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Impact of COVID-19 on the quantile connectedness between energy, metals and agriculture commodities

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ABSTRACT

With many studies highlighting the heterogeneous impact of the COVID-19 pandemic on different commodity markets, this study provides evidence of quantile connectedness between energy, metals, and agriculture commodity markets before and during the COVID-19 outbreak. Since mean-based measures of connectedness are not necessarily suitable to measure connectedness in the crisis period, especially in the tails of the return distribution, thus in this study, we use the newly developed approach of quantile-based connectedness. The full-sample analysis results show that return shocks only propagate within the energy commodity group. The findings manifest that transmission of return spillovers is stronger in the left and right tails of the conditional return distribution. In addition, the results unveil that degree of tail-dependence between energy, metals, and agriculture commodities are time-varying. Meanwhile, our sub-sample analysis clearly shows that the commodity market return connectedness demonstrates a significant shift over time due to COVID-19 shocks. There is evidence of strong transmission of return shocks between energy, metals, and agriculture commodities during the COVID-19 fiasco. Finally, the results also illustrate that softs and livestock commodities hold significant diversification benefits for energy market investors.

1. Introduction

Nowadays, commodity markets are increasingly interconnected like other financial markets (Caporin et al., 2020). In particular, after the global financial crisis (GFC), cross-commodity linkages have drawn the attention of academicians, policymakers, and investors. Commodities are increasingly considered as an essential component of investment portfolios by investors and portfolio managers. Moreover, the financialization of commodity market has played a vibrant role in attracting a large influx of investors into commodity markets, resulting in increased liquidity and ease of trading (Chong and Miffre, 2010; Silvennoinen and Thorp, 2013; Naeem et al., 2020). Also, trade and financial liberalization, globalization, and technological development have strengthened cross-commodity linkages. On the other hand, global market integration and the financialization of commodity markets have led to increased price volatilities and speculation, which serves as the channel for the transmission of risk and return spillovers across different commodity classes. Since the interconnections among different commodities hold significant implications related to business cycle analysis, asset allocation, and risk management, therefore a large body of literature has documented the causal relationships between different commodity markets (e.g., Rehman et al., 2018; Zhang and Broadstock, 2018; Kang et al., 2019; Ji et al., 2020; Mandacı et al., 2020; Tiwari et al., 2020).

The rapid spread of the novel Coronavirus turned into a global health emergency after World Health Organization (WHO) declared the COVID-19 outbreak as a global pandemic. The COVID-19 pandemic stirred up an unprecedented episode of global crisis marked with exceptional social and economic turbulences. Goodell (2020) argues that the COVID-19 fiasco gave rise to destructive economic damages never witnessed before. In particular, the disastrous effects of the outbreak on economic activity and financial markets were more pronounced and different than any of the previous historical shocks (e.g.,

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global financial crisis 2007–08, SARS outbreak, droughts, and floods) because of its distinctive features such as quarantine measures, travel ban, restriction on mobility of goods at the domestic and global level.

Similar to other financial markets, the commodity market also felt the dent created by the pandemic. A growing body of literature has examined the influence of uncertainties associated with pandemics on the commodity market (Salisu et al., 2020; Wang et al., 2020; Ezeaku and Asongu, 2020; Bakas and Triantafyllou, 2020; Bouri et al., 2020a, 2020b). Although the impact of the COVID-19 pandemic varied across different commodity groups, still, movement restrictions caused significant supply and demand shocks to the commodity market (Rajput et al., 2020). For example, since energy and metal commodities are directly connected with economic activity, the slowdown of the global economy due to virus spread negatively impacted these hard commodities (Ozili and Arun, 2020; Erken et al., 2020).[1] On the contrary, lockdowns and mobility restrictions caused disrupted food supply chains, which stimulated panic buying and hoarding behavior among the purchasers in the early days of the pandemic and led to increased demand for essential food and agricultural commodities (Prentice et al., 2020; Vercammen, 2020; Hobbs, 2020; Benton, 2020).

Consequently, agricultural commodities' prices exhibited resilience during the outbreak period (Rubbaniy et al., 2020). Many questions have emerged about interlinkages between different commodities due to the extreme price movements experienced in the commodity market during the pandemic. Investors are also particularly keen to discern potential hedging options among different commodity groups to mitigate price crash risk and achieve portfolio diversification. Given this, the study aims to shed light on the return connectedness network of a large number of commodities before and during the COVID-19 outbreak. We seek to establish the role COVID-19 pandemic in shaping up the patterns of return connectedness across different commodity classes. By doing this, we will comprehend whether the structure of return connectedness among commodities demonstrates any shift over time due to COVID-19 shocks.

In light of the catastrophic events experienced during the COVID-19 outbreak, there is a renewed interest in understanding how the pandemic shaped up the structural dynamics of the connectedness network among different commodities. Therefore, a growing number of studies are documenting the risk and return connectedness among different commodity groups during the outbreak period (e.g., Umar et al., 2021a, 2021b; Hung, 2021; Sun et al., 2021; Song et al., 2021). In this backdrop, the study focuses on examining the impact of the COVID-19 pandemic on the tail dependency structure of the return spillovers network among major commodity markets. For this purpose, we rely on a new method that expands the conventional mean-based vector autoregression (VAR) framework of Diebold and Yilmaz (2012, 2014) to a quantile-based level. The conventional spillover index offers an effective approach to detect risk and return spillovers among financial markets; still, the method is not very effective in measuring extreme spillovers. The model estimates are based on the mean of the distribution and ignore any specific quantiles. Therefore, the approach underestimates the actual impacts of the spillovers among financial markets. Also, the underlying model uses the OLS approach to estimate VAR, which also limits the model's effectiveness.

In contrast, the extreme spillover index of Su et al. (2019) uses quantile regression, which is a much more suitable econometric tool to capture the real effects of spillovers among financial markets. For instance, the left tail probabilities illustrate extreme downward movements which are associated with bearish market outcomes such as periods of extreme systematic risk. Thus, estimating the spillovers at extreme left tail offers much more useful insight about the spillovers among financial markets during crisis periods. Given these advantages, the extreme spillover approach estimates error variance decompositions at a pre-specified quantile level. Moreover, a two-step procedure is employed for the quantile variance decomposition analysis model. In the first step, quantile regression is utilized to forecast the VAR model and attain forecast errors at specific quantiles. Second, the spillover index is calculated from the variance decompositions. In this context, our analysis not only addresses the dynamics of average return spillovers among commodities in static and time-varying settings, but also covers the return spillovers across extreme upper and lower quantiles. Moreover, we fit VAR models at the 5th and 95th percentiles in the quantile regression to capture the impact of extreme negative and positive shocks on the return connectedness network of commodities. We apply this to the daily prices of 34 commodities (part of the energy, metals, and agricultural commodity groups) from January 02, 2006, to October 10, 2020. This quantile-based approach enables us to uncover the tail return propagation among underlying commodities before and during the COVID-19 outbreak. This analysis will also reveal more useful asset allocation and risk management information than concentrating only on the middle quantile.

Our study contributes to the literature in various ways. First, we are the first to present evidence on the extreme connectedness network of major commodities. Although many studies have examined the cross-commodity return connectedness using diverse methods (e,g., Yahya et al., 2019; Xiao et al., 2020; Uddin et al., 2019; Umar et al., 2019), however, still, there is lack of research on documenting the extreme dependency structure of the network of return spillovers among different commodity groups. Second, we also demonstrate the influence of the COVID-19 pandemic on the tail-dependency network of commodities. During the COVID-19 virus spread period, pandemic fear triggered extreme uncertainty in the financial markets, which led to panic trading and severe economic losses. Therefore, academicians are still exploring alternative portfolio and risk management strategies to shield against such natural calamities. In light of this, many studies have highlighted the linkages among different commodity groups during the pandemic period (e.g., Tiwari et al., 2020; Mensi et al., 2014). Nevertheless, in this study, we present the influence of the outbreak on the extreme return connectedness network of many commodities and commodity groups. In this way, the study provides useful insights for investors regarding hedging options among commodities to achieve superior portfolio performance during such crisis periods.

Our main results uncover many interesting findings. First, our full sample results show that return spillovers only exist within commodity groups, wherein the strongest return connectedness is discovered among energy commodities. Also, the results illustrate that return spillovers in lower and upper quantile are stronger than median quantile. This result highlights the lack of effectiveness of using conditional mean-based estimators to measure the return spillovers associated with extreme commodity market movements. Second, the results also show that spillovers among commodities vary with middle, lower and upper quantile. Third, our sub-sample analysis results also confirm the significant influence of the COVID-19 pandemic on the dependency structure of the network of return spillovers among major commodities. Consequently, we observe the transmission of return shocks between different commodity groups during the outbreak period. Again, we note excess return spillovers in the extreme quantiles compared to the mean quantile in the COVID-19 period. Finally, our results also stress the potential hedging and diversification of livestock and soft commodity groups during the COVID-19 crisis.

The remainder of the paper is organized in four sections. The section 2 covers the related literature. The next section describes the methodology of the paper. The section 4 presents the empirical results. The last section concludes the paper.

2. Literature review

Pindyck and Rotemberg (1990) pioneering work asserts that

[1] However, the prices of precious metals such gold and silver continued to trade at bullish trend during the COVID-19 pandemic.

commodity prices strongly co-move due to their similar behavior. These findings led to the development of a new avenue of research, and after that, countless studies examined the spillovers among commodity prices, returns, and volatilities (e.g., Serra, 2011; Du and McPhail, 2012; Lahiani et al., 2013; Nazlioglu et al., 2013; Mensi et al., 2014; Koirala et al., 2015; Zhang and Tu, 2016; Cabrera and Schulz, 2016; Kang et al., 2017; Dutta and Noor, 2017; Zhang and Broadstock, 2018; Chan et al., 2018; Yahya et al., 2019; Tiwari et al., 2020; Ji et al., 2020; Li and Su, 2020; Yip et al., 2020; Khalfaoui et al., 2021). For example, Du and McPhail (2012) illustrate significant volatility spillovers between the agricultural commodities and crude oil market. Mensi et al. (2014) investigate the return and volatility spillovers among cereal and energy commodities. The findings show strong linkages between the underlying markets, where OPEC news announcements significantly influence the energy-cereal nexus. Kang et al. (2017) examine the return and volatility spillovers among six commodity futures markets, where the results confirm bi-directional risk and return spillovers among the underlying commodity markets. Also, the magnitude of spillovers substantially increased during the period of GFC. Zhang and Broadstock (2018) show a dramatic shift in the connectedness network of commodities after GFC. The evidence highlights that the co-dependence in the price changes of six major commodity groups increased from 14.82% (pre-crisis average) to 47.87% after GFC. Dahl et al. (2020) found asymmetric and bi-directional information flows between the agricultural and crude oil commodity markets, and such a relationship is pronounced during periods of an economic slowdown. Similarly, Kang et al. (2019) use the frequency domain spillover method of Baruník and Křehlík (2018) to show bi-directional and asymmetric connectedness between oil and agriculture markets at all frequency bands. Umar et al. (2019) examine the price connectedness among oil and metal commodities in the time and frequency domains. The evidence shows that total connectedness varies in different frequencies. Besides, Tiwari et al. (2020) document the connectedness and time-frequency causality among metals, energy, and agricultural commodities. Here, the findings reveal that the agricultural commodity group is most affected by shocks in the system. In the same way, Albulescu et al. (2020) examine the extreme dependencies among metals, energy, and agricultural commodities. The evidence shows that co-movement between the underlying markets increases during extreme situations. In addition, Umar et al. (2021c) examine connectedness among nine commodities classes for a time span covering more than two centuries. The findings highlight that precious metals, grains, softs and base metals are a transmitter of spillovers to other commodity markets. In fact, the connectedness across commodity markets soared during crisis periods. Furthermore, Rehman and Vo (2021) investigate the return integration among energy commodities, industrial metals and precious metals. The findings of the study uncovered a moderate level of integration among the underlying markets in the short- and medium-term. In contrast, the coherence level increases in the long-run, especially during the crisis periods.

