraine crisis on the Indian economy using input-output modeling. *Journal of Global Operations and Strategic Sourcing*.
36. Shen, J., Najand, M., Dong, F., & He, W. (2017). News and social media emotions in the commodity market. *Review of Behavioral Finance*, *9*(2), 148–168.
37. Taghizadeh-Hesary, F., Rasoulinezhad, E., & Yoshino, N. (2019). Energy and Food Security: Linkages through Price Volatility. *Energy Policy*, *128*, 796–806.
38. Trujillo-Barrera, A., Mallory, M., & Garcia, P. (2012). Volatility spillovers in U.S. crude oil, ethanol, and corn futures markets. *Journal of Agricultural and Resource Economics*, *37*(2), 247–262.
39. Wang, J., Shao, W., & Kim, J. (2020). Analysis of the impact of COVID-19 on the correlations between crude oil and agricultural futures. *Chaos, Solitons and Fractals*, *136*.
40. Wang, Y., Bouri, E., Fareed, Z., & Dai, Y. (2022). Geopolitical risk and the systemic risk in the commodity markets under the war in Ukraine. *Finance Research Letters*, *49*.
41. Wei Su, C., Wang, X.-Q., Tao, R., & Oana-Ramona, L. (2019). Do oil prices drive agricultural commodity prices? Further evidence in a global bio-energy context. *Energy*, *172*, 691–701.

42. Wei, W., Zhang, L., & He, Q. (2023). Spillovers between crude oil, carbon allowances, and agricultural futures during extreme events. *Environmental Economics and Policy Studies*, 25(4), 809-826.
43. Wu, J., Zhang, Z., & Wang, Y. (2023). The impact of temperature intervals on China's commodity futures: A varying-coefficient interval-valued time series model. *Quantitative Finance*, 23(5), 749-764.
44. Wu, F., Guan, Z., & Myers, R. J. (2011). Volatility spillover effects and cross hedging in corn and crude oil futures. *Journal of Futures Markets*, *31*(11), 1052–1075.
45. Yin, Y., & Cao, Z. (2024). Financialization and its impact on global commodity markets: Evidence from energy, metal, and agricultural futures. *Journal of Commodity Markets*, 28, 19-34.
46. Zmami, M., & Ben-Salha, O. (2019). Does oil price drive world food prices? Evidence from linear and nonlinear ARDL modeling. *Economies*, *7*(1).