Estimating risk transmission over different time horizon between agriculture and energy commodities: Evidence from TVP-VAR

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1 Introduction

Commodities play a very crucial role in a country's economy, mainly due to their geopolitical and financial significance. Oil is the primary energy source which influences the price movement of other commodities. Studies indicate that if crude oil prices stay elevated for an extended period, the current surge in food commodity prices is likely to persist for a significantly longer duration compared to previous periods of boom [1].

Oil prices tend to affect the prices of agricultural commodities because farmers use a lot of oil to produce fertilisers and pesticides for the betterment of their crops. Oil is also required in transportation, so when oil prices go up, the prices for the consumer also goes up. Oil and agricultural commodity prices went up sharply from 2006 to mid-2008. Studies show that the food crisis during this period was due to the rising oil prices [2]. When oil prices go up, people tend to switch to biofuels, which are made from corn and soybeans. This will lead to the increase in the price of other agricultural commodities since the planting area is limited [3].

Another school of thought among the researchers suggested that global economic activity is responsible for higher agricultural commodity prices [4] [5]. During the period of 2003-2008, the booming Asian giants India and China were responsible for the third commodity boom [5]. This meant that those countries were using more raw materials than the developed economies which led to the increase in demand and hence the increase in the oil price.

The increase in financialization of energy and commodity markets offer a variety of tradeoffs for investors and consumers. The connectedness of different markets plays an important role while managing risk and making an investment strategy. Investors and other stakeholders always look to protect their investment. The most common way is to diversify their portfolios across different markets. But the analysis of connectedness between different markets shows us that the shocks from one market can spillover to the other markets [6]. The interest in oil and commodity prices is not new, but it has increased in recent years due to the potential for diversification and other benefits. In addition, the spillover between oil and the agricultural market has gained attention in the context of risk management.

The relationship between oil and agricultural commodities is complex and has a significant impact on the global economy. In times of crisis such as the Global Financial Crisis of 2008 or the COVID-19 pandemic, this relationship became more complex and unpredictable.In addition to this, the COVID-19 pandemic has restricted people's demand both domestically and internationally, which has led to a significant decrease in the demand for oil from the transportation sector during that period [7]. The high price volatility of oil and food commodities is a major concern for investors, as it could lead to huge losses.

There have been many studies after the COVID-19 period to study further the connectedness between oil and commodities during the period of shocks in the economy. It was found that both the agricultural commodities prices and oil prices remained immune to the shocks that originated in both the market during the entire period of COVID-19 pandemic [8].

While numerous studies have been done in the global market and in the western-arab region, we want to see how the connectedness between the agricultural commodity prices and the oil prices hold in the Indian scenario. The Indian oil basket consists of weighted average of Dubai and Oman Crude and the Brent Crude crude oil prices. The majority of oil in India is imported from Brent Crude. We have used the Indian Crude Oil index as the energy commodity in our research. We explore the connectedness between Energy (Crude oil Index) and 6 popularly traded agricultural commodity assets' (Sugar, Wheat, Cotton, Soybean Oil, Guar Gum, Coffee) short run and long run connectedness using the time varying parameter vector autoregressions (TVP-VAR). This method is based on the work of Baruník and Křehlík (2018) andAntonakakis et al. (2020).

The TVP-VAR method has several advantages of the previously used methods to find the connectedness. The TVP-VAR framework can give us a more accurate measurement of the dynamic evolution of connectedness. It is also very useful for investors as it differentiates between short and long run connectedness effects taking into account the time-varying coefficient and variance-covariance structure. No observations are lost as it overcomes the outlier sensitivity and avoids the flattened out parameters. The method will also provide each connectedness measure with a confidence interval.

The study will answer the questions of the impact of the prices of Crude oil on the Indian agricultural commodity prices. We will be covering extreme and tranquil events. The changes in the tranquil and extreme events will be observed and the connectedness measure will be listed out with a confidence interval. Further, this paper will also try to answer the transmission of the spillover from the oil prices to agricultural prices during the short term and long term horizon.

Since the global financial crisis, commodity markets have become more inter-

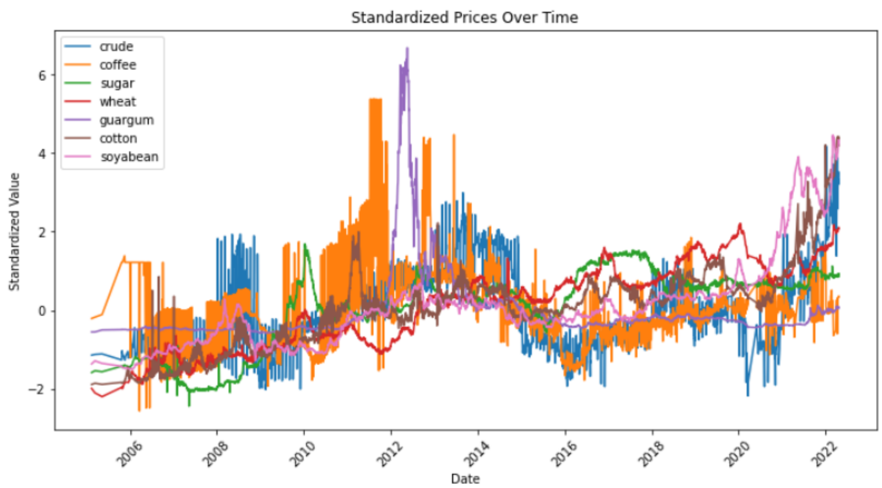

Figure 1: Standardized oil and agricultural commodities price series

connected with other financial markets. This is due to globalisation, financial liberalisation, trade integration and the financialization of commodities. The financialization of commodities has made them more liquid and easier to trade which has attracted a large number of investors. This financialization has made commodities into useful tools for diversification and hedging. The downside to this is that the commodities markets have become more vulnerable to speculation. This can lead to volatility spillovers between commodity markets, which can pose significant challenges for investors and policymakers.