Apart from the empirical evidence on the spillovers among commodity prices, returns and volatilities, there is another strand in the literature that documents the impact of macroeconomic factors and environment on the risk and return dynamics of commodity markets (e.g., Gargano and Timmermann, 2014; Bakas and Triantafyllou, 2018; Prokopczuk et al., 2019; Hu et al., 2020). In this spirit, the COVID-19 outbreak has presented the academic community with a new scenario of global distress, and therefore a growing number of studies are examining the effects of pandemic uncertainty on commodity markets. For instance, Bakas and Triantafyllou (2020) investigate the impact of the COVID-19 pandemic on the volatility of the commodity price index. The evidence depicts the strong negative influence of pandemics on commodity volatility, especially in the crude oil market, while the pandemic effect on the gold market is positive but less significant. Salisu et al. (2020) show a positive association between pandemic fear and commodity returns and stress safe-haven function of commodities during the COVID-19 pandemic. Rajput et al. (2020) show that oil and metal commodities are most affected by outbreaks because of the reduction in demand and economic activity, whereas agricultural commodities are least influenced as they are indirectly associated with economic activities. Wang et al. (2020) show the influence of the COVID-19 outbreak on the cross-correlations of crude oil and agricultural futures markets. The evidence highlights strong co-movement between sugar and oil, and such relations are pronounced under the period of the COVID-19 crisis. Umar et al. (2021a, 2021b, 2021c) investigate the dynamic return and risk connectedness among three major agricultural commodities markets: grain, livestock, and softs. The evidence shows that risk and return connectedness among the underlying markets fluctuates over time, reaching its peak during the COVID-19 outbreak. In addition, Ezeaku and Asongu (2020) examine the resilience of the soft commodity class during the early days of the pandemic. The evidence highlights the resilience of the softs commodity market, as the soft commodities maintain a strong upward trend as compared to during the COVID-19.

Similarly, Rubbaniy et al. (2020) also advocate the safe-haven properties of softs commodity groups during the pandemic. While a growing body of literature documents the pandemic effects on different commodity markets, little attention has been paid to exploring the tail dependency structure of the network of return spillovers among commodities and across commodity classes. In this regard, the study contributes to the literature by documenting the return connectedness network of many commodities before and during the COVID-19 outbreak. Hung (2021) explores the time and frequency connectedness among crude oil and agricultural commodities during COVID-19 period by employing the spillover index approach and wavelet coherence method. The results suggest that spillover linkages among the underlying markets increased during the outbreak period as compared to the pre-COVID-19 period. Lin and Su (2021) investigate the influence of COVID-19 pandemic on the cross-market linkages among energy commodities. The findings suggest dramatic rise in connectedness among energy commodities during the COVID-19 period. However, this soaring connectedness lasted for two months and then fell back to the previous level.

The previous studies use a diverse range of econometric methods to examine the spillovers among commodity prices, returns, and volatilities, which include regression analysis (Salisu et al., 2020), VAR-based spillovers methods (Mensi et al., 2014; Bakas and Triantafyllou, 2020), GARCH family models (Luo and Ji, 2018; Umar et al., 2019; Du and McPhail, 2012; Nagayev et al., 2016), copulas models (Yahya et al., 2019; Sun et al., 2020; Albulescu et al., 2020), wavelet and causality analysis (Jiang and Yoon, 2020; Sharif et al., 2020) and TVP-VAR method (Adekoya and Oliyide, 2020; Umar et al., 2019). However, we utilize the newly introduced quantile-based connectedness method in this study, which extends Diebold and Yilmaz (2012, 2014) mean-based vector autoregression (VAR) approach. Therefore, among the major contributions of this study is to employ novel quantile-based connectedness approach to explore the extreme return connectedness among a large number of commodities across different commodity groups during pre and post COVID-19 outbreak period. Various studies employ the methodology to measure the extreme spillovers among financial markets (e.g., Bouri et al., 2020a, 2020b; Saeed et al., 2020; Naeem et al., 2021). Recently, many studies have utilized quantile connectedness framework to document the linkages among various commodity markets. For example, Jena et al. (2021) examine the connectedness among six fuel markets by employing a novel Quantile VAR spillover approach. The results unveil high connectedness at the extreme quantiles (5th and 95th) as compared to median quantile (50th quantile). In the same way, Cui et al. (2021) examine time and frequency, extreme spillovers and dynamic association among crude oil prices and China's commodity futures. For this purpose, the authors use quantile regression, wavelet coherence and DECO-FIAPARCH (1,d,1) model. The findings uncover that oil market has high connectedness with fuel oil, copper and natural rubber. Also, the results suggest that extreme connectedness at lower quantile is higher than of the mean quantile. In addition, the findings reveal that connectedness among the underlying markets increases during periods of economic downturn such as GFC, oil price plunge and recent COVID-19 outbreak crisis.

3. Data & methodology

3.1. Data

In order to estimate tail dependency structure of return spillovers among major commodities the study utilizes 1st generic Bloomberg futures of 34 commodities. Here the term future contract is defined as an agreement among buyers and sellers of physical commodities or related financial instruments at a pre-established price and date. The commodities belong to five broader categories such as energy, metals, grains and oilseeds, livestock, and softs. The commodities in energy category include Brent oil, Gas oil, Gasoline, Heating oil, natural gas, Propane and WTI crude oil. Secondly, the metals category is comprised of Aluminum, Copper, Gold, Lead, Nickel, Palladium, Platinum, Silver, Tin and Zinc. Thirdly, the grains and oilseeds category include Canola, Corn, Oats, Rough rice, Soybean meal, Soybean oil and wheat.

In the same way, livestock category includes Feeder cattle, Lean Hog, Live cattle and pork belly. Finally, the softs include Cocoa, Coffee, Cotton, Ethanol, Lumber, Milk, Orange juice, Rubber and sugar. All the contracts are denominated in USD. The contracts are listed quarterly (Mar, Jun, Sep, Dec) and financially settled. We obtain daily prices for all the underlying future contracts from January 02, 2006, to October 10, 2020. The sample duration effectively enables us to capture the impact of covid-19 outbreak on the connectedness network of commodities. The sub-sample analysis covers the time-period from January 01, 2020, to October 10, 2020, when the COVID-19 virus spread across the globe. All the data is sourced from Bloomberg.com.

3.2. The quantile VAR model

We use N-variable vector autoregression to measure directional spillovers in the underlying commodity markets. The dependence of y_n on x_n in each quantile α (α ∈ (0,1)) of the probability distribution is measured similar to Koenker and Bassett (1978). The following equation shows the quantile deviation using the VAR process of nth order:

$$y_n = c(\alpha) + \sum_{a=1}^{p} Bi(\alpha) y_{n-a} + et(\alpha), n = 1, \dots, N \tag{1}$$

Here, Yn depicts the n vector of the dependent variable, whereas C (α) represents the n vector of intercept and et (α) denotes the residual of the quantile α.Bi (α) represents the lagged coefficients at quantile α, with a = 1,…,z, which can be verified by considering that the residuals satisfy the limitation of population quantile, Qα (et(α)|yn-1, …, yn-z) = 0. In fact, the term αth the quantile of response y can be written as follows:

$$Q\alpha(et(\alpha)\,|yn-1, \dots, yn-z) = c(\alpha) + \sum_{i=1}^{z} \widehat{B}i(\alpha) y_{n-a} \tag{2}$$

Considering the right-side variables in Eq. (2), our problem appropriation contains a different regression model. The above model used the framework of Cecchetti and Li (2008) to access the quantile regression basis for each equation.

3.3. The quantile spillover indices derived from Diebold–Yilmaz

The network spillover in each quantile α is evaluated based on quantile variance decomposition based on conceptualization by Diebold and Yilmaz (2012, 2014). Accordingly, the Eq. (1) can be rewritten in the form of vector moving average process for an infinite order:

$$y_n = \mu(\alpha) + \sum_{s=0}^{\infty} A_s(\alpha) e_{n-s}(\alpha), n = 1, \dots, N \tag{3}$$

With,

$$\mu(\alpha) = (I_t - B_1(\alpha) - \dots - Bz(\alpha))^{-1} c(\alpha), A_s(\alpha)$$

$$= \begin{cases} 0, s < 0 \\ I_t, s = 0 \\ B_1(\alpha)A_{s-1}(\alpha) + \dots + B_g(\alpha)A_{s-z}(\alpha), s > 0. \end{cases}$$

Where y_n is denoted by sum of residuals e_t at every quantile α.

Our study employed the methods of Koop et al. (1996) and Pesaran and Shin (1998), considering the Cholesky-factor ordering problem. Hence our assessment is equable to variable ordering. Moreover, a total of contributions and the variance of forecast error are not necessarily equal to one because each variable's spillover is not equally sided. Therefore, for a forecast horizon F, The following equation represents the evaluation of generalized forecast error variance decomposition (GFEVD) of each variable attributable to shocks of various variables:

$$\theta_{aj}^{g}(\mathrm{F}) = \frac{\sigma_{aj}^{-1} \sum_{f=0}^{\mathrm{F}-1} \left(e_a' A_f \Sigma e_j\right)^2}{\sum_{f=0}^{F-1} \left(e_i' A_\mathrm{f} \sum A_\mathrm{f}' e_a\right)} \tag{4}$$

Here in the Eq. (4), θ_{aj}g (F) represents the jth variable to the variance of forecast error of the variable a at horizon F, a vector of errors in the variance matrix is denoted by ∑, σ_{aj} depicts the jth diagonal element of the Σ matrix, and vector with a value of 1 for the ath element and 0 otherwise is given by ea. The following equation represents the variance decomposition matrix in each entry

$$\widetilde{\theta}_{aj}^{g}(\mathrm{F}) = \frac{\theta_{aj}^{g}(\mathrm{F})}{\sum_{j=1}^{T} \theta_{aj}^{g}(\mathrm{F})} \tag{5}$$

Diebold and Yilmaz (2012, 2014) method was used to formulate the various estimation of connectedness at αth conditional quantile with the help of a generalized forecast error variance decomposition to calculate a measure of connectedness. Hence, the net connectedness (TC) index at quantile α is written as:

$$TC(\alpha) = \frac{\sum_{a=1}^{T} \sum_{j=1, i \neq j}^{\mathrm{T}} \sigma_{aj}^{\mathrm{F}}(\alpha)}{\sum_{a=1}^{\mathrm{T}} \sum_{j=1}^{T} \sigma_{aj}^{\mathrm{F}}(\alpha)} \times 100 \tag{6}$$

Consequently, the directional connectedness to index a from all other indexes at quantile α is (presented as "TO") written as:

$$C_{a\leftarrow}(\alpha) = \frac{\sum_{j=1, i \neq j}^{T} \mathrm{f}(\alpha)}{\sum_{j=1}^{T} \sigma_{ij}^{f}(\alpha)} \times 100 \tag{7}$$

Similarly, the directional connectedness from index i to all other indexes at quantile τ is (presented as "FROM") written as:

$$C_{\to a}(\alpha) = \frac{\sum_{j=1, i \neq j}^{T} \sigma_{ij}^{f}(\alpha)}{\sum_{j=1}^{\mathrm{T}} \sigma_{ij}^{f}(\alpha)} \times 100 \tag{8}$$

In light of the above, the net volatility spillover connectedness is expressed as:

$$NC(\alpha) = C_{\to a}(\alpha) - C_{a\leftarrow}(\alpha) \tag{9}$$

Finally, the pairwise connectedness at quantile α is denoted as:

$$ZC(\alpha) = \sigma_{ja}^{f}(\alpha) - \sigma_{aj}^{f}(\alpha) \tag{10}$$

Following Diebold and Yılmaz (2014) and Bouri et al. (2020a, 2020b) the time variations is estimated using rolling window approach. In addition, here based on Bayesian information criterion a VAR lag order of 1 is utilized to measure connectedness and a 10 step ahead forecast error variance decomposition.

