Modelling systemic risk of energy and non-energy commodity markets during the COVID-19 pandemic

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Abstract
COVID-19 led restrictions make it imperative to study how pandemic affects the systemic risk profile of global commodities network. Therefore, we investigate the systemic risk profile of global commodities network as represented by energy and nonenergy commodity markets (precious metals, industrial metals, and agriculture) in pre- and post-crisis period. We use neural network quantile regression approach of Keilbar and Wang (Empir Econ 62:1–26, 2021) using daily data for the period 01 January 2018–27 October 2021. The findings suggest that at the onset of COVID-19, the two firm-specific risk measures namely value at risk and conditional value of risk explode pointing to increasing systemic risk in COVID-19 period. The risk spillover network analysis reveals moderate to high lower tail connectedness of commodities within each sector and low tail connectedness of energy commodities with the other sectors for both pre- and post-COVID-19 periods. The Systemic Network Risk Index reveals an abrupt increase in systemic risk at the start of pandemic, followed by gradual stabilization. We rank commodities in terms of systemic fragility index and observe that in post COVID-19 period, gold, silver, copper, and zinc are the most fragile commodities while wheat and sugar are the least fragile commodities. We use Systemic Hazard Index to rank

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commodities with respect to their risk contribution to global commodities network. During post COVID-19 period, the energy commodities (except natural gas) contribute most to the systemic risk. Our study has important implications for policymakers and the investment industry.

**Keywords**  Energy · Commodities · COVID-19 · Neural network quantile regression · CoVaR

**JEL Classification**  C45 · Q02 · F02

1 Introduction

In pre COVID-19 world, governed by the notion of ‘comparative advantage’, the agents could freely exchange goods and services by using advanced modes of communication. For example, the energy-rich countries were not necessarily required to grow their own grains as they could always procure them by mutual trade with agriculture-based economies. The pandemic-enforced restrictions on movement severely hampered free trade leading to huge demand–supply gaps of essential commodities and posed threats of breakdown to the world’s economic system (Karim et al., 2022a, 2022b). The embargo on physical mobility of goods can result in shortage of different commodities, rising inflation and ensuing global economic meltdown. Hence, it is imperative for policymakers and other stakeholders to investigate how COVID-19 affects the systemic risk of global commodities network. In line with the existing literature (Diebold et al., 2017), the systemic risk of global commodities network is represented by four major commodity markets namely energy, precious metals, industrial metals, and agriculture owing to their size and their centrality (productive uses) within the global economic system. This study contributes to the existing literature by exploring how COVID-19 affects the systemic risk of world commodities network by analyzing risk spillover effects across four commodity groups, performing systemic risk analysis at system level, and identifying systemically relevant commodities (Naeem et al., 2022a, 2022b).

The importance of commodities can be understood from the fact that they serve as a key input to production activity across the globe and a major output of many emerging economies (Chevallier & Ielpo, 2013). The fluctuations in demand/supply patterns of commodities strongly affect common business cycles. Consequently, the measurement of connectedness (central to risk measurement and management) of commodities in real-time is of special relevance for designing policy requiring real-time monitoring. The energy-related commodities are visibly at center stage owing to their importance in several stages of the economic cycle, with troughs and spikes directly linked with current as well as expected degrees of general economic activity (Khalfaoui et al., 2021). They affect other commodity markets through multiple channels. The surging energy prices increase transportation costs, fertilizer prices and higher electricity costs that in turn directly and indirectly influence the global commodity markets including precious metals, industrial metals, and agriculture. It is, therefore, important to examine the dynamic connectedness between energy and nonenergy commodities. Understandably, COVID-19 pandemic unsettled the existing demand/supply patterns of global commodity markets. The restrictions on physical mobility resulted in halting of transportation activity, cuts in energy generation and slow economic activity thereby reshaping the systemic risk of global commodities network. Therefore, it is essential to assess the systemic
risk of global commodities network in pre- and post-crisis periods for better policy advisory and effective portfolio risk management.

The conventional quantitative risk measure like value-at-risk (VaR) and conditional value-at-risk (CoVaR) focus on risk influence of an individual commodity to the entire network. These approaches only analyze systemic risk in linear and bivariate contexts. We, therefore, take inspiration from neural networks to calibrate systemic risk of global commodity network. Given the unpredictable macroeconomic environment, complex dependency channels of global commodity markets, and nonlinear price movements of commodities, the neural network approach may be reckoned as a suitable choice to model systemic risk of global commodity market networks (Pai & Ilango, 2020). We use the neural network methodology of Keilbar and Wang (2021) to quantify systemic risk due to its suitability for fitting nonlinear functions and better prediction performance.