2 Data

In this paper we investigate the connectedness between the prices of Indian crude oil index and the spot prices of 6 agricultural commodity assets (Sugar, Wheat, Cotton, Soybean Oil, Guar Gum and Coffee) over the period from February 2005 to April 2022. The data for all Crude oil index and the agricultural commodities is taken from Centre for Monitoring Indian Economy (CMIE).

Statistics					
	Mean	Standard Deviation	Median	Skewness	Kurtosis
crude oil	4048.79834	1164.366277	3783	0.611336	-0.022273
coffee	10339.05426	3009.001325	10000	1.358542	3.920566
sugar	2956.165479	754.183376	3173	-0.73636	-0.561059
wheat	1448.745688	327.726355	1519.65	0.089878	-1.174861
guargum	11582.2271	14210.21845	7250	3.970781	18.021739
cotton	4404.974049	1405.879367	4459.35	0.679311	1.697873
soyabean	6673.564649	2143.440498	6481.4	1.860628	4.363374
Dickey-Fuller Test Results:					
	ADF Statistic	P-Value	Lags Used	No. of Observations	
crude oil	-0.726054	0.839885	26	3707	
coffee	-3.010315	0.033942	29	3704	
sugar	-1.439101	0.563394	10	3723	
wheat	-0.878577	0.794945	14	3719	
guargum	-3.092408	0.02712	30	3703	
cotton	0.531469	0.985799	13	3720	
soyabean	1.221878	0.996134	30	3703	
Critical Values					
crude oil	{'1%':	-3.432115264086939,	'5%':	-2.862319996	
coffee	{'1%':	-3.432116694829155,	'5%':	-2.862320628	
sugar	{'1%':	3.4321076724309196,	'5%':	-2.862316642	
wheat	{'1%':	-3.432109564216738,	'5%':	-2.862317478	
guargum	{'1%':	3.4321171722587502,	'5%':	-2.862320838	
cotton	{'1%':	-3.432109090888611,	'5%':	-2.862317269	
soyabean	{'1%':	3.4321171722587502,	2.862320838		

Table 1 Fig. 2. Summary Statistics

Figure 1 shows the standardized prices of the crude oil index of India and the six highly traded commodities over the period from January 2000 to December 2022. The standardized prices are calculated by dividing the actual price of each commodity by its standard deviation. This makes it easier to compare the prices of different commodities, which may have different price scales. The plot shows that the standardized prices of the seven commodities are generally positively correlated, meaning that they tend to move together over time. This is supported by the fact that the correlation coefficients between the seven commodities are all positive and statistically significant. The plot also shows that the standardized prices of the seven commodities have experienced periods of both positive and negative returns. However, the overall trend has been positive, with all seven commodities experiencing a net increase in price over the period from January 2000 to December 2022. The most notable period of divergence between the standardized prices of the seven commodities occurred between 2008 and 2010. Another notable period of divergence occurred in 2020 when the crude oil price underperformed with the other commodities. This was due to the COVID-19 pandemic, which led to a sharp decrease in the demand for crude oil.

The summary statistics in Table 1 indicate that the price volatility is, on average, highest for Guar Gum, followed by Coffee and Soyabean oil. The skewness of all price volatilities is significantly right skewed, the kurtosis of all price volatilities is leptokurtic, meaning that the distribution of prices is more peaked than a normal distribution supporting the Jarque and Bera (1980) normality test statistics that none of the series is normally distributed. The ADF test shows that all series are stationary, meaning that they do not have a unit root. The Ljung-Box test shows that all series are autocorrelated, meaning that the current value of the series is correlated with its past values. The ARCH/GARCH test shows that all series exhibit ARCH/GARCH errors on atleast the 1% significance level (Fisher and Gallagher, 2012). Those statistics support our decision of modelling the interdependencies employing a TVP-VAR with heteroscedastic variance-covariances. According to the non-parametric Kendall rank correlation coefficients, all absolute returns are positively correlated.

3 Methodology

We present the TVP-VAR-based frequency connectedness framework, which integrates the research of Baruník and Křehlík (2018) and Antonakakis et al. (2020). The latter has already integrated the TVP-VAR framework of Koop and Korobilis (2014) with the connectedness approach of Diebold and Y1lmaz (2012, 2014). Some of the limitations of the rolling-window VAR methodology, including (i) the arbitrary rolling-window size, (ii) loss of observations, and (iii) outlier sensitive parameters, have been demonstrated to be addressed by the TVP-VAR-based connectivity approach. Since both investigations use daily data, we use the same TVP-VAR specification as Antonakakis et al. (2018) and Gabauer and Gupta (2018). Specifically, we're estimating a TVPVAR(1) in accordance with the recommendations of the Bayesian information criterion (BIC), which is summarized as follows:

$$
\begin{aligned}
\boldsymbol{z}_t &= \boldsymbol{\lambda}_t \boldsymbol{z}_{t-1} + \boldsymbol{\epsilon}_t & \boldsymbol{\epsilon}_t &\sim N\left(\mathbf{0}, \boldsymbol{\Sigma}_t\right) \\
\operatorname{vec}\left(\boldsymbol{\lambda}_t\right) &= \operatorname{vec}\left(\boldsymbol{\lambda}_{t-1}\right) + \boldsymbol{v}_t & \boldsymbol{v}_t &\sim N\left(\mathbf{0}, \boldsymbol{R}_t\right)
\end{aligned}
$$