4. Empirical results and findings

4.1. Static return connectedness analysis (full sample)

First, we estimate the network of return connectedness among 34 commodities using the quantile VAR model. Fig. 1 displays estimates of connectedness at the conditional mean ($\tau = 0.5$) for the full sample. In this study, we use a 260-days rolling window and 10-days-ahead forecast horizon to study extreme connectedness among the sample commodities. Also, we chose the optimum lag length of the VAR model as one based on the Akaike information criterion. The findings illustrate that energy commodities are the largest transmitter of return shocks to other commodities in the network. However, the underlying return connectedness between commodity classes is not clear due to a large number of pairwise linkages. Thus, to better visualize the major connections between different commodity categories, we apply hard thresholding (the estimated values smaller than the average of the first 100 largest pairwise connectedness measures are set to be 0) to retain the largest values in the connectedness network.

Fig. 2 exhibits the network of return connectedness of commodities after thresholding under the normal market conditions. It can be noted that return connections are within the commodity classes, i.e., energy, metals, grains, and oilseeds, and livestock. The strongest connections are observed within the energy commodity category, where strong bi-directional return spillovers prevail between energy commodities. The results also display weak return connectedness within the metals category, but the strong transmission of return spillovers from the gold to silver market is eminent. The results are somewhat comparable to Diebold et al. (2017) and Balli et al. (2019), who also advocate strong interconnections between energy commodities and precious metals. Further, the results also unveil strong return connectedness within the grains and oilseeds commodity class. However, rough rice is disconnected from the rest of the commodities in the grains and oilseeds category. Furthermore, the results showcase strong bi-directional return linkages between feeder cattle and live cattle. Finally, our findings also show that all the commodities within the softs category are disconnected.

Next, we calculate connectedness measures at the extreme left and right tails to differentiate between the extreme return spillovers associated with extreme negative and positive shocks. Fig. 3 depicts the network of return connectedness at the extreme left tail ($\tau = 0.05$). The extreme lower tail results highlight increased return connectedness among different commodity classes compared to the median quantile. The findings corroborate a notable thread of literature, which argues that informational spillovers among different commodities swell during the crisis periods (e.g., Kang et al., 2017; Balli et al., 2019, Kang et al., 2019). However, after thresholding, the results reveal return connectedness exists only within commodity groups. (See Fig. 4.)

Once more, we find the strongest return connectedness between energy commodities, whereas commodities within softs group are entirely isolated. The findings suggest potential hedging the softs commodity group for price fluctuations in other major commodity classes. Similarly, Fig. 5 presents the network of return connectedness at the extreme right tail. The extreme upper tail findings are similar to extreme lower tail and report soaring return connectedness among commodity classes compared to the normal market state. The results indicate the significant impact of extreme market outcomes on the return connectedness network of underlying commodity groups. Moreover, the findings are reinforced by the argument of Ma et al. (2021), who suggest that market sentiments significantly affect the connectedness network of different commodity groups. (See Fig. 6.)

4.2. Dynamic return connectedness analysis

Second, we use rolling window analysis to investigate all commodities' time-varying return connectedness. The analysis is performed for the mean, lower quantile and upper quantile. Fig. 7 shows the total dynamic connectedness among the commodities at the median quantile ($\tau = 0.5$). The results clearly display many spikes and drops in the total

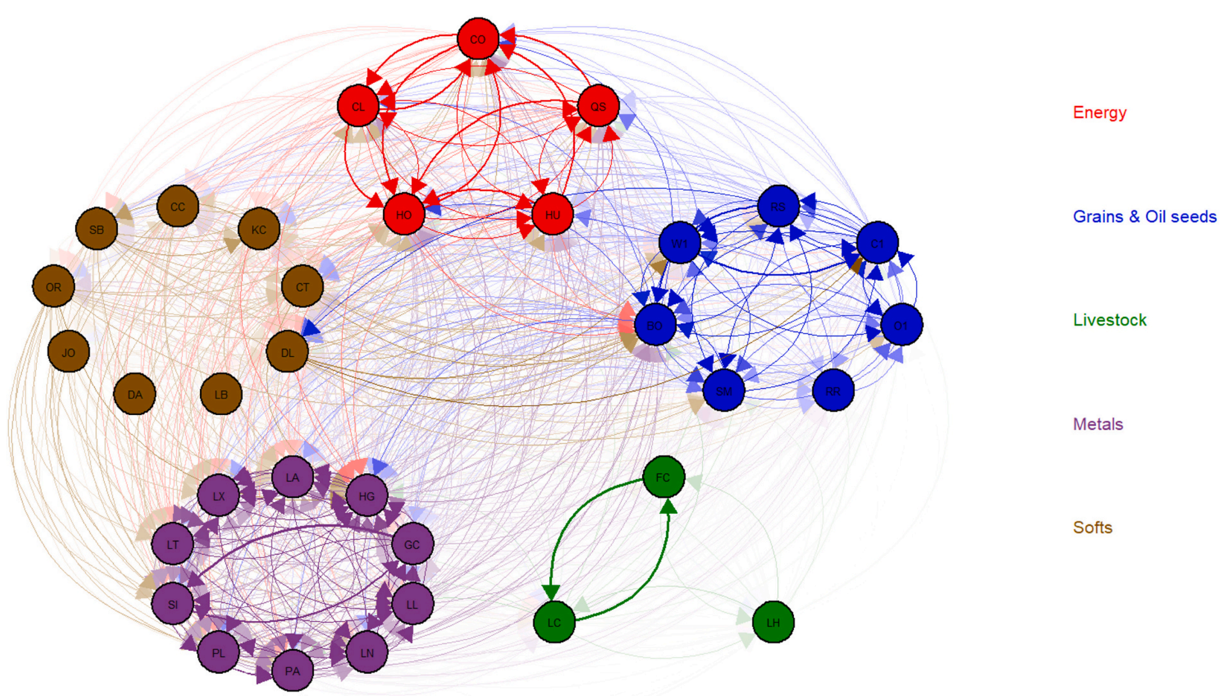

Fig. 1. Return connectedness network among commodities at the median quantile.
Note: This Figure shows the connectedness among 34 sampled commodities, classified by class. Each class/group is represented by a color.

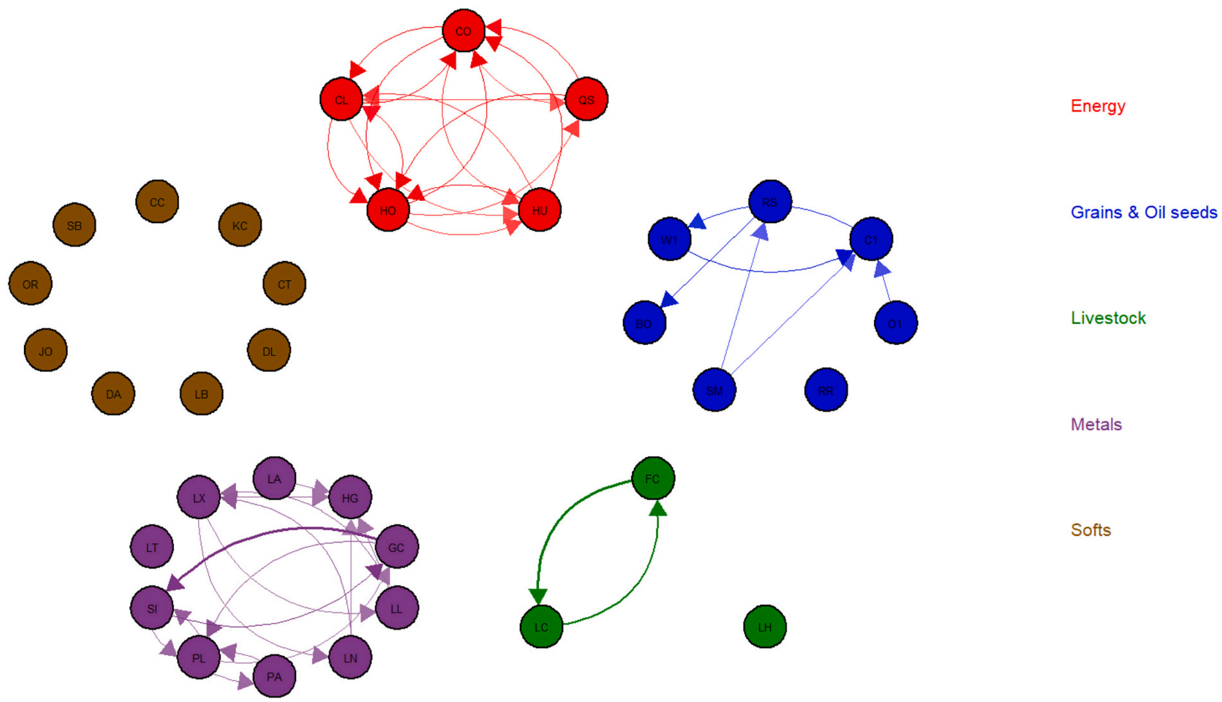

Fig. 2. Return connectedness network among commodities at the median quantile after thresholding.
Note: This Figure shows the connectedness among 34 sampled commodities, classified by class. Each class/group is represented by a color. We only keep the values larger than the average of the 100 largest individual pairwise connectedness.