Our findings reveal that at the onset of COVID-19, both VaR and CoVaR explode suggesting increase in systemic risk. The risk spillover network analysis in pre- and post-crisis periods shows moderate to high lower tail connectedness of commodities within each sector. There is low tail connectedness of energy commodities with the other sectors. In the pre-crisis period, the spillover effects within commodity groups are mostly symmetric (except industrial metals). In the crisis period, there is higher (symmetric) connectedness among member commodities in each group and intragroup risk clusters get denser. Furthermore, there are visible intergroup spillover effects that are mostly unidirectional. This finding is intuitive as certain commodities are risk transmitters owing to their importance in global economies. On the other hand, various commodities only absorb shocks due to their dependence on stronger commodities. The systemic risk analysis is twofold. First, the Systemic Network Risk Index reveals an abrupt increase in systemic risk at the start of pandemic, followed by gradual stabilization. Second, we rank commodities in terms of Systemic Fragility Index as well as Systemic Hazard Index. During pre COVID-19 period, corn, livestock, palladium and silver are most fragile commodities. In post COVID-19 period, gold, silver, copper and zinc emerge as most fragile commodities. The least fragile commodities in post COVID-19 world are wheat and sugar. Moving ahead, in pre- and post-crisis periods, four energy commodities (brent crude oil, heating oil, WTI crude oil and unleaded gasoline) and wheat are among top five commodities that contribute most to the systemic risk. The remaining commodities include tin, sugar and cocoa.

We contribute to the literature in several ways: first, we use a very novel neural network approach to calibrate the systemic risk profile of 27 commodities belonging to four distinct commodity groups that refer to the global commodity market in pre- and post-crisis periods. To the best of our knowledge, this assessment is not performed in the current literature. Second, we sort the commodities to evaluate their respective sensitivity to system-wide shocks and their respective abilities to transmit systemic risk. This information is helpful in forming commodity portfolios and designing risk management strategies. Third, we add to the literature on the effects of pandemic on global markets. Our findings may help the stakeholders in forging better strategies for the recovery of global commodity markets.

The rest of the work is as follows: Sect. 2 provides the review of existing literature. Section 3 explains data and methodology. Section 4 reports results and interpretations. Section 5 concludes the study.
2 Review of related literature

The relationship of energy with other markets is dynamic and anecdotally multi-dimensional. Being the major factor of production in any economy, the impact of volatility in energy prices influences the decisions of various economic agents (Guhathakurta et al., 2020; Karim & Naeem, 2021, 2022). The dynamics of commodity markets are changed in the last two decades due to increase in demand by emerging markets, changes in the dynamics of supply–demand conditions, and the financialization of commodities (Al-Yahyaee et al., 2019). In this regard, the recent health crisis of COVID-19 has renewed the debate on the complexities of the economic system through dependency and interconnected markets (Kang & Lee, 2019) and systemic risk (Keilbar & Wang, 2021).

After the global financial crisis, there is an extensive amount of literature studying the impact of oil prices on stock returns with results of a negative relationship (Tien & Hung, 2022; Bai & Koong, 2018; Bashir et al., 2012; S.-S. Chen, 2010; Cong & Shen, 2013; Kilian & Park, 2009), positive relationship (Demirer et al., 2015; Jain & Biswal, 2016; Kayalar et al., 2017; Mezghani & Boujelbène, 2018; Ramos & Veiga, 2013) and no link among both asset classes (Bachmeier & Nadimi, 2018; Reboredo & Rivera-Castro, 2014).

To understand the systemic connectedness among various asset classes including energy, metals and agricultural commodities, as summarized in table 1, earlier literature has used GARCH family models (Dahl et al., 2020; Kang et al., 2017; Karali & Ramirez, 2014; Karim et al., 2022c, 2022d; Wu et al., 2011), VaR (Caporin et al., 2021; Guhathakurta et al., 2020; Ji et al., 2020; Zhang & Broadstock, 2020; Al-Yahyaee et al., 2019; Balli et al., 2019; Umar et al., 2022; Kang et al., 2019; Singh et al., 2019), multifractal approach (Madani & Ftiti, 2021), CoVaR and copula approaches (Ameur et al., 2020; Naeem & Karim, 2021; Reboredo, 2015), graph theory analysis (Lautier & Raynaud, 2012) and Bayesian analysis (Du et al., 2011).

Among the early studies, Wu et al. (2011) report strong linkages between crude oil and corn cash and that these linkages vary over time. By incorporating major macroeconomic variables, Karali and Ramirez (2014) assessed spillover effect and time-varying volatility in the energy market. The results exhibit the presence of asymmetric effect and bidirectional relationship of natural gas with both crude and heating oil. However, the crude oil volatility is intensified following major natural, financial or political events. Most of these studies used GARCH family models. Following the spillover index (Diebold & Yilmaz, 2012) and multivariate DECO-GARCH, Kang et al. (2017) documented a bidirectional pattern of strong return and volatility spillover during economic turmoil which implies lower level diversification. Further, Silver and Gold were the major risk emitters to commodity markets during global financial crises while WTI, rice, wheat, and corn were the risk receiver. Dahl et al. (2020) and Naeem et al. (2022c) also reported similar findings.