where $\boldsymbol{z}_t, \boldsymbol{z}_{t-1}$ and ϵ_t are $N \times 1$ dimensional vectors, representing all oil price series in $t, t-1$, and the corresponding error term, respectively. $\boldsymbol{\lambda}_t$ and Σ_t are $N \times N$ dimensional matrices demonstrating the time-varying VAR coefficients and the time-varying variance-covariances whereas $\operatorname{vec}(\boldsymbol{\lambda}_t)$ and $\boldsymbol{v}_t$ are $N^2 \times 1$ dimensional vectors and $\boldsymbol{R}_t$ is a $N^2 \times N^2$ dimensional matrix.

Since the concept of the generalized forecast error variance decomposition (GFEVD) introduced by Koop et al. (1996) and Pesaran and Shin (1998) is built upon the Wold representation theorem we have to transform the estimated TVP-VAR model into its TVP-VMA process by the following equality: $\boldsymbol{z}_t = \sum_{i=1}^{p} \boldsymbol{\lambda}_{it} \boldsymbol{x}_{t-i} + \boldsymbol{\epsilon}_t = \sum_{j=0}^{\infty} \boldsymbol{\Phi}_{jt} \boldsymbol{\epsilon}_{t-j}$. We prefer the GFEVD over its orthogonal counterpart as the retrieved results are completely invariant of the variable ordering. Additionally, Wiesen et al. (2018) stress out, that the GFEVD should be employed if no theoretical framework - which would allow to identify the error structure - is available. The GFEVD can be interpreted as the effect a shock in variable j has on variable i in terms of its forecast error variance and can be written in the following form:

$\tau_{ijt}(H) = \frac{(\boldsymbol{\Sigma}_t)^{-1}_{jj} \sum_{h=0}^{H} \left((\boldsymbol{\Phi}_h \boldsymbol{\Sigma}_t)_{ijt} \right)^2}{\sum_{h=0}^{H} \left(\boldsymbol{\Phi}_h \boldsymbol{\Sigma}_t \boldsymbol{\Phi}'_h \right)_{ii}}$

$\tilde{\tau}_{ijt}(H) = \frac{\tau_{ijt}(H)}{\sum_{k=1}^{N} \tau_{ijt}(H)}$

where $\tilde{\tau}_{ijt}(H)$ denotes the contribution of the j th variable to the variance of the forecast error of the i th variable at horizon H. As the rows of $\tilde{\tau}_{ijt}(H)$ do not sum up to one, we need to normalize them which results in $\tilde{\tau}_{ijt}$. Through the normalization, we get the following identities: $\sum_{i=1}^{N} \tilde{\tau}_{ijt}(H) = 1$ and $\sum_{j=1}^{N} \sum_{i=1}^{N} \tilde{\tau}_{ijt}(H) = N$.

Every connectivity metric can be computed in the next step. To commence, we compute the net pairwise connectedness using the following method: $NPDC_{ijt}(H) = \tilde{\tau}_{ijt}(H) - \tilde{\tau}_{jit}(H)$.

If $NPDC_{ijt}(H) > 0\,(NPDC_{ijt}(H) < 0$ it means that variable j influences variable i more (less) than vice versa.

The total directional connectedness TO others measures how much of a shock in variable i is transmitted to all other variables j : $TO_{it}(H) = \sum_{i=1, i \neq j}^{N} \tilde{\tau}_{jit}(H)$

The total directional connectedness FROM others measures how much variable i is receiving from shocks in all other variables j :$F\,\mathrm{ROM}_{it}(H) = \sum_{j=1, i \neq j}^{N} \tilde{\tau}_{ijt}(H)$

The net total directional connectedness represents the difference between the total directional connectedness TO others and the total directional connectedness FROM others, which can be interpreted as the influence variable i has on the analysed network. $NET_{it}(H) = TO_{it}(H) - FROM_{it}(H)$

If the $NET_{it} > 0\,(NET_{it} < 0)$ variable i influences all others j more (less) than being influenced by them. Thus, it is considered as a net transmitter (receiver) of shocks.

Instead of the originally proposed total connectedness index (TCI), we implement the corrected TCI of Chatziantoniou and Gabauer (2021) and Gabauer (2021) which measures the degree of network interconnectedness:

$$\begin{aligned} TCI_t(H) &= \frac{N}{N-1} \sum_{i=1}^{N} TO_{it}(H) \\ &= \frac{N}{N-1} \sum_{i=1}^{N} FROM_{it}(H) \quad 0 \leq TCI_t(H) \leq 1 \text{ if } H \to \infty \end{aligned}$$

In other words this measure illustrates the average impact a shock in one variable has on all others. The higher this value the higher is the market risk and vice versa.