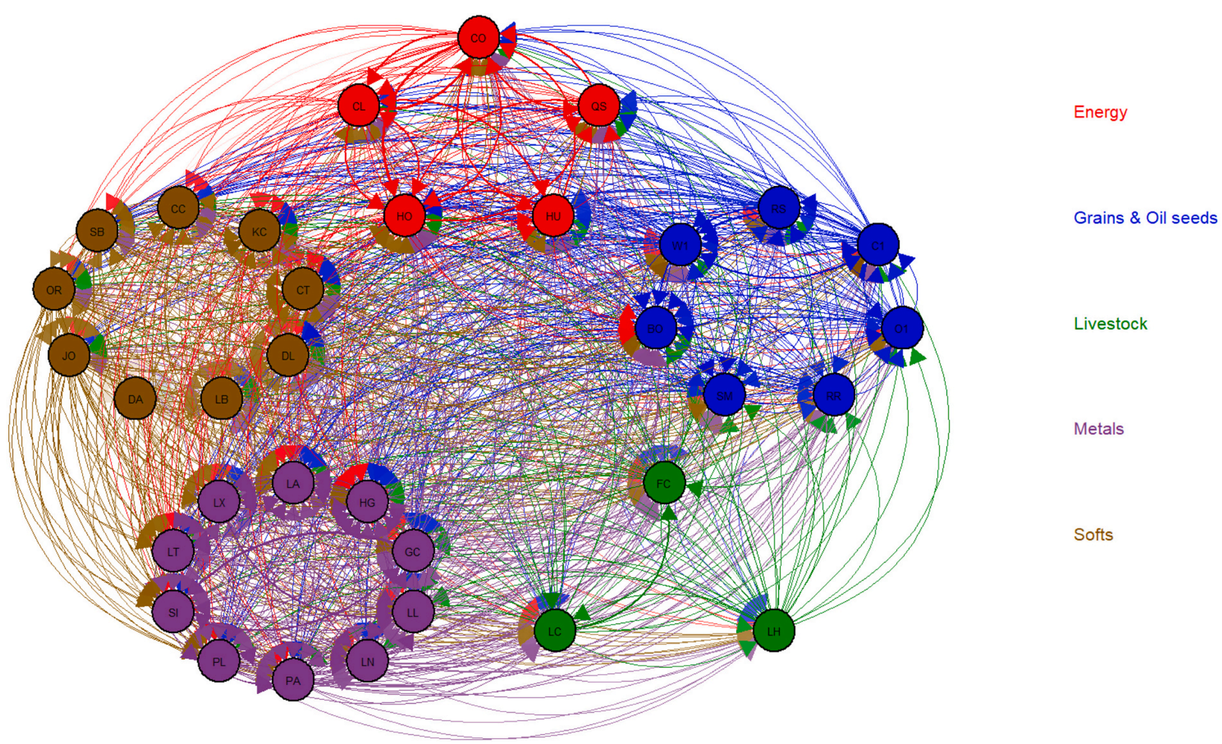

Fig. 3. Return connectedness network among commodities at the extreme left tail.
Note: Refer to note in Fig. 1.

connectedness confirming the time-varying nature of the return connectedness network. One can distinctly see the significant impact of economic and financial conditions on the connectedness network of commodities. For instance, the total connectedness among the commodities spiked during the Global Financial Crisis (GFC) 2007–08. The findings complement the earlier evidence that indicates connectedness among commodities swelled during the GFC (e.g., Grosche and Heckelei, 2016). Similarly, we also note heightened total connectedness corresponding to the European debt crisis 2012–13, the oil price crash in 2016, and the COVID-19 outbreak.

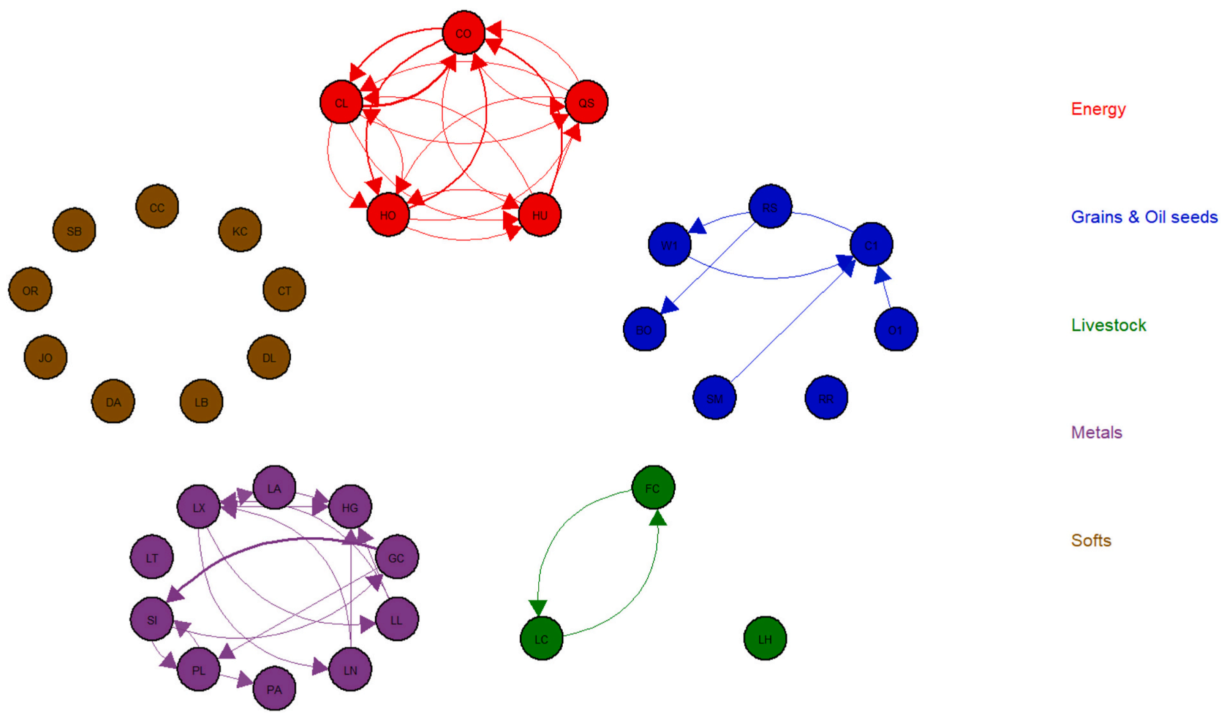

Fig. 4. Return connectedness network among commodities at the extreme left tail after thresholding.
Note: Refer to note in Fig. 2.

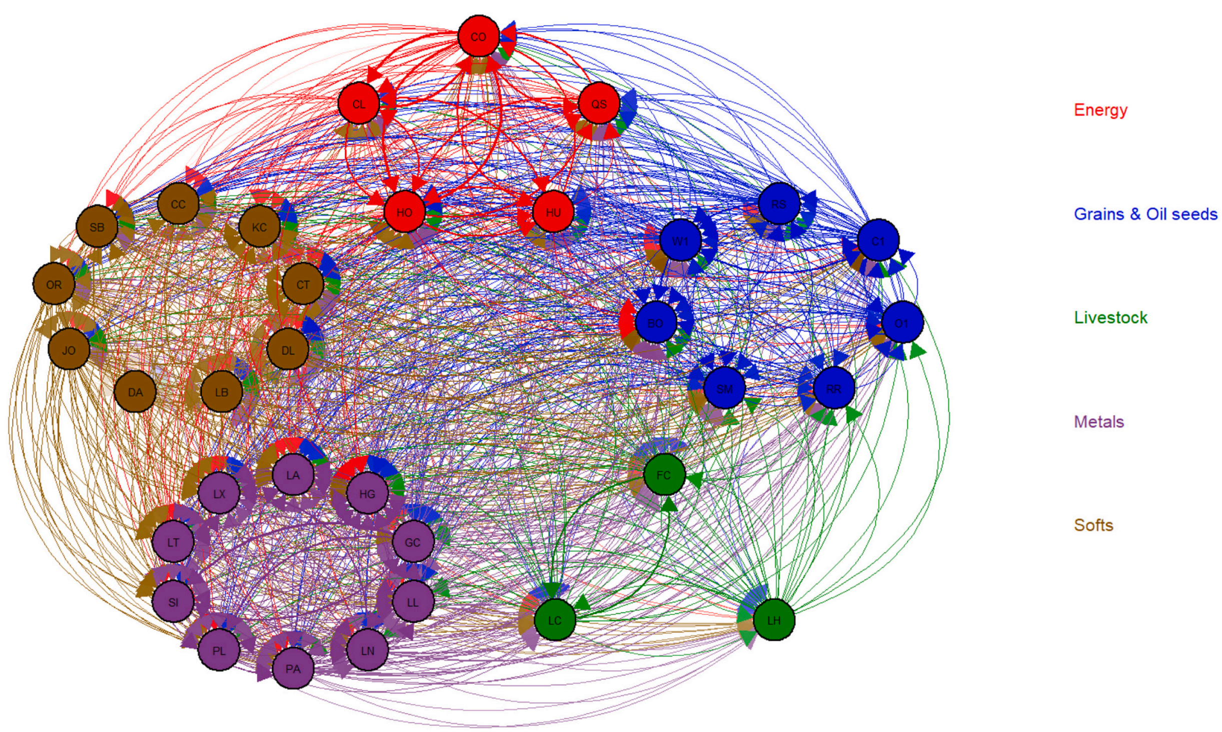

Fig. 5. Return connectedness network among commodities at the extreme right tail.
Note: Refer to note in Fig. 1.

Next, we observe that total connectedness among commodities at both the left and right tails (presented in Figs. 8 and 9, respectively) is much higher than the median quantile; however, the range of variations is much lower and varies 90–95%. Such large connectedness among commodity returns at both extreme tails highlights the sensitivity of commodity prices to both negative and positive shocks.

Up next, we show the dynamic net connectedness among commodity categories, including energy (red), grains and oilseeds (blue), livestock (green), metals (purple), and softs (orange). We present the net connectedness estimates for the median, upper and lower quantiles in Figs. 10, 11, and 12. Again, the results confirm the time-varying nature of net connectedness among the underlying commodity classes. Wherein

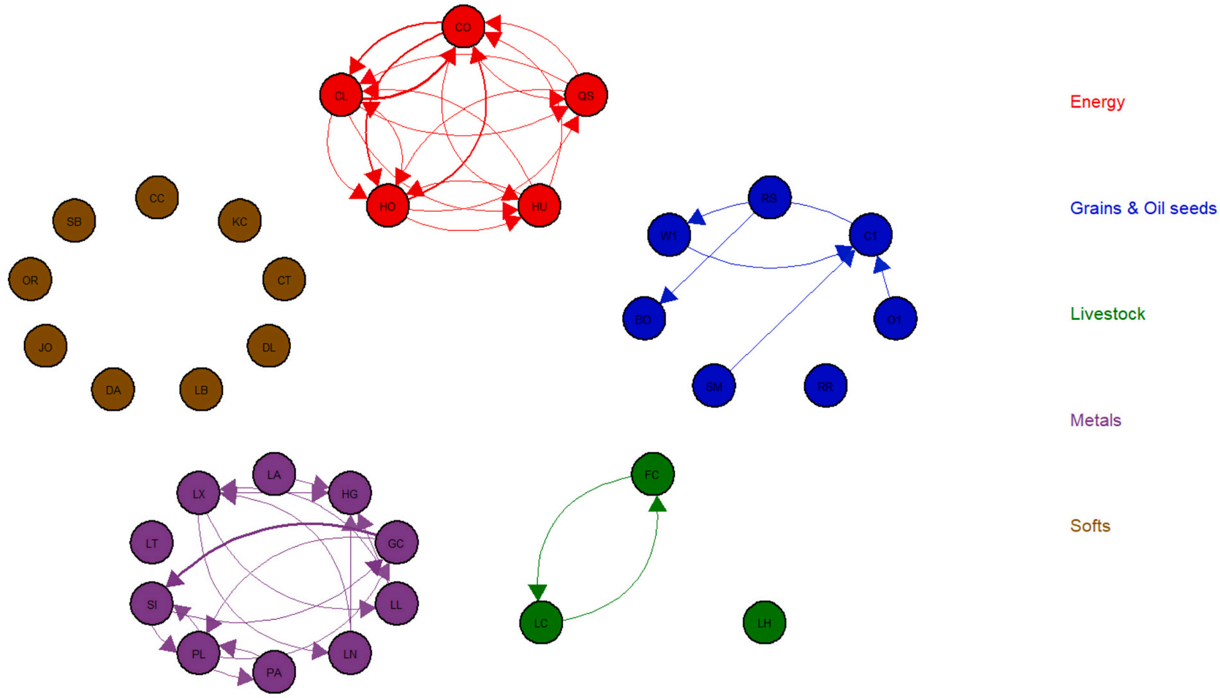

Fig. 6. Return connectedness network among commodities at the extreme right tail after thresholding.
Note: Refer to note in Fig. 2.