After the introduction of VaR based measure of volatility spillover (Diebold & Yilmaz, 2009, 2012), several researchers investigate the connectedness among different commodity markets to explore the risk-return characteristics of commodities and their candidacy in portfolio construction. For example, Al-Yahyaee et al. (2019) investigate the dynamic connectedness between oil, metal and stock markets of GCC countries with a strong presence of spillover effect during financial crises. Further, their results suggest mix portfolio of GCC equities and commodities for portfolio diversification. Balli et al. (2019) assessed spillover among uncertainties and found increase in interconnectedness in commodity uncertainties during financial crises and the 2014–2016 collapse of oil prices while spillover is high among specific commodity classes with evidence of precious metals as safe haven. Guhathakurta
| Article                  | Study period       | Methodology          | Asset class/type                                      | Database       | Main findings                                                                 |
|-------------------------|--------------------|----------------------|-------------------------------------------------------|----------------|--------------------------------------------------------------------------------|
| Umar et al. (2021)      | January 2020-July 2020 | SWC and WCPD       | Energy, metals, agricultural commodities, and livestock commodities | DataStream     | Commodity markets provide diversification opportunities during covid times     |
| Caporin et al. (2021)   | September 2009-December 2019 | VAR and GFEVD     | Energy, grains, and metals                             | Kibot.com      | Lower level of volatility connectedness for positive volatilities than negative volatilities |
| Zhu et al. (2021)       | 2006–2018          | Gaussian graphical and logit model | Global oil market                                     | DataStream     | Strong evidence of spillover of bilateral system risk in global oil market     |
|                         |                    |                      |                                                       |                | Trade competition is a major determinant of spillover in oil market             |
| Madani and Füti (2021)  | 2017–2019          | multifractal approach | Gold, oil, and currency market                        | Bloomberg      | Gold is a strong (weak) hedge for currency (oil) movements                     |
|                         |                    |                      |                                                       |                | Overall, gold offers safe haven opportunities during turmoil times             |
| Article                        | Study period                  | Methodology                              | Asset class/type                                      | Database                      | Main findings                                                                 |
|-------------------------------|-------------------------------|------------------------------------------|-------------------------------------------------------|-------------------------------|-------------------------------------------------------------------------------|
| Zhang and Broadstock (2020)   | January 1982-June 2017        | VAR and Granger causality approach       | Oil, beverage, food, raw materials, fertilizers and metal | World Bank commodity price indices | Strong dependence among oil and other commodity markets after GFC             |
| Ji et al. (2020)              | September 2008-December 2016  | VAR and FEVD                             | Energy, metals, and agricultural commodities           | DCOT                          | Agricultural and energy markets are involved in cross-hedging Swap dealers and index trader operate in two markets either in metal and agriculture or energy and agriculture Geopolitical risk can affect the stability of energy market |
| Guhathakurta et al. (2020)    | March 1996-June 2018          | VAR and global dynamic programming       | Oil, metal, and agricultural commodities              | DataStream                    | Significant connectedness between Oil, Metal and agricultural commodities Oil is the major contributor in the volatilities of other markets |
| Article                  | Study period               | Methodology                        | Asset class/type                          | Database         | Main findings                                                                                                                                                                                                 |
|-------------------------|----------------------------|------------------------------------|-------------------------------------------|------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Ameur et al. (2020)     | November 2014-October 2017 | CoVaR and copula approaches        | Oil and natural gas futures               | Bloomberg        | There is tail risk dependence between oil and natural gas with higher spillover from former to later Extreme negative shocks produce intensive spillover effect                                                                 |
| Dahl et al. (2020)      | July 1986-June 2016        | EGARCH and VAR                     | Oil and agriculture commodities          | CRB              | Bidirectional volatility spillover between crude oil and agricultural commodities during economic turmoil time                                                                                                                                                           |
| Balli et al. (2019)     | January 2007- December 2016| VAR and stochastic volatility (SV) model | Energy, metals and agricultural commodities | DataStream       | Connectedness increases among commodities after GFC Metal commodities can serve as safe haven during economic turmoil                                                                                                                                                 |
| Singh et al. (2019)     | January 2000-June 2016     | GEVD and VAR                       | Oil, commodity (metals and agri), forex, equity, and bond markets | DataStream and, Bloomberg | Inclusion oil reduces (increases) connectedness before (after) crises                                                                                                                                       |
| Article               | Study period       | Methodology                        | Asset class/type               | Database                              | Main findings                                                                 |
|----------------------|--------------------|------------------------------------|-------------------------------|---------------------------------------|-------------------------------------------------------------------------------|
| Kang et al. (2019)   | January 1990-March 2017 | VAR and GFEVD                      | Oil and agriculture commodities | Food and Agricultural Organization (FAO) data, and IMF | Increase in volatility spillover between agricultural commodities and Oil market and that it is bidirectional at all frequency bands |
| Al-Yahyaee et al. (2019) | September 2005-October 2016 | VAR, multivariate DECO-FIAPARCH model | Energy, metals, and stock indices | Bloomberg                              | Strong connectedness between energy, metals and GCC stock indices               |
| Kang et al. (2017)   | January 2002-July 2016 | VAR, DECO-GARCH model              | Oil, metal, and agricultural commodity | EIA and CBOT                          | Strong connectedness among all commodities during financial crises Silver and Gold are the major risk emitters |
| Reboredo (2015)      | December 2005-December 2013 | Copula approach                    | Oil and clean energy indices   | Bloomberg, EIA and Société Générale   | Systemic tail-dependence between renewable energy and oil market               |
| Karali and Ramirez (2014) | January 1994- February 2011 | GARCH-BEKK                        | Energy market and macroeconomic variables | DataStream                           | Spillover of volatility between crude oil and gas, and heating oil and gas    |
| Article                | Study period      | Methodology         | Asset class/type                           | Database | Main findings                                                                 |
|-----------------------|-------------------|---------------------|--------------------------------------------|----------|-------------------------------------------------------------------------------|
| Lautier and Raynaud   | 2000–2009         | Graph theory analysis | Energy, financial assets and agriculture commodities | DataStream | Oil is a major candidate of price shock transmission and has strong link with agricultural and financial assets |
| Du et al. (2011)      | November 1998-January 2009 | Bayesian analysis | Oil and agriculture commodities | CBOT | Strong volatility spillover between crude oil and agricultural commodities after 2006 |
| Wu et al. (2011)      | January 1992-June 2009 | GARCH models       | Crude oil and corn                        | CBOT | Time-varying volatility spillover effect between corn and crude oil            |
et al. (2020) confirm the findings of Balli et al. (2019) and reported strong connectedness of oil and commodity markets with precious metals as safe haven assets during crisis time.