We have so far concentrated on the time domain connectivity assessment. Likewise, we proceed with the frequency domain connectivity evaluation. By using Stiassny's (1996) spectral decomposition method, we may investigate the connectedness relationship in the frequency domain. First, we consider the frequency response function, $\boldsymbol{\Phi}\left(e^{-i\omega}\right) = \sum_{h=0}^{\infty} e^{-i\omega h} \boldsymbol{\Phi}_h$, where $i = \sqrt{-1}$ and ω denotes the frequency to continue with the spectral density of x_t at frequency ω which can be defined as a Fourier transformation of the TVP-VMA (∞) :

$\boldsymbol{S}_x(\omega) = \sum_{h=-\infty}^{\infty} E\left(\boldsymbol{z}_t \boldsymbol{x}'_{t-h}\right) e^{-i\omega h} = \boldsymbol{\Phi}_t\left(e^{-i\omega h}\right) \boldsymbol{\Sigma}_t \boldsymbol{\Phi}'_t\left(e^{+i\omega h}\right)$

The frequency GFEVD is the combination of the spectral density and the GFEVD. As in the time domain case we need to normalize the frequency GFEVD which can be formulated as follows,

$\tau_{ijt}(\omega) = \frac{(\boldsymbol{\Sigma}_t)_{jj}^{-1} \left|\sum_{h=0}^{\infty} \left(\boldsymbol{\Phi}_t\left(e^{-i\omega h}\right)\Sigma_t\right)_{ijt}\right|^2}{\sum_{h=0}^{\infty} \left(\boldsymbol{\Phi}_t(e^{-i\omega h})\boldsymbol{\Sigma}_t \boldsymbol{\Phi}_t(e^{i\omega h})\right)_{ii}}$

$\tilde{\tau}_{ijt}(\omega) = \frac{\tau_{ijt}(\omega)}{\sum_{k=1}^{N} \tau_{ijt}(\omega)}$

where $\tilde{\tau}_{ijt}(\omega)$ represents the portion of the spectrum of the i th variable at a given frequency ω that can be attributed to a shock in the j th variable. It can be interpreted as a within-frequency indicator.

To assess short-term and long-term connectedness rather than connectedness at a single frequency, we aggregate all frequencies within a specific range, $d = (a, b) : a, b \in (-\pi, \pi), a < b : \tilde{\tau}_{ijt}(d) = \int_a^b \tilde{\tau}_{ijt}(\omega) d\omega$ From here, we can calculate exactly the same connectedness measures as in Diebold and Y1lmaz $(2012, 2014)$ which can be interpreted identically, however, in this case they refer to frequency connectedness measures that provide information about spillovers in a certain frequency range d :

$$
\begin{aligned}
NPDC_{ijt}(d) &= \tilde{\tau}_{ijt}(d) - \tilde{\tau}_{jit}(d) \\
TO_{it}(d) &= \sum_{i=1, i\neq j}^{N} \tilde{\tau}_{jit}(d) \\
FROM_{it}(d) &= \sum_{i=1, i\neq j}^{N} \tilde{\tau}_{ijt}(d) \\
NET_{it}(d) &= TO_{it}(d) - FROM_{it}(d) \\
TCI_t(d) &= \frac{N}{N-1} \sum_{i=1}^{N} TO_{it}(d) = \frac{N}{N-1} \sum_{i=1}^{N} FROM_{it}(d)
\end{aligned}
$$

All measures provide information about the specific range, but, not of the overall impact. Baruník and Krehlík (2018) suggest to weight all contribution measures of each frequency band d with respect to the overall system by, $\Gamma(d) = \sum_{i,j=1}^{N} \tilde{\tau}_{ijt}(d)/N$.

$$
\begin{aligned}
NPD\tilde{C}_{ijt}(d) &= \Gamma(d) \cdot NPDC_{ijt}(d) \\
T\tilde{O}_{it}(d) &= \Gamma(d) \cdot TO_{it}(d) \\
FRO\tilde{M}_{it}(d) &= \Gamma(d) \cdot FROM_{it}(d) \\
NE\tilde{T}_{it}(d) &= \Gamma(d) \cdot NET_{it}(d) \\
TC\tilde{I}_t(d) &= \Gamma(d) \cdot TCI_t(d)
\end{aligned}
$$

Finally, we show the relationship between the frequency-domain measures of Baruník and Křehlík (2018) to the Diebold and Y1lmaz (2012, 2014) time-domain measures:

$$NPDC_{ijt}(H) = \sum_d NPDC_{ijt}(d)$$

$$TO_{it}(H) = \sum_d TO_{it}(d)$$

$$FROM_{it}(H) = \sum_d FROM_{it}(d)$$

$$NET_{it}(H) = \sum_d NET_{it}(d)$$

$$TCI_t(H) = \sum_d TCI_t(d)$$

4 Results and Discussion

The high degree of connectedness between crude oil prices and commodity prices in India has implications for investors and policymakers. Investors should be aware of the potential for shocks to crude oil prices to transmit to other markets and impact their investments. Policymakers should also be aware of the potential for shocks to commodity prices to have a wider impact on the economy.

4.1 Averaged dynamic connectedness

Let's start by discussing the average outcomes, which represent the overall results across the entire duration of our study, without taking into account the specific effects of events that occurred at particular points in time. Table 2 contains various sets of results: (i) values based on the complete dataset, (ii) high-frequency data presented in parentheses, and (iii) low-frequency data enclosed in brackets. The low-frequency results help us distinguish between the short-term and long-term outcomes within the full sample period.

To clarify from the outset, the elements found along the main diagonal of Table 2 represent shocks related to individual variables, often referred to as idiosyncratic shocks. In contrast, the off-diagonal elements pertain to the interplay among variables within the specific network. For instance, if we focus on the diagonal entry under the 'Coffee' column, we can see that 74.09% of the connectedness (with 53.16% in the short term and 20.93% in the long term) can be attributed to shocks originating from this particular type of crude oil. The remaining 25.91% is attributed to interactions taking place across the entire network of variables.