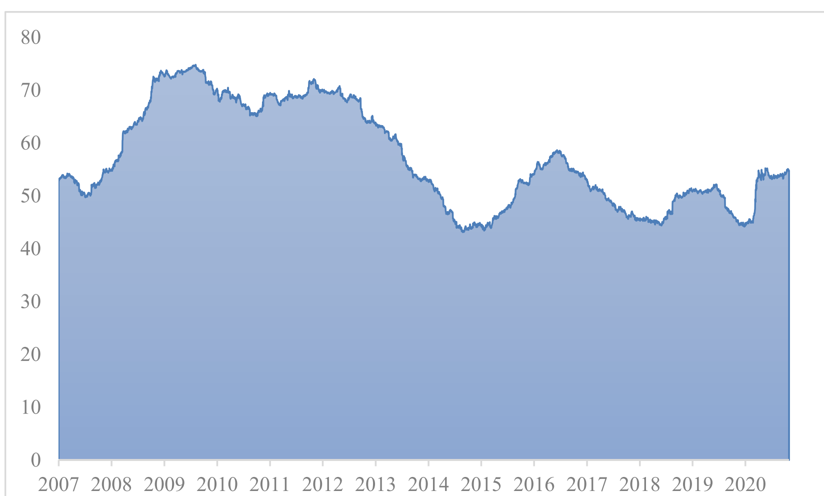

Fig. 7. Total time-varying return connectedness among commodities at the median quantile.
Note. This figure shows the rolling-window version of total connectedness. The rolling-window size 260 days.

the results distinctly highlight that the energy commodity group has the highest total net connectedness with the rest of commodity groups across the median, lower and upper tails. Here the results conform to the notion that the energy commodity group is more financialized than other commodity categories. Thus this enables the energy commodity class to act as the main transmitter of shocks to the rest of the commodity groups indicating strong interlinkages among them (Diebold et al., 2017; Zhang and Broadstock, 2018). The results also show that livestock has the lowest time-varying net connectedness with other commodity groups, demonstrating the potential safe-haven function of the livestock commodity group to hedge the price crash risk in other commodity categories. (See Figs. 13–15.)

4.3. *Impact of COVID-19 pandemic on return connectedness network*

So far, we have unveiled the evidence of static and dynamic return connectedness network of commodities for the full sample period. This section presents additional sub-sample analysis results, which correspond to the COVID-19 outbreak period. Here, we examine the impact of a pandemic on the return connectedness network of the underlying commodities. Moreover, we seek to understand whether the virus spread has significantly reshaped the commodity returns network structure.

Fig. 16 illustrates the return connectedness network at median quantile (τ = 0.5) for the sub-sample analysis. The results uncover significant influences of COVID-19 pandemic on the connectedness network of commodities. In fact, some major structural changes are observed during the outbreak period. The findings align with the notion

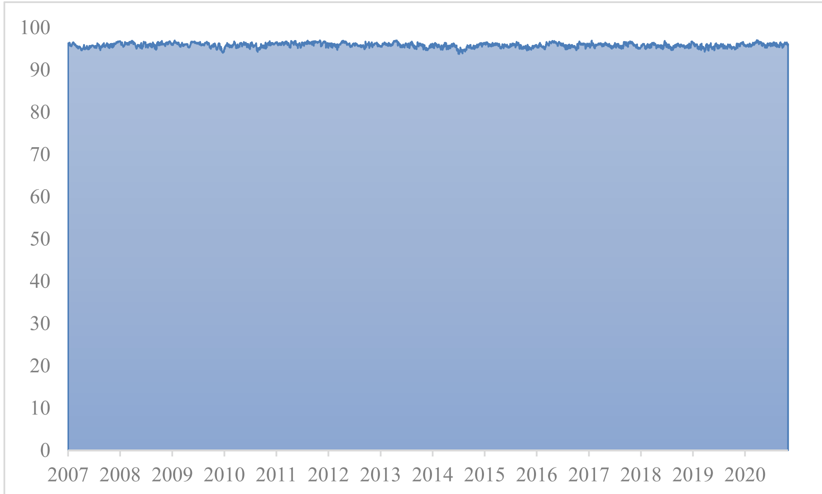

Fig. 8. Total time-varying return connectedness among commodities at the extreme left tail.
Note. This figure shows the rolling-window version of total connectedness. The rolling-window size 260 days.

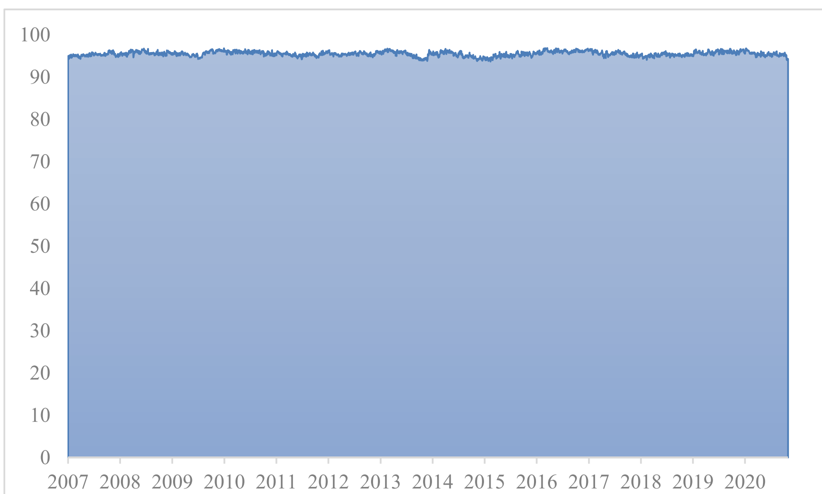

Fig. 9. Total time-varying return connectedness among commodities at the extreme right tail.
Note. This figure shows the rolling-window version of total connectedness. The rolling-window size 260 days.

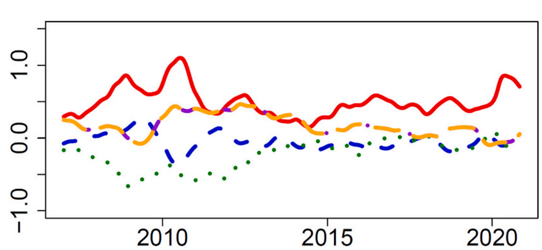

Fig. 10. Total time-varying net return connectedness among commodities at the median quantile.
Note. This figure shows the rolling-window version of net connectedness. Energy, Grains & Oil Seed, Live Stock, Metals and Softs are represented by red, blue, green, purple, and orange, respectively.

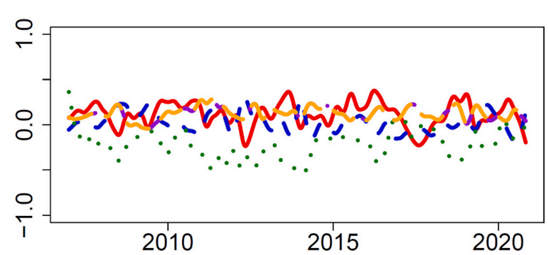

Fig. 11. Total time-varying net return connectedness among commodities at the extreme left tail.
Note. This figure shows the rolling-window version of net connectedness. Energy, Grains & Oil Seed, Live Stock, Metals and Softs are represented by red, blue, green, purple, and orange, respectively.

that stresses the significant role of crisis events on the evolution of commodity connectedness networks (Silvennoinen and Thorp, 2013; Bouri et al., 2021). One can see notable return spillovers among commodities during the COVID-19 pandemic period in comparison to the full sample duration. The results clearly follow the evidence that suggests escalated connectedness among different commodities classes during the outbreak period (e.g., Hung, 2021; Sun et al., 2021; Iqbal et al., 2022). Also, the results highlight various instances of bi-directional spillovers among different commodity groups. Surprisingly, after thresholding, the results illustrate a lack of connectedness among commodities within the same commodity category. Instead, the

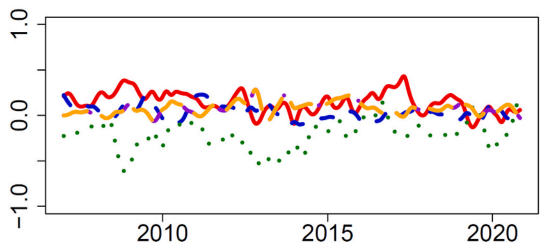

Fig. 12. Total time-varying net return connectedness among commodities at the extreme right tail.
Note. This figure shows the rolling-window version of net connectedness. Energy, Grains & Oil Seed, Live Stock, Metals and Softs are represented by red, blue, green, purple, and orange, respectively.

majority of the return spillovers are traced between different commodity classes. In this vein, the results display that grain and oilseeds group is a largest transmitter of return shocks to other commodity groups, and metals category in the largest receiver of return spillovers. In addition, the returns of softs and livestock groups are less influenced by the rest of the commodity classes, highlighting the potential diversifier role of these commodity groups. The results are similar to Umar et al. (2019), who also report low return and volatility connectedness of soft and livestock commodity groups among the major agricultural commodity markets. The results also add to the findings of Rubbaniy et al. (2020), who stress the safe-haven properties of softs commodity groups during the spread of the novel Coronavirus pandemic. Furthermore, the results also display that feeder cattle are the most disconnected commodity in the commodity return network during the outbreak period.

Next, we report the extreme negative return spillovers among the commodities during the COVID-19 outbreak period. Again it is clear that excess return spillovers exist in the extreme lower tail as compared to the median quantile. The results are somewhat explained by the argument that stresses connectedness among markets is stronger in turmoil periods than under normal market conditions (e,g., Ang and Bekaert, 2002). The results of extreme lower quantile (see Figs. 16 and 17) display that grain and energy commodities are the largest transmitters of return shocks, and soft and metals categories are the largest receivers of return shocks. Again, we note that livestock commodities are relatively disconnected, displaying strong options for investors to take flight to safety during periods of escalated economic and financial stress. nIn the same way, the results of extreme upper tail also reveal excess return spillovers than median quantile. The findings are again in line with contagion literature that emphasizes the spillover effects of extreme events on extreme lower and upper tails (e.g., Londono, 2019). Overall, the findings shed light on the influential and unique impact of COVID-19 outbreak on the connectedness network of commodities and its implications for market participants in commodity market. The findings stress that such natural calamities can significantly alter the linkages among different commodity group, leading to unprecedented opportunities and threats for economic agents in the commodity markets. (See Fig. 18.)