Using an intraday multifractal approach, Madani and Ftiti (2021) assessed the dependency between gold, oil and currency during extreme and calm market conditions. They revealed gold as weak (strong) candidate of hedge against oil (currency). Nonetheless, gold exhibit safe haven properties under both market conditions, especially for currency market.

Similarly, Ameur et al. (2020) used different measures of systemic risk including copula approach to explore the dependency between energy markets. Overall, they reported a strong spillover between gas and oil market, however, the risk dependency is more pronounced from oil to gas than oil to gas and the spillover effect is stronger for negative shocks as compared to positive shocks. Oil market also has a strong connectedness with clean/green markets (Reboredo, 2015; Mensi et al., 2022). Du et al. (2011) employed Bayesian-based Monti Carlo simulation and found interdependence among crude oil, wheat and corn markets after 2006 (i.e., start of global financial crises).

The above review suggests that contemporary literature has yet to address the systemic risk of global commodity markets. In addition, we are not aware of how the commodities behave during crisis periods. Moreover, the literature on commodities does not enlighten us regarding the commodities least/most affected by economic downturns and the commodities that are too big to fail. The present study fulfills these gaps by applying neural network quantile regression approach.

3 Empirical framework

3.1 Data and methodology

We perform systemic risk analysis of energy market and three other important commodity markets including precious metal, industrial metals, and agriculture (see Table 2) for pre- and post-COVID-19 periods. The objective is to investigate how pandemic influenced systemic risk of global commodities network. The sampled economic sectors (comprising 27 commodities) constitute systemic risk relevance to international commodity markets owing to their extensive industrial and household usage. We use daily log differenced price returns of the sampled commodities for the period from 1 January, 2018 and 27 October, 2021. Our sample period includes 2 ¼ years of pre-COVID and 1 ½ years of post-COVID periods and appears suitable for the analysis. In addition to commodity price returns, we also incorporate the following set of global factors in our analysis:

i. Chicago Board Options Exchange (CBOE) Stock Market Volatility Index (VIX)
ii. CBOE Crude Oil Volatility Index (OVX)
iii. CBOE Gold Volatility Index (GVZ)
iv. CBOE Eurocurrency Volatility Index (EVZ)
v. Merrill Lynch Option Volatility Estimate (MOVE)
vi. United States Economic Policy Uncertainty (US EPU)
vii. United Kingdom Economic Policy Uncertainty (UK EPU)
viii. Infectious Diseases Equity Market Volatility Tracker (EMV)

These global factors are quantifiable measures of market risk and investors’ sentiments and used in our analysis to estimate VaR. The data is sourced from Yahoo Finance. To perform the estimations, we use a rolling window of 260 days (equivalent to 1 year).
Table 2 Descriptive statistics