When we examine individual types of agricultural commodities, we can observe that, on average, Cotton stands out as the primary source of transmitting developments within this network of variables, accounting for 52.78%. Following it are Wheat at 16.64% and Soybean at 0.16%. Concerning the time periods

	Crude	Coffee	Sugar	Wheat	Guargum	Cotton	Soyabean	FROM others
Crude	85.27 (51.98) [33.29]	7.43 (4.53) [2.9]	12.00 (6.38) [5.62]	15.77 (8.93) [6.84]	18.12 (10.77) [7.35]	20.94 (11.91) [9.03]	10.63 (5.50) [5.13]	84.89 (48.02) [36.87]
Coffee	9.08 (5.72) [3.36]	74.09 (53.16) [20.93]	16.27 (10.45) [5.82]	14.73 (10.24) [4.49]	9.34 (5.83) [3.51]	15.34 (10.33) [5.01]	6.84 (4.27) [2.57]	71.59 (46.84) [24.75]
Sugar	9.50 (4.88) [4.62]	12.29 (6.57) [5.72]	83.56 (43.12) [40.44]	26.77 (13.90) [12.87]	16.59 (8.43) [8.16]	23.94 (12.42) [11.52]	21.09 (10.68) [10.41]	110.18 (56.88) [53.30]
Wheat	10.78 (6.21) [4.57]	12.25 (6.99) [5.26]	21.61 (11.53) [10.08]	71.91 (38.44) [33.47]	17.10 (9.43) [7.67]	24.75 (13.92) [10.83]	26.44 (13.47) [12.97]	112.93 (61.56) [51.37]
Guargum	12.15 (6.31) [5.84]	9.89 (5.10) [4.79]	20.29 (10.21) [10.08]	30.74 (15.56) [15.18]	80.66 (41.22) [39.44]	22.49 (11.50) [10.99]	20.06 (10.10) [9.96]	115.63 (58.78) [56.85]
Cotton	11.66 (7.84) [3.82]	9.81 (6.93) [2.88]	13.11 (8.15) [4.96]	22.39 (14.39) [8.00]	10.74 (7.62) [3.12]	85.93 (49.13) [36.80]	10.63 (5.95) [4.68]	78.33 (50.87) [27.46]
Soyabean	8.38 (4.22) [4.16]	7.74 (3.94) [3.80]	16.09 (8.10) [7.99]	19.18 (9.66) [9.52]	20.47 (10.29) [10.18]	23.66 (11.90) [11.76]	102.54 (51.88) [50.66]	95.53 (48.12) [47.41]
TO	61.56 (35.18) [26.38]	59.41 (34.05) [25.36]	99.37 (54.83) [44.54]	129.58 (72.67) [56.91]	92.36 (52.37) [39.99]	131.11 (71.98) [59.13]	95.69 (49.97) [45.72]	669.08 (371.06) [298.02]
NET	-2.34 (-12.83) [10.49]	-12.18 (-12.78) [0.60]	-10.81 (-2.05) [-8.76]	16.64 (11.11) [5.53]	-23.27 (-6.41) [-16.86]	52.78 (21.11) [31.67]	0.16 (1.85) [-1.69]	

Figure 2: Average dynamic connectedness. Notes: The table is combination of 3 values for each entry in the format - Total, (Short term), [Long term].

or frequency bands, it's noteworthy that the network processes information at a slower pace for Cotton. This is because its connectedness to the network is predominantly influenced by long-term dynamics, with the value of 31.67% In contrast, Wheat tends to transmit volatility spillovers in the network primarily in the short term, representing 11.11

Shifting our attention to the net-recipients, Table 2 makes it clear that, on average, the primary recipient in this network is Guargum, with an average of -23.27%. It's followed by Coffee which has an average of -12.18%. Regarding the frequency bands, Guargum is notably more affected in the long term, with -16.86%, whereas Coffee is primarily impacted in the short term, with -12.78%.

While the values presented in Table 2 offer insights into the average behavior of the network, our empirical framework enables a more dynamic analysis, which can be highly valuable for gaining a deeper understanding of the underlying relationships. In other words, looking solely at the average behavior provides a limited perspective on the risk-contagion dynamics that shape the interactions among the network's variables. This approach essentially conceals the influence of specific events that occurred during the study period.

To ensure that we do not overlook critical information, we continue our analysis by examining dynamic measures of volatility connectedness. This approach allows us to assess the impact of specific political and economic events that might have had a substantial influence on the network's development.

4.2 Total dynamic connectedness

This is the dynamic evolution of the total connectedness index (TCI). TCI is the measure of network connectedness or the average impact that a shock in price of a variable has on the other variables. Higher this value shows a higher market risk and vice versa. The figure shows overall evolution in TCI (black shaded region), short-run TCI (pink outlined region) and evolution in the long run too (green shaded region).
Connectedness shows

- How that these commodities move together
- These patterns of co movement depict risk spillover between the commodities and dependency between them.

During recent times, interlinkage of the oil market with agricultural commodities has gained much attention due to this diversification potential. The sudden

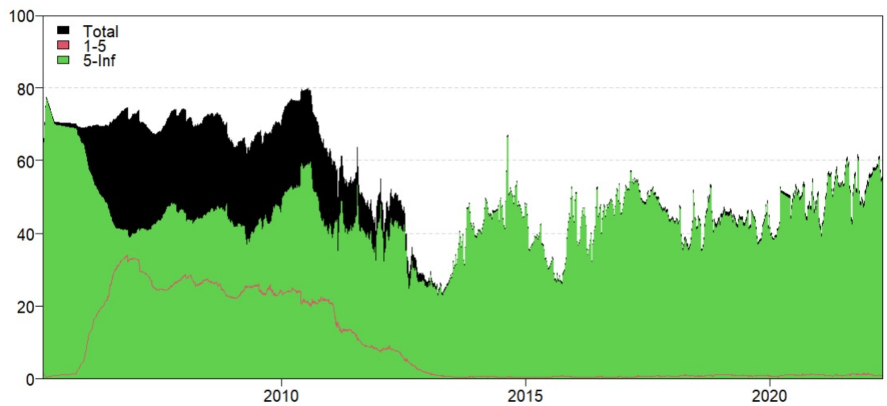

Figure 3: Dynamic total connectedness. Notes: The black area illustrates the dynamic total connectedness while the short-term and long-term dynamic total connectedness are illustrated in red and green, respectively.