4.4. Robustness check using Diebold and Yilmaz (2012)

To repel any concerns that our results are method-specific, we estimate the return connectedness network among 34 commodities using the widely recognized spillover index approach of Diebold and Yilmaz (2012). Once again we use a 260-days rolling window and 10-days-ahead forecast horizon to document mean-based connectedness among commodities. The optimum lag length of the VAR model is one based on the Akaike information criterion. The underlying approach offers simple and insightful econometric tool to capture the risk and return spillovers among financial markets. In order to avoid the problems associated with Diebold and Yilmaz (2009), the approach employs a generalized vector autoregressive framework to forecast-error variance decompositions. The model is especially useful for formulating portfolio strategies under different market conditions as compared to the Granger causality and CoVaR approach (Su et al., 2019). In light of this, a large body of literature has employed the method to estimate mean-based risk and return spillovers among financial markets (e,g., Diebold and Yılmaz,

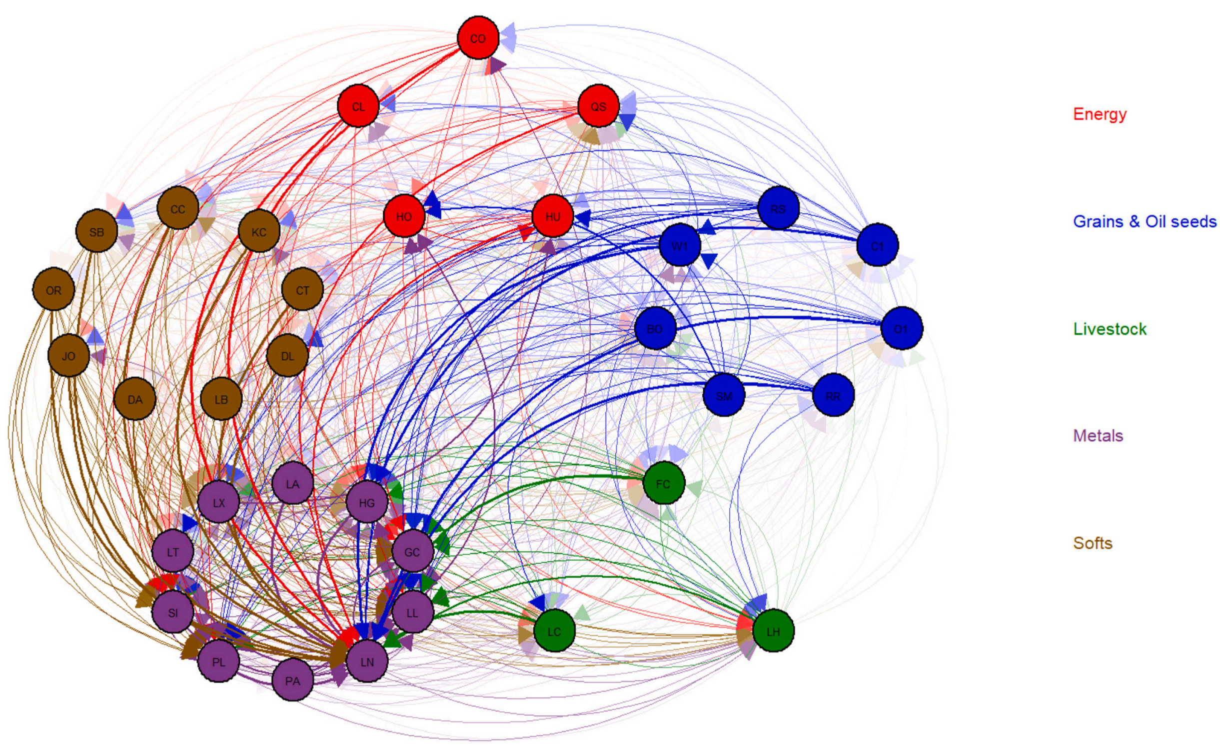

Fig. 13. Return connectedness network among commodities at the median quantile – COVID sub-sample.
Note: Refer to note in Fig. 1.

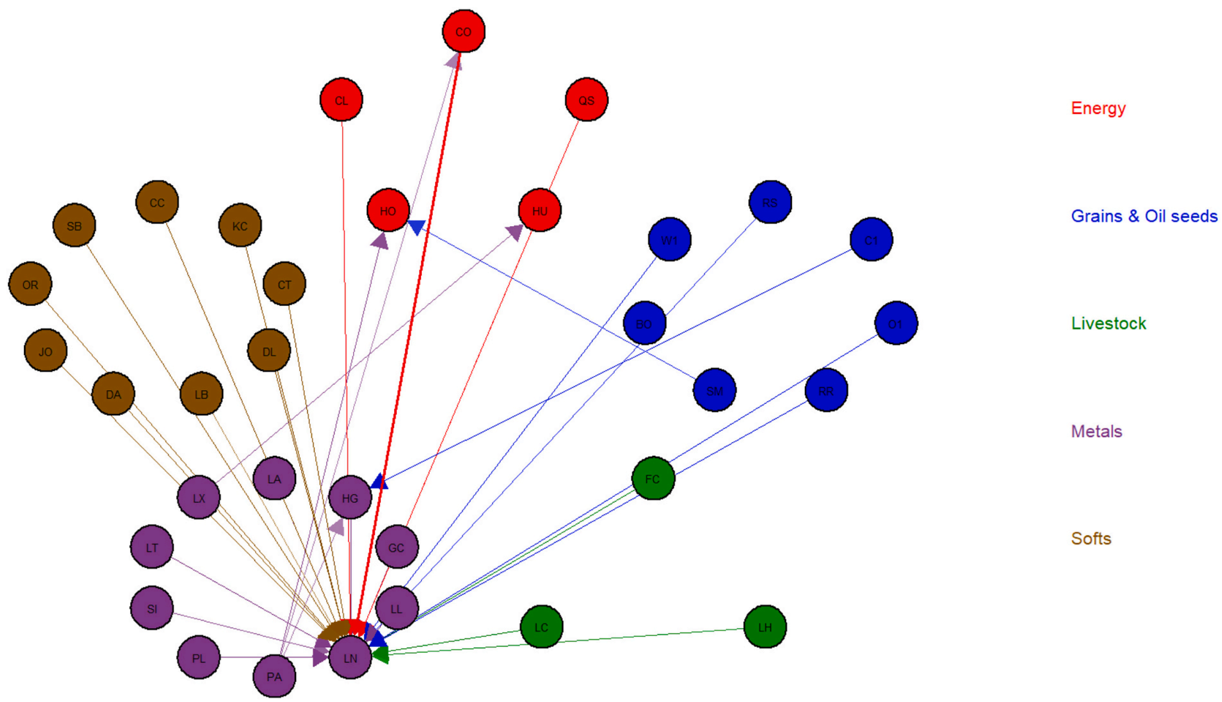

Fig. 14. Return connectedness network among commodities at the median quantile after thresholding – COVID sub-sample.
Note: Refer to note in Fig. 2.

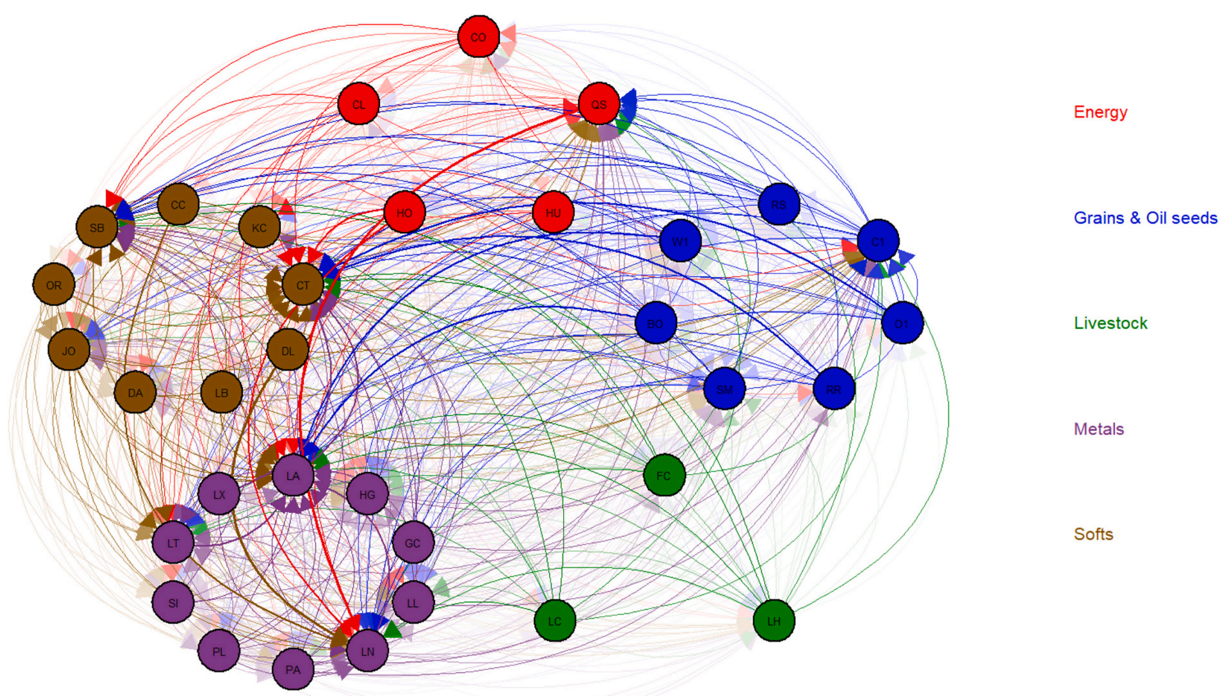

Fig. 15. Return connectedness network among commodities at the extreme left tail – COVID sub-sample.
Note: Refer to note in Fig. 1.

2014; Greenwood-Nimmo et al., 2016; Zhang, 2017; Farid et al., 2021). Against this backdrop, the results presented in this section serve as a robustness check for our analysis and second our earlier presented evidence.