| Groups   | S# | Commodity market | Symbol | Mean | Maximum | Minimum | Std.Dev | Skewness | Kurtosis | JB     | ARCH | Q(20) |
|----------|----|------------------|--------|------|---------|---------|---------|----------|----------|--------|-------|-------|
| Energy   | 1  | S&P GSCI         | WTI    | 0.0003 | 0.438  | − 0.569 | 0.039  | − 2.305 | 69.013   | 199,571.11 | 256.869 | 145.774 |
|          | 2  | S&P GSCI         | BRNT   | 0.0002 | 0.191  | − 0.268 | 0.026  | − 1.352 | 23.102   | 22,575.77 | 179.915 | 36.575 |
|          | 3  | S&P GSCI         | GOL    | 0.0002 | 0.115  | − 0.163 | 0.022  | − 0.695 | 8.166    | 2866.15  | 219.998 | 47.895 |
|          | 4  | S&P GSCI         | HOL    | 0.0002 | 0.11   | − 0.177 | 0.022  | − 0.892 | 10.792   | 4995.48  | 145.034 | 18.705 |
|          | 5  | S&P GSCI         | NGS    | 0.0007 | 0.166  | − 0.192 | 0.029  | 0.092   | 4.864    | 990.81   | 144.857 | 24.249 |
|          | 6  | S&P GSCI         | UGS    | 0.0003 | 0.193  | − 0.264 | 0.029  | − 1.855 | 24.544   | 25,711.97 | 314.457 | 93.631 |
| Precious | 7  | S&P GSCI         | GLD    | 0.0003 | 0.056  | − 0.051 | 0.009  | − 0.294 | 6.3      | 1672.75  | 125.753 | 48.274 |
|         | 8  | S&P GSCI         | SLV    | 0.0003 | 0.089  | − 0.123 | 0.019  | − 0.808 | 7.872    | 2697.55  | 140.425 | 39.92 |
|         | 9  | S&P GSCI         | PLT    | 0.0001 | 0.112  | − 0.122 | 0.019  | − 0.424 | 6.031    | 1550.07  | 187.446 | 72.353 |
| Groups | Commodity | S# | Symbol | Mean | Maximum | Minimum | Std.Dev. | Skewness | Kurtosis | JB | ARCH | Q(20) |
|--------|-----------|----|--------|------|---------|---------|----------|----------|----------|----|------|------|
| Industrial metals | Palladium | 10 | PLD | 0.0006 | 0.229 | −0.238 | 0.024 | −0.632 | 22.525 | 21,239.78 | 315.838 | 76,908 |
| | Aluminum | 11 | ALM | 0.0002 | 0.054 | −0.077 | 0.077 | 0.012 | −0.023 | 3.472 | 199,571.11 | 312.02 | 36.57 |
| | Copper | 12 | COP | 0.0003 | 0.046 | −0.081 | 0.081 | 0.012 | −0.341 | 2.633 | 22,575.77 | 286.66 | 0.57 |
| | Lead | 13 | LED | 0 | 0.057 | −0.075 | 0.075 | 0.014 | −0.187 | 1.445 | 219,998 | 47,895 | 0.76 |
| Agriculture | Nickel | 14 | NKL | 0.0004 | 0.085 | −0.077 | 0.077 | 0.017 | 0.05 | 1.598 | 4995.48 | 990.81 | 18.70 |
| | Tin | 15 | TIN | 0.0006 | 0.068 | −0.103 | 0.103 | 0.014 | 0.081 | 7.744 | 25,711.97 | 314,457 | 24.24 |
| | Zine | 16 | ZNC | 0 | 0.074 | −0.065 | 0.065 | 0.014 | 0.062 | 1.312 | 25,711.97 | 314,457 | 24.24 |
| | Cocoa Index | 17 | COC | 0.0003 | 0.056 | −0.053 | 0.053 | 0.017 | 0.012 | 0.211 | 167,725 | 125,753 | 48.27 |
| Groups | S# | Commodity                      | Symbol | Mean  | Maximum | Minimum | Std.Dev | Skewness | Kurtosis | JB       | ARCH     | Q(20)    |
|--------|----|--------------------------------|--------|-------|---------|---------|---------|----------|----------|----------|----------|----------|
|        | 18 | S&P GSCI                      | COF    | 0.0005| 0.096   | −0.09   | 0.02    | 0.217    | 1.789    | 2697.55  | 140.425  | 39.92    |
|        | 19 | S&P GSCI                      | CRN    | 0.0005| 0.069   | −0.07   | 0.015   | −0.115   | 3.253    | 1550.07  | 187.446  | 72.353   |
|        | 20 | S&P GSCI                      | CTN    | 0.0003| 0.052   | −0.055  | 0.014   | −0.152   | 1.317    | 21,239.78| 315.838  | 76.908   |
|        | 21 | S&P GSCI                      | FEDR   | 0.0001| 0.075   | −0.059  | 0.012   | 0.161    | 3.425    | 199,571.11| 256.869  | 145.774  |
|        | 22 | S&P GSCI                      | LCTL   | 0.0001| 0.055   | −0.058  | 0.012   | −0.17    | 3.527    | 22,575.77| 179.915  | 36.575   |
|        | 23 | S&P GSCI                      | SOBN   | 0.0003| 0.064   | −0.07   | 0.012   | −0.169   | 4.413    | 2866.15  | 219.998  | 47.895   |
|        | 24 | S&P GSCI                      | SUGR   | 0.0003| 0.059   | −0.058  | 0.017   | 0.045    | 0.848    | 4995.48  | 145.034  | 18.705   |
|        | 25 | S&P GSCI                      | WHT    | 0.0006| 0.062   | −0.052  | 0.016   | 0.357    | 0.464    | 990.81   | 144.857  | 24.249   |
|        | 26 | S&P GSCI                      | WHKN   | 0.0006| 0.069   | −0.06   | 0.018   | 0.172    | 0.495    | 25,711.97| 314.457  | 93.631   |
|        | 27 | S&P GSCI                      | SBOL   | 0.0006| 0.068   | −0.1    | 0.014   | −0.491   | 3.971    | 1672.75  | 125.753  | 48.274   |