upward movement of prices due to the crisis of 2008 and COVID-19 causes an increase in the prices of these commodities which caused a serious issue for developing nations as millions are pushed into poverty. (De Hoyos and Medvedev, 2011)

Policies are an important development that heavily impact this market. Bioethanol (coming primarily from corn) and biodiesel (which comes primarily from soybeans) are considered to be technological substitutes for conventional fuels such as diesel and gasoline). Since production of these biofuels is heavily dependent on supply of agricultural commodities, it is expected that there is a tight market integration between energy and agricultural markets, and this market integration is likely to be the most important change to occur in agriculture in decades (Tyner and Taheripour, 2008). As production of biofuels continues to rise, demand for these commodities is expected to increase which causes food prices to increase. Since fuels have been blended with ethanol for environmental purposes, (Avalos, 2014) argued that these two markets were historically independent until 2006, when ethanol usage became large enough to influence world energy prices. These policies for fuel blending began in India in the year 2003 when 5% ethanol blended petrol began to be sold.

However, in the scenario between prices of Indian crude index and the six agricultural commodities throughout the sampled time period we observe varying values between 30% and 80% approximately. This shows that these markets not quite highly integrated as was thought to be. There is very less short run connectedness beyond 2013, where total and long run connectedness values approximately remain equal. This short run connectedness starts with a peak and then a downward trend till 2013 where its magnitude remains close to 0. Thus, the variables of the network seem to more integrated in the long run than in the short run despite changing global developments. This implies that echo from past shocks is strong to influence connectedness from ongoing developments.

4.3 Net total directional connectedness

Net total directional connectedness (NTDC) is a measure of the overall strength of the directional spillovers from one asset or market to another. It is calculated by taking the sum of all the positive directional spillovers from asset A to asset B and subtracting the sum of all the negative directional spillovers from asset A to asset B. NTDC can be used to justify the statement that crude oil prices are affected by commodity prices because it shows that there is a strong directional connection between crude oil and other commodities. For example, a study by the National Bureau of Economic Research found that crude oil has a strong net directional connection to other commodities, such as soybeans and zinc.[9]

Net total directional connectedness is a useful tool for understanding the complex relationships between different asset markets. It can be used to identify the markets that are most interconnected and therefore most vulnerable to shocks. This information can be used by investors to make more informed investment decisions We found that the connectedness between crude oil prices and commodity prices in India has increased over time. It is worth noting in the figure below that before 2008 financial crisis, crude oil was consistently taking shocks from other variables mentioned in this study but after the crisis, when crude prices drastically surged to $150 per barrel from $90 per barrel , we can see that crude started giving shocks to the other commodities. Also around 2013, the shocks transmitted by crude were again positive because of price surge in crude post Cremia invasion by Russia, Chineese financial crisis and OPEC production cut. After 2015, crude oil prices have been consistently receiving the shocks from the commodity prices. In the post covid era of the year 2020, it was slightly above 0 giving shocks to other commodities but when the markets settled, it is seen that the prices started receiving the shocks again.

Soyabean prices are the most sensitive to shocks. This is likely because soybeans are a major feedstock for biodiesel production and hence the Crude prices are one of the influencing factors in this case. We can see that until 2008 financial crisis, the soyabean prices have been giving out shocks but post crisis it started taking them from others. After 2010 it is difficult to decisively tell whether soyabean is taking or giving shocks out which simply means it is very volatile in terms of shocks. Like soyabean, even the wheat commodity has fluctuations in the connectedness. Its quite possible because wheat is not specifically influencing factor in terms of oil prices. So the shocks it might be experiencing or giving out might not be very much relevant in the energy sector connectedness study.

Guar gum prices are also relatively sensitive to shocks to Crude oil prices. This is likely because guar gum is used in a variety of industrial products, including hydraulic fracturing fluids. Also the guargum prices are giving out

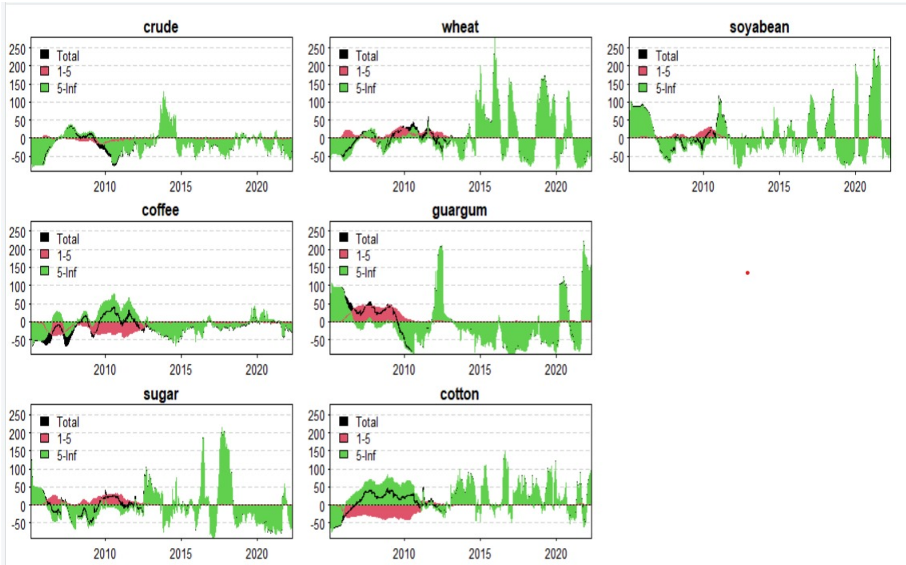

Figure 4: Net total directional connectedness. Notes: The black areas illustrate the net total directional connectedness while the short-term and long-term dynamic net total directional connectedness are illustrated in red and green, respectively.