Fig. 19 displays the static return connectedness network estimated using Diebold and Yilmaz (2012) method. Again, the results portray some degree of return spillovers between different commodity groups; however, these linkages are unclear due to many pairwise connections. Hence, we apply thresholding and retain only the largest values (see Fig. 20). Once again, our full sample period results indicate that spillovers among different commodity groups do not persist. Instead, we note only intra-group spillovers among commodities. As the results illustrate that return connectedness only prevails within commodity groups, highlighting strongest return connectedness is observed within

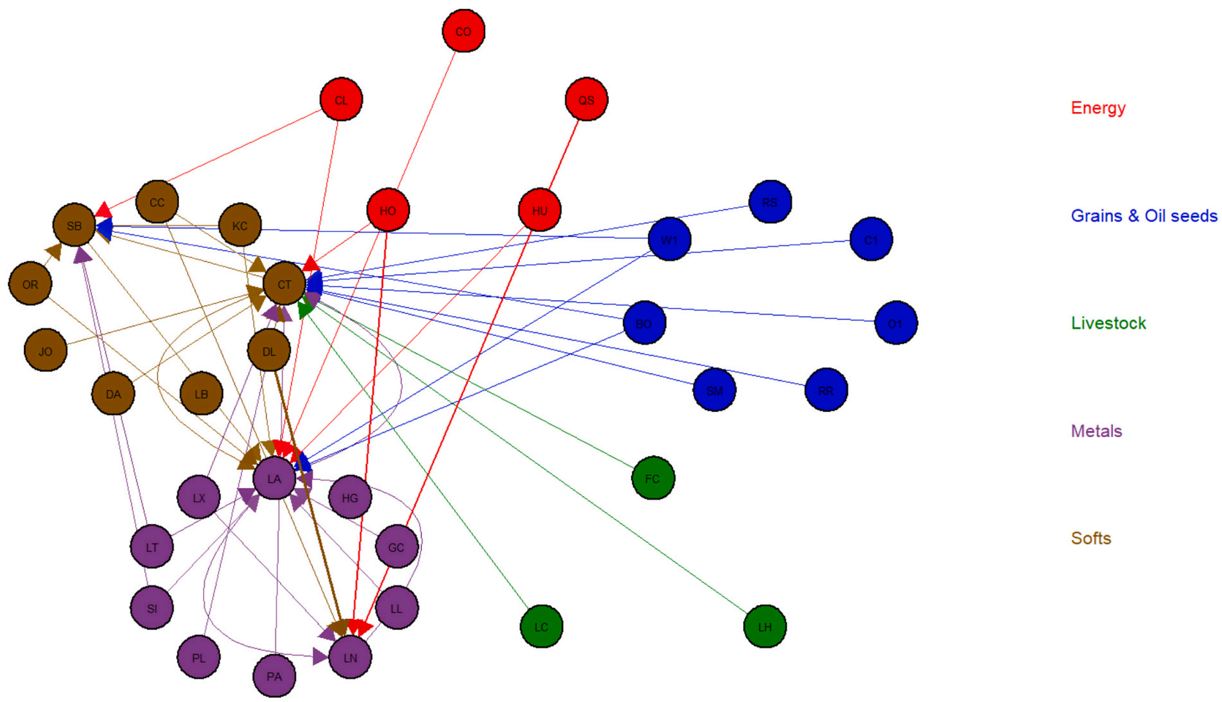

Fig. 16. Return connectedness network among commodities at the extreme left tail after thresholding – COVID sub-sample.
Note: Refer to note in Fig. 2.

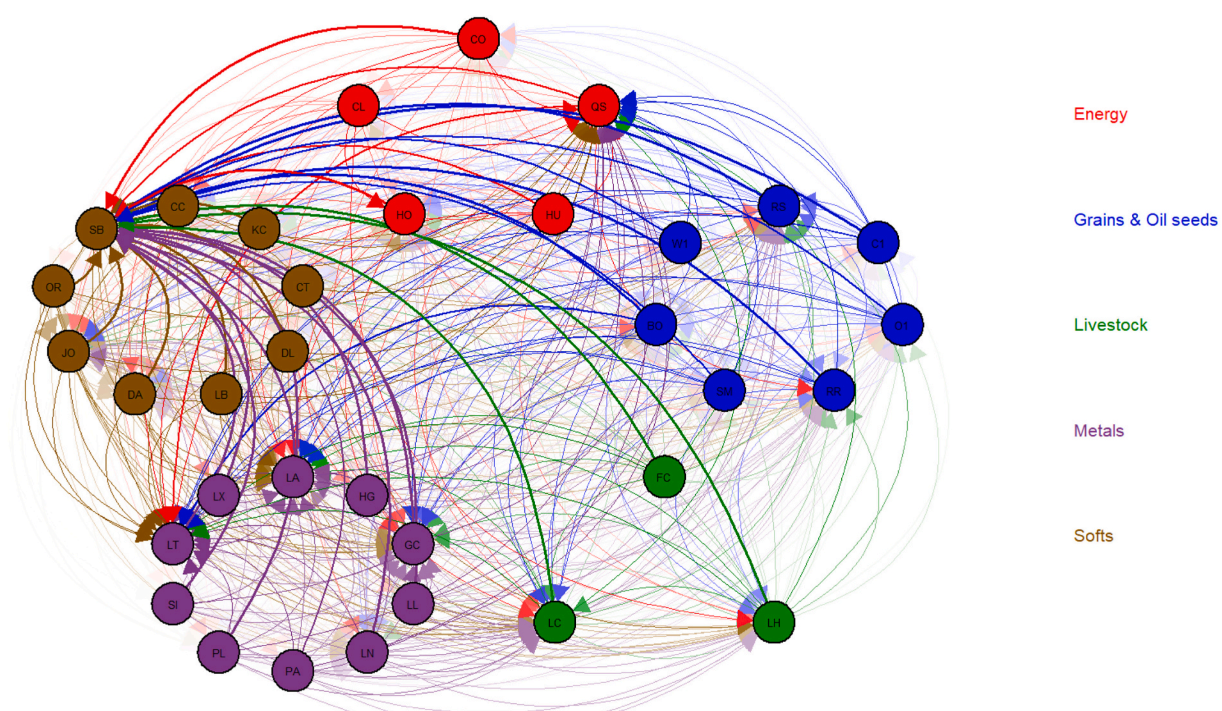

Fig. 17. Return connectedness network among commodities at the extreme right tail – COVID sub-sample.
Note: Refer to note in Fig. 1.

energy commodities. We also observe strong return linkages among metals, grains, and oilseeds, whereas the softs group commodities are totally disconnected. The findings once again highlight diversification and hedging benefits for portfolio managers investing across different commodity groups. Moreover, the findings again suggest that softs commodities are disconnected from rest of the sample commodities, which stresses the diversification and hedging properties of the underlying commodities or commodity group. Finally, Fig. 21 exhibits the time-varying total connectedness network of commodities using the Diebold and Yilmaz (2012) approach. The results confirm the time-varying nature of connectedness among commodities. The dynamic connectedness network significantly impacts economic and financial conditions on the return connectedness network. The large spikes in the connectedness network correspond to important events such as GFC

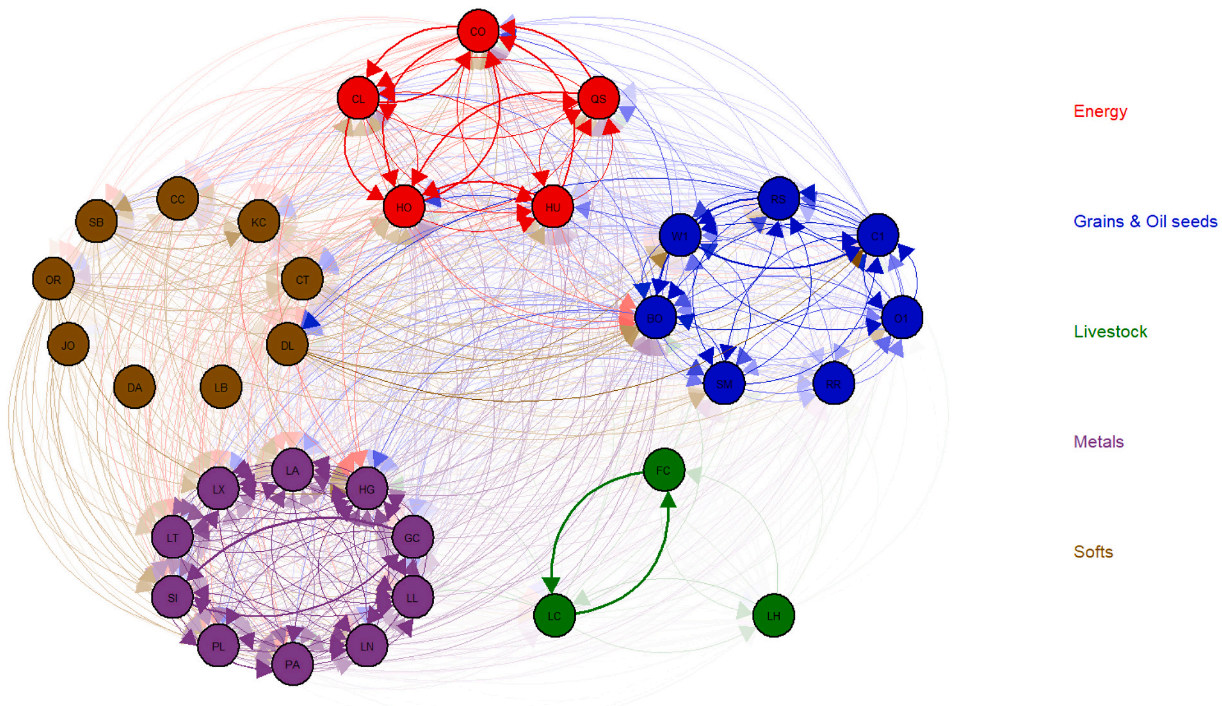

Fig. 19. Return connectedness network among commodities using Diebold and Yilmaz (2012).
Note: Refer to note in Fig. 1.

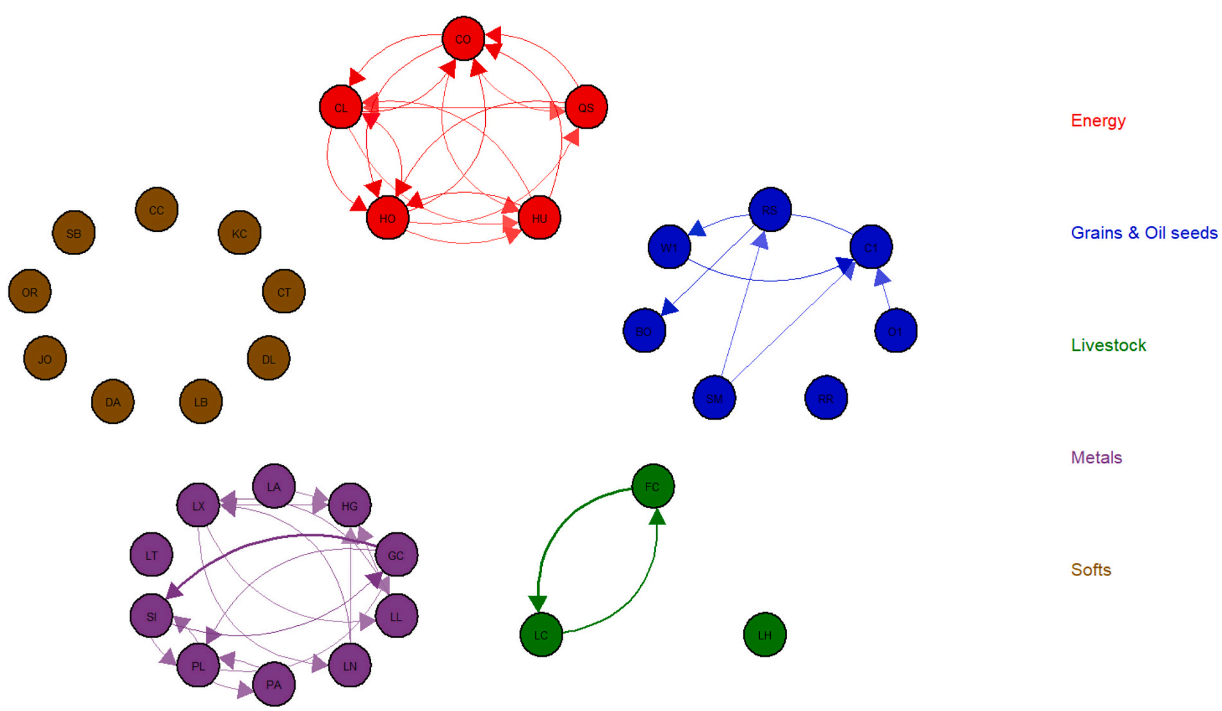

Fig. 20. Return connectedness network among commodities using Diebold and Yilmaz (2012) after thresholding.
Note: Refer to note in Fig. 2.