*a*Indicates significance at 1% level
We explore the dynamics of our dataset in different ways. We first estimate descriptive statistics for the sample period (Table 2). It is noticed that the energy sector manifests highest volatility and WTI is the most volatile commodity. Except for PLD, the volatility pattern of other commodities follows a range of 1.2% to 2.0% implying a close to similar risk profile of non-energy sectors. The skewness (non-zero values), Kurtosis (highly positive values) and Jarque Bera (very high values) statistics suggest that the returns distributions of commodity indices are non-normal fat-tailed distributions. Furthermore, the results of ARCH test indicate the presence of ARCH effects in the sampled returns distributions. Finally, the results of Ljung-Box Q test point to the presence of autocorrelation in data. We also prepare the Quantile–Quantile plots of the sampled commodities (Fig. 1). In case of 22 commodities (i.e., except LED, NKL, COC, ZNC and WHKN), the data follows non-normal fat-tailed distribution.

In the next step, we assess the correlation pattern of sampled commodities by using Correlation heatmap (Fig. 2). It is found that, for the sample period, except NGS, all the other energy commodities are showing high positive correlation with each other. Similarly, there is moderately high positive correlation among precious metals. Also, there is moderate positive correlation among industrial metals. For agriculture-based commodities, CRN is highly correlated (positive) with SOBN, SUGR and SBOL. In addition, FEDR is positively correlated with SOBN apparently because Soybeans serves as fodder for livestock. Finally, SOBN is also positively correlated with WHT, WHKN and SBOL.

We also report the summary statistics for our global factors (Table 3). The data series generally manifest high kurtosis and large values of Jarque–Bera statistics, pointing to the non-normality of data. We also provide the correlation matrix (Table 4). We find high correlation among the pairs of volatility indices except MOVE demonstrating lower correlation with other indices.

### 3.2 Neural network quantile regression

Our research objective is to assess the impact of crises on the systemic risk of global commodities network. We are aware that these assets follow irregular and nonlinear price movements owing to macroeconomic factors, government regulations and fluctuating market conditions. As a result, their return series manifest high noise, nonlinearity, no randomness, nonstationary and high volatility (Pai & Ilango, 2020). We argue that in view of these characteristics, a commodity network resembles a neural network (mimicking human mind) and neural network quantile regression (NNQR) methodology of Keilbar and Wang (2021) may be effectively used to model systemic risk of sin stocks portfolios. In contemporary literature, neural networks are widely used to solve forecasting and predictions related problems.

The special case of non-parametric sieve estimator is single hidden neural network and often called as black box (Chen, 2007; Grenander, 1981). The complexity of estimator $h_\theta$ is required to raise proportionally fast with increase in sample size ‘$n$’. The structure of neural network sieve can be described as given below, for $t = 1, 2, ..., n$,

$$Y_t = h_\theta (X_t) + \varepsilon_t$$

$$= \sum_{m=1}^{M_n} \omega_m^o \psi \left( \sum_{k=1}^{K} \omega_k^h X_{k,t} + b_k^h \right) + b_0 + \varepsilon_t$$

(1)

where dependent variable is $Y_t$, $X_t$ represents a vector of main explanatory variables with ‘$K$’ dimensions, and the error term is $\varepsilon_t$. We assume nonlinear $\psi (\cdot)$ to be an already known
Fig. 1 Q-Q plots
and fixed activation function; for example, sigmoid functions which includes rectifier linear unit (RLU) identified as $\psi(z) = \max(z, 0)$ or $\psi(z) = \tanh(z)$. The output layer parameters ($\omega_o$ and $b_o$) and hidden layer parameters ($\omega_h$ and $b_h$) are the two main parameters. As noted above, the space of sieve parameter increases with increase of sample size $n$. More specifically, the hidden nodes reach to infinity $M_n \to \infty$ when $n$ approaches to infinity, $n \to \infty$.

It is very straightforward to apply neural networks within the setting of quantile regression. Following Koenker and Bassett Jr (1978, 1982), we consider linear quantile regression equation with fixed quantile level $\tau$ as given below:

$$Y_t = X_t \beta + \varepsilon_t, \ t = 1, 2, \ldots, n$$ (2)

where $Q^\tau(\varepsilon_t | X_t) = 0$ and we assume the dependent variable $Y_t$ can be explained as a linear function of $X_t$. We then solve the following minimization problem to get quantile estimator:

$$\min_{\beta} \sum_{t=1}^{n} \rho_\tau(Y_t - X_t \beta)$$ (3)