shocks until 2010 but later on it started receiving until 2012. There was a sudden spike for about 1 year in the shock transmission of guargum to the other commodities and crude oil prices. Later it was just receiving shocks from other variables until 2020.

Coffee prices are less sensitive to shocks to crude oil prices than soybean and guar gum prices. This is likely because wheat is a staple food commodity and consumers are less likely to cut back on coffee consumption when fuel prices rise. It is also seen that cotton has been giving out shocks in long term until 2011 but in the short term, it has been taking shocks attributing to the connectedness. For sugar, its evident that sugar has been receiving the shocks until 2010 but in the short term dynamic net total directional connectedness it is giving out shocks until 2013. After that there are sudden spikes and sudden drops in the shocks for sugar in the years 2016, 2018 and 2019. Post 2020 covid era, it can be inferred that sugar has been consistently receiving shocks.

4.4 Net pairwise directional connectedness

We conclude our analysis and discussion by considering different commodities paired with crude oil index using a method called "Net Pairwise Directional Connectedness" (NPDC). NPDC is a method for measuring the direction and magnitude of the spillover effects between two variables.

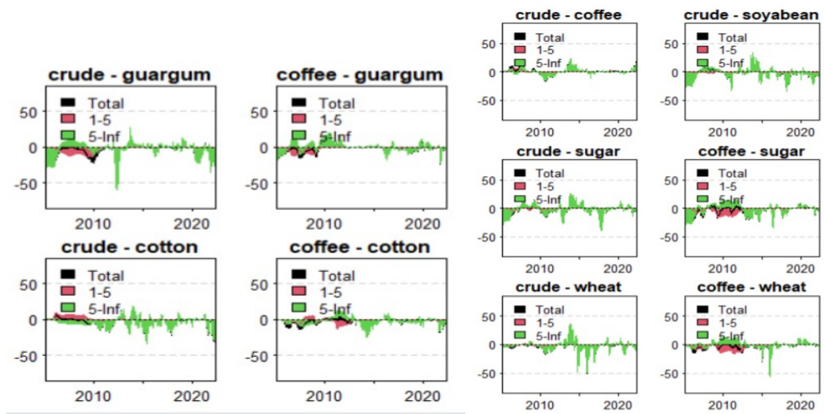

Figure 5: Net Pairwise Directional correctedness - The black area illustrates the dynamic net pairwise directional connectedness while the short-term and long-term dynamic net pairwise directional connectedness are illustrated in pink and green, respectively.

Results are illustrated in the below figure. These results provide a more detailed picture of the evolution of connectedness over time and practically validate the above analysis.

It should be noted that the order in which each variable appears in the title of the panel in the following figure's panels affects how each variable's net position is interpreted. To be more precise, we use the variable that occurs first in the title to interpret the findings. A positive NPDC value indicates that the first variable is a net transmitter of shocks to the second variable. A negative NPDC value indicates that the first variable is a net recipient of shocks from the second variable.

In this regard, starting with the panels we notice the following. First, the crude index was the transmitter for smaller shocks to coffee in the beginning and then received substantial shocks from coffee starting in 2010 continuing throughout 2011, and then wearing off. Then finally crude oil transmitted a huge shock to coffee in between 2013 and 2014 followed by connectedness being more or less constant showing better interconnectivity later on. Turning to sugar, there were tremendous amounts of shocks received and transmitted from both ends throughout the period showing less connectivity. Crude oil was the transmitter of moderate shocks to Sugar from the years around 2007-2009 and a larger shock in around 2014 wearing off till 2015 and was the receiver of substantial shocks from Coffee from the years around 2004-2006, 2011, 2013, and 2017.

Moving on to Wheat, connectedness fluctuates around relatively negligible levels in the beginning till 2010, however, then Wheat transmits a moderate shock at the beginning of 2010 lasting till the beginning of 2013, and further transmits 3 tremendously substantial shocks in the period from late 2014 to 2017. Throughout the entire sample period, Crude only transmits one substantial shock in the beginning of 2014 which shows that Wheat is the major transmitter of shocks between these two. Guargum, as observed, is also mainly the transmitter of shocks to Crude in the given sample period. Crude receives a moderate shock in the beginning of the sample period that is from 2004-2005 and then Crude transmits a single shock in the end of 2013 followed by 3 substantial shocks from Guargum in the mid-2012, 2020 and 2021 respectively. Between the period 2014-2020, it is observed that the connectedness fluctuates around relatively negligible levels. Cotton, is observed to be the transmitter of light and moderate shocks from the beginning of the period till the end of 2012. Further, it receives 2 moderate shocks from Crude in mid-2013 and around the beginning of 2014. Apart from this, Cotton keeps transmitting moderate and severe shocks to Crude throughout the period such as at the end of 2013, the beginning of 2015, mid-2017, and the end of the sample period i.e. 2021-2023. Finally, Soyabean shows a similar trend in shocks as Cotton did with Crude having only received only substantial shock from Crude in 2014. Rest of the sample period, Soyabean has been the major transmitter of shock, some substantial ones and the rest being moderate shocks.