2007–08, European debt crisis 2012–13, oil price crash in 2016, Brexit, and COVID-19 outbreak. The results imply that diversification opportunities decrease in the commodity sector during crisis periods. Therefore, portfolio managers and investors in the commodity market should seek safe-haven options across different asset classes to hedge their risks.

Alternatively, we use different lags and rolling windows for the robustness check of our main findings. The estimated results are displayed in Fig. 22. The results confirm our main findings and display the time-varying nature of connectedness among commodities, which soar during periods of economic slowdown. Moreover, the estimations confirm the robustness of our results across different lags and rolling windows and repel any doubts about the validity of our findings.

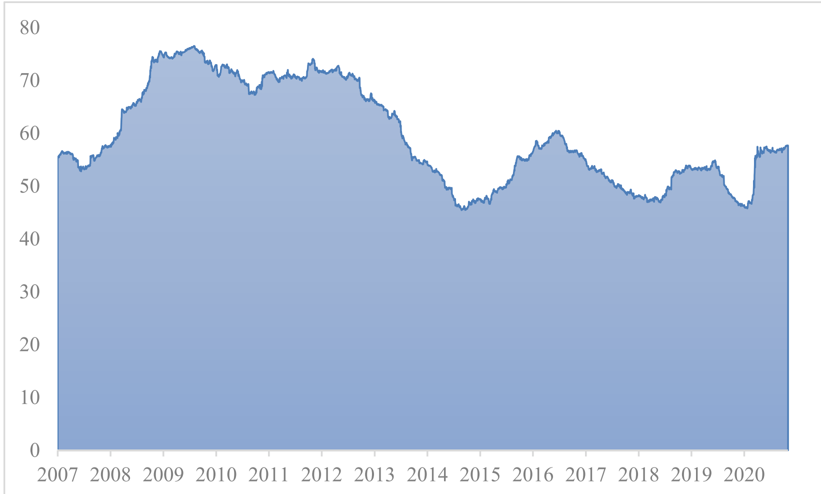

Fig. 21. Total time-varying return connectedness among commodities using Diebold and Yilmaz (2012).
Note. This figure shows the rolling-window version of total connectedness using Diebold and Yilmaz (2012). The rolling-window size is 260 days.

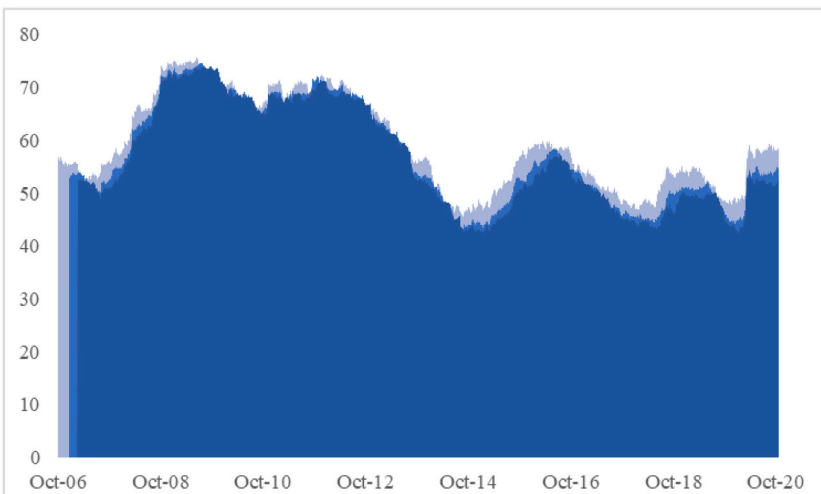

Fig. 22. Total time-varying return connectedness among commodities at the median quantile.
Note. Notes: This figure shows the results for each other combination of window-length $w \in \{200; 260; 300\}$ and forecast-horizon $h \in \{5; 10; 15\}$.

5. Conclusion and policy implications

Implying that mean-based measures of connectedness may not necessarily replicate the estimates of extreme right and left tails, especially in the presence of extreme positive and negative (e,g. COVID-19 pandemic) shocks in the market. Therefore, we utilize a novel quantile-based measure of return spillover, which permits us to differentiate and compare the network of connectedness at the median, upper and lower quantile. Resultantly, we contribute to the academic literature by comprehensively documenting the return spillovers among metals, energy, and agricultural commodities before and during the COVID-19 outbreak. Using daily data of 34 commodities, the study's main findings uncover some dissimilar levels and patterns of connectedness before and during pandemic episodes at middle, lower and upper quantiles.

Interestingly, our full sample analysis findings show that return shocks propagate only among commodities within the same commodity group. The results show that the transmission of return spillovers is stronger in the left and right tails of the conditional return distribution. The findings highlight that using median or mean-based connectedness measures can mask the dissimilar patterns of connectedness persisting in the tails. Hence, in the light of our findings, we reinforce that quantile-based estimates of connectedness are a natural extension of prevailing average-based methods of connectedness. Further, the lower quantile dependence generally co-moves with upper quantile dependence, which suggests that extreme negative shocks are associated with an increase in strengthening lower-tail connectedness coupled with a simultaneous increase in weakening upper-tail connectedness. Furthermore, the findings also unveil that the degree of tail-dependence among commodities is time-varying.

Our sub-sample analysis results clearly show the significant impact of the COVID-19 pandemic on the tail dependency structure of the network of return spillovers among commodities. We note the structure of return connectedness among commodities demonstrates a significant shift over time due to COVID-19 shocks, as there is evidence depicting the strong transmission of returns shocks across different commodity groups during the COVID-19 fiasco. Once again, we observe excess return spillovers in the extreme tails compared to the median quantile in the COVID-19 period. Also, results indicate that the softs and livestock commodity groups are isolated from the other commodity groups, highlighting the potential hedging and safe-haven properties of the underlying commodity categories, especially in the outbreak period.

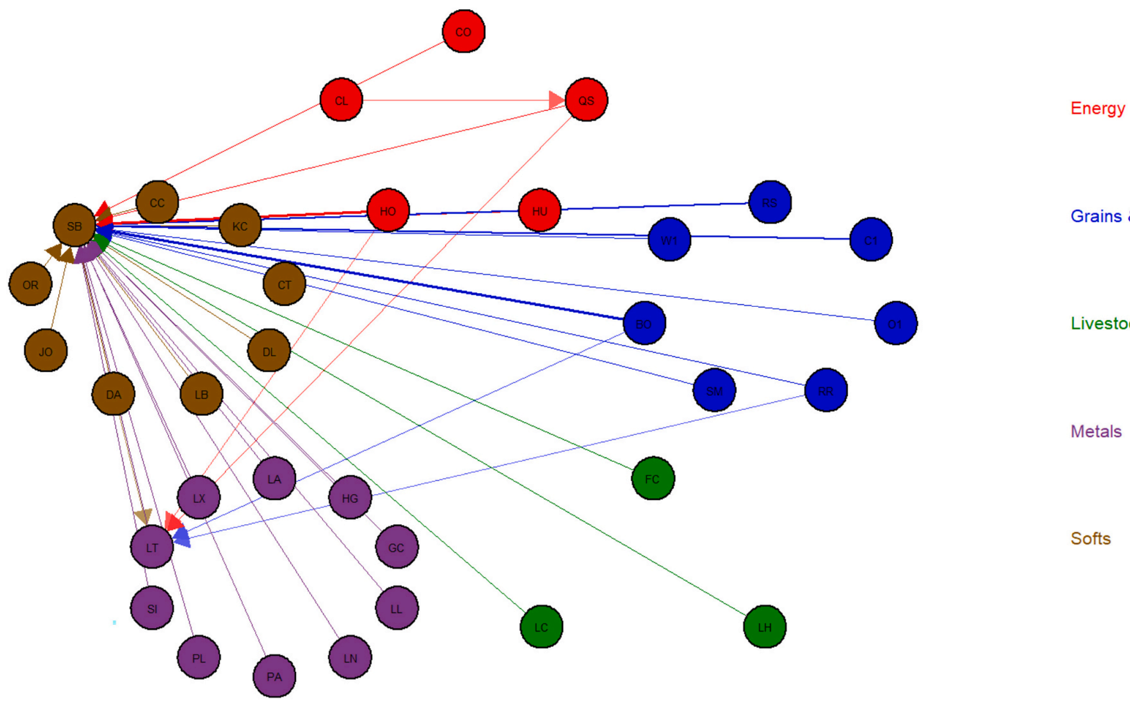

Fig. 18. Return connectedness network among commodities at the extreme right tail after thresholding – COVID sub-sample.
Note: Refer to note in Fig. 2.

Accordingly, investors seeking diversification opportunities can invest in softs and livestock commodities to minimize their losses in natural calamities such COVID-19 pandemic.

The findings of the study hold multifaceted implications for investors and policymakers. For instance, policymakers can utilize the analysis insights to formulate policy tools and monitoring mechanisms, effectively mitigating the unfavorable effects arising from extreme return spillovers among different commodity markets. In particular, the findings of extreme connectedness measures in the upper tail, middle, and lower tail stress that regulators should pay close attention to devising suitable policies to reduce the adverse effects of extreme negative shocks such as COVID-19 outbreak on commodity markets as only focusing on average shocks in the system of connectedness could lead to sub-optimal stabilizing policies. Accordingly, the policymakers in the commodity sector should introduce a well-articulated emergency response framework to shield market participants from negative shocks of such crisis events. Moreover, a future-looking extreme risk spillover warning mechanism to protect from financial and systematic risks is necessary for the stability of the commodity sector.

Similarly, the findings are also useful for traders and investors who can utilize the findings to improve their risk management practices and refine trading decisions. For instance, the findings demonstrate high connectedness among commodities within same category during normal market conditions, so investors and portfolio managers should not include all the assets from a single commodity class in their portfolios. Instead, portfolios comprised of commodities from different groups will offer better diversification and hedging performance. In fact, the cross-market hedging opportunities under normal circumstances can also be utilized to offset risks in a particular commodity or commodity group. In addition, the results suggest that connectedness among different commodity groups soared during the COVID-19 period. Therefore, investors should look to other assets classes for diversification and flight to safety during crisis periods. In this backdrop, portfolio managers and investors in commodity markets should formulate dynamic and alternative portfolios and regularly rebalance their portfolios according to the market circumstances. In this way, portfolio managers and investors in the commodity market can be better positioned in the future to survive the environment of high risk, such as the COVID-19 pandemic.

CRediT authorship contribution statement

Saqib Farid: Conceptualization, Writing – original draft, Writing – review & editing. **Muhammad Abubakr Naeem:** Conceptualization, Writing – review & editing, Data curation, Data curation, Methodology, Software, Formal analysis, Visualization. **Andrea Paltrinieri:** Writing – original draft, Writing – review & editing, Supervision. **Rabindra Nepal:** Writing – review & editing, Supervision, Funding acquisition, Project administration.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2022.105962.

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