Fig. 2 Correlation plots
|       | Mean  | Median | Max   | Min   | SD   | Skewness | Kurtosis | Jarque–Bera |
|-------|-------|--------|-------|-------|------|----------|----------|-------------|
| VIX   | 21.473| 18.710 | 82.690| 11.540| 9.704| 2.600    | 12.460   | 3578.812*** |
| OVX   | 45.731| 37.380 | 325.150| 24.000| 30.329| 4.093    | 23.605   | 15,096.050*** |
| GVZ   | 16.873| 15.960 | 48.980| 8.880 | 5.691| 1.436    | 6.890    | 717.835***   |
| EVZ   | 6.584 | 6.250  | 19.310| 4.130 | 1.689| 2.795    | 16.438   | 6504.447***  |
| MOVE  | 60.146| 58.000 | 163.700| 36.600| 15.511| 2.178    | 11.386   | 2742.132***  |
| USEPU | 177.755| 132.750| 807.660| 19.850| 127.797| 1.655    | 5.741    | 567.053***   |
| UKEPU | 301.593| 216.900| 1448.830| 34.430| 225.114| 1.659    | 5.661    | 555.493***   |
| EMV   | 10.903| 8.180  | 68.370| 0.000 | 12.045| 1.453    | 5.560    | 460.615***   |

***Indicates a 1% level of significance
Table 4 Correlation matrix for market risk and investors’ sentiment factors

|     | VIX  | OVX  | GVZ   | EVZ   | MOVE  | USEPU | UKEPU | EMV  |
|-----|------|------|-------|-------|-------|-------|-------|------|
| VIX | 1    |      |       |       |       |       |       |      |
| OVX | 0.784| 1    |       |       |       |       |       |      |
| GVZ | 0.860| 0.697| 1     |       |       |       |       |      |
| EVZ | 0.886| 0.725| 0.828| 1     |       |       |       |      |
| MOVE| 0.394| 0.374| 0.275| 0.356| 1     |       |       |      |
| USEPU| 0.726| 0.734| 0.740| 0.692| 0.056| 1     |       |      |
| UKEPU| 0.693| 0.691| 0.720| 0.650| 0.011| 0.919| 1     |      |
| EMV | 0.815| 0.652| 0.807| 0.712| 0.216| 0.717| 0.702| 1    |

where $\rho_{\tau} = |z| \cdot |\tau - I(z < 0)|$ indicates a function of the quantile loss. We employ the linear programming approach to approximate the conditional quantile through neural network sieve estimator.

$$\min_{\theta} \sum_{t=1}^{n} \rho_{\tau}\{Y_t - h_\theta(X_t)\}$$  \hspace{1cm} (4)

There may be certain overfitting issues associated with neural networks owing to their high-capacity nature which can be mitigated by right choice of their structure and hyperparameters. Generally, hyperparameters are selected on the basis of cross-validation criterion. In another approach, hyperparameters can be selected by charging extra forfeit terms $L_1$ and $L_2$ on the weight parameters $\omega_{h,k,m}$ and $\omega_{o,m}$ which lead us to the following optimization problem: -

$$\min_{h_\theta} \sum_{t=1}^{n} \rho_{\tau}\{Y_t - h_\theta(X_t)\} + \lambda_1 \| (\omega_{h,k,m}, \omega_{o,m})^T \|_1 + \lambda_2 \| (\omega_{h,k,m}, \omega_{o,m})^T \|_2$$  \hspace{1cm} (5)

where $\| \cdot \|_1$ and $\| \cdot \|_2$ indicates $L_1$ — norm and $L_2$ — norm while $\lambda_1$ and $\lambda_2$ are regularization parameters.

3.3 Measuring systemic risk

Following Keilbar and Wang (2021), we compute the systemic risk by applying the following four steps. Firstly, for the estimation Value-at-Risk (VaR), we run linear quantile regression by taking into account a number of risk factors as independent variables such as energy, precious metals etc. In the second step, we use the results obtained in the first step to measure conditional VaR (CoVaR) through quantile regression neural network for all the series under investigation. Thirdly, we model systemic risk spillover effect by measuring marginal effects which provide us time-varying systemic risk network. Finally, three different measures of systemic risk network analysis are employed.

3.3.1 Measurement of VaR

VaR quantifies maximum financial losses over a specific time period with certain degree of confidence. More specifically, the estimation of VaR provides the basis to take into account
the systemic risk for energy, precious metal, industrial metal and agricultural commodity markets. The $\tau$ th quantile of return distribution may be given as below:

$$P(X_{it} \leq \text{VaR}_{it}^{\tau}) = \tau$$

(1)

where $X_{it}$ represents the return of a particular series $i$ at time $t$ and $\tau \in (0, 1)$ provides the degree of quantile. We then compare three unique specifications. By following Engle and Manganelli (2004), we first apply the approach of dynamic quantile called as Conditional autoregressive value at risk (CA ViaR). We model VaR as latent process and use the symmetric absolute value (SA V) as follows:

$$\text{VaR}^\text{SA}_{it} = \beta_{i,1} + \beta_{i,2}\text{VaR}^\text{SA}_{i,t-1} + \beta_{i,3}\left|X_{i,t-1}\right|$$