Both the direction and the magnitude of pairwise connectedness are indeed in line with previous results for net directional connectedness. As we wrap up this section, it is important to highlight that, despite the robust integration in the crude oil market, we also observe that, at certain times, the network's variables may act as net transmitters or net recipients of shocks. This may indicate the possibility of portfolio diversification.

Findings about long-term connectedness, with specific reference to frequency bands, may, in fact, be more relevant to long-term investors who, after carefully weighing developments in markets, could base the construction of portfolios on net transmitters of longer-term shocks. Conversely, findings regarding short-run connectedness may be more relevant for speculative purposes.

As a result, this study may be helpful to investors seeking to improve risk management and policy makers hoping to get a deeper comprehension of changes in the commodities market.

5 Conclusion

This study offers ground for further exploration of changes in the crude oil market and its causation on commodity markets. Subsequent research endeavors may concentrate on investigating the degree to which specific events have a greater impact on long-term connectivity than others. In this sense, formal statistical evaluations of variables that directly drive the frequency-based connection across time would be intriguing, and now remain a limitation of our work, even though we offered speculative reasons. For example, the historical significance of geopolitical uncertainty can be thoroughly examined, as can the implications for oil market risks following the current Russia-Ukraine conflict.

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In this study we considered the concept of the 'common pool' for different types of commodities and crude oil and set out to further examine the extent of integration and the potential for risk-contagion within a network of variables comprising (i) Coffee, (ii) Wheat, (iii) Soyabean, (iv) Sugar, (v) Guargum, as well as (vi) Cotton reference.

In order to achieve this, we applied the dynamic connectivity technique based on a TVP–VAR model, following the lead of Antonakakis et al. (2020). Simultaneously, we looked separately at connectedness that happened in the short and long runs in order to find events that had a rather extended impact on the global crude oil market. In other words, following Baruník and Křehlík (2018) , we thought about connectivity inside both a high frequency (i.e., 5 days) and a low frequency band (i.e., from 5 to 100 days).

In summary, Table 2 outlines average outcomes and inter-variable dynamics in the agricultural commodities network. While Cotton proves a significant transmitter, Guargum emerges as the primary net-recipient. However, relying solely on averages overlooks nuanced risk-contagion dynamics. Our dynamic analysis unveils the impact of specific events, providing a more comprehensive understanding.

Adding up to this, using net total directional connectedness, we were able to gauge the impact of crude over all the other commodities. We were also able to mark specific historical effects of crude price fluctuations, which resulted in crude giving shock pulses to other commodities. However, when widely examined, crude was considered a shock receiver for most periods(extended range).

Next, we additionally took into account net directional and net pairwise connectivity metrics to determine the real interaction between the various types of commodities and crude oil. Every variety of commodity can function in the network as a net transmitting or net receiving entity. Singular incidents that occurred during the study's sample period may be able to shed light on the circumstances in which various types transitioned between roles over time. Conversely, greater ambiguity about how lockdowns can affect the economy might be able to shed light on the prevalence of long-run connectivity, which we found to be especially strong in our net directional and net pairwise analyses.

The market is not that highly integrated as predicted, but remaining around just around the 40-50% range. However there is a high long run connectedness compared to short run connectedness which suggests that the variables don't really respond swiftly to market developments. Some time bands show high connectedness which can be attributed to events that strongly influence this network between oil and agricultural commodities.

6 References

1 Oil spills on other commodities - ScienceDirect

2 Speculation and volatility spillover in the crude oil and agricultural commodity markets: A Bayesian analysis - ScienceDirect

3 The substitutive effect of biofuels on fossil fuels in the lower and higher crude oil price periods - ScienceDirect

4 How to Understand High Food Prices - Gilbert - 2010 - Journal of Agricultural Economics - Wiley Online Library

5 The anatomy of three commodity booms - ScienceDirect

6 Period specific volatility spillover based connectedness between oil and other commodity prices and their portfolio implications - ScienceDirect

7 A target-oriented bi-attribute user equilibrium model with travelers' perception errors on the tolled traffic network - ScienceDirect

8 Connectedness between oil and agricultural commodity prices during tranquil and volatile period. Is crude oil a victim indeed? - ScienceDirect

9 Commodity Connectedness - National bureau of economic research

10 Baruník and Křehlík Measuring the Frequency Dynamics of Financial Connectedness and Systemic Risk(2018)

11 Geopolitical risk and forecastability of tail risk in the oil market: Evidence from over a century of monthly data : Salisu et al.,Christian Pierdzioch , Rangan Gupta - 2021

12 Refined Measures of Dynamic Connectedness based on Time-Varying Parameter Vector Autoregressions, Nikolaos Antonakakis , Ioannis Chatziantoniou, andDavid Gabauer (2020)

13 Oil prices and agricultural commodity markets: Evidence from pre and during COVID-19 outbreak, Ngo Thai Hung 2021

14 De Hoyos, R.E. and Medvedev, D. (2011), Poverty Effects of Higher Food Prices: A Global Perspective. Review of Development Economics, 15: 387-402.

15 (Tyner, Wallace and Taheripour, Farzad. "Biofuels, Policy Options, and Their Implications: Analyses Using Partial and General Equilibrium Approaches" Journal of Agricultural and Food Industrial Organization 2008)