(2)

By using lagged values of Var along with the absolute value of lagged return, we determine the existing level of VaR. The second specification involves asymmetric slope CA ViaR as given below:

$$\text{VaR}^\text{AS}_{it} = \beta_{i,1} + \beta_{i,2}\text{VaR}^\text{AS}_{i,t-1} + \beta_{i,3}\left(X_{i,t-1}\right)^+ + \beta_{i,4}\left(X_{i,t-1}\right)^-$$

(3)

The above specification offers different responses depending on the direction of returns. In the final specification, we follow Härdle et al. (2016) and incorporate macro-state variables $M_{t-1}$ to compute the VaR for each series $i$ by linear quantile regression.

$$X_{i,t} = \alpha_i + \gamma_i M_{t-1} + \epsilon_{i,t}$$

(4)

where the conditional quantile error term $Q^\tau(\epsilon_{it}|M_{t-1}) = 0$ which eventually gives the fitted value of quantile regression as below:

$$\text{VaR}^\text{LQR}_{it} = \tilde{\alpha}_i + \tilde{\gamma}_i M_{t-1}$$

(5)

VaR is widely used to measures the level of tail risk for a single market series and does not consider in the systematic context. However, to calibrate conditional risk, the primary step is to estimate VaR for individual market series.

### 3.3.2 CoVaR and Neural quantile regression

To understand systematically important market series within each market, we also incorporate CoVaR risk measure which diverge from VaR and takes into account financially distress situations for each market. Following Härdle et al. (2016) and Keilbar and Wang (2021), we consider all the market series at their VaR value to be financially distressed.

$$P\left( X_{j,t} \leq \text{CoVaR}_{j,t}^{\tau} | X_{-j,t} = \text{VaR}^-_{j,t-1} \right) = \tau$$

(6)

where $X_{-jt}$ represents a vector of returns for sampled commodity series except $j$ at time $t$ and $\text{VaR}^-_{j,t}$ represent the vector of VaRs. It is plausible that conditional quantile function of any commodity series can vary and nonlinearly react with respect to the critical level of other commodities. Hence, for measuring risk spillovers, linear quantile regression may not be a suitable approach. To account for nonlinearity and interdependence in the data, we employ neural network quantile regression to regress the conditional quantile of returns of commodity $j$ on the returns of the overall market.

$$X_{jt} = h_\theta(X_{-jt}) + \epsilon_{jt}$$
\[ Q^\tau(\varepsilon_{j,t} | X_{-j,t}) = 0 \] represents the conditional quantile error term. We now assess the fitted neural network at the distress condition to measure CoVaR of commodity \( j \)

\[ \text{CoVaR}_j^\tau = \hat{h}_0(\text{VaR}_{-j,t}^\tau) \]

where \( \hat{h}_0 \) denotes neural network. We interpret the CoVaR as the \( \tau \)th quantile of the loss distribution for hypothetically distress condition i.e., all the other commodity series are at their VaR.

### 3.3.3 Calculating risk spillover

Using the weights obtained by neural network quantile regression approach, we estimate the risk spillover effects among all directed pairs of commodities. For this purpose, we take the partial derivative of the conditional quantile of the returns of commodity \( j \) against its relevant commodity \( i \).

\[ \frac{\partial Q^\tau(X_{jt} | X_{-j,t})}{\partial X_{it}} = \frac{\partial}{\partial X_{it}} \sum_{m=1}^{M_n} w_m^o \varphi' \left( \sum_{k \neq j}^{k} w_{k,m}^h X_{k,t} + b_m^h \right) + b_o \] (9)

We measure sigmoid tangent activation function as

\[ \psi'(z) = \frac{2}{(\exp^{-z/2} + \exp^{z/2})^2} \] (11)

ReLu activation function is defined as

\[ \frac{\partial Q^\tau(X_{jt} | X_{-j,t})}{\partial X_{i,t}} = \sum_{m=1}^{M_n} w_m^o w_i^h \mathbf{1} \left( \sum_{k \neq j}^{k} w_{k,m}^h X_{k,t} + b_m^h > 0 \right) \] (12)

where \( \mathbf{1} (\cdot) \) represents the indicator function. As our prime interest is in assessing the lower tail dependence, we evaluate the marginal effects at distress conditions by using following relationship:

\[ \frac{\partial Q^\tau(X_{jt} | X_{-j,t})}{\partial X_{i,t}} \bigg|_{X_{-j,t}} = \text{VaR}_{-j,t}^\tau = \sum_{m=1}^{M_n} w_m^o w_i^h \varphi' \left( \sum_{k \neq j}^{k} w_{k,m}^h \text{VaR}_{k,t}^\tau + b_m^h \right) \] (13)

These marginal effects ultimately provide the spillover adjacency matrix for each directed pair of commodity series at time \( t \):

\[ A_t = \begin{pmatrix} 0 & a_{12,t} & \cdots & a_{1K,t} \\ a_{21,t} & 0 & \cdots & a_{2K,t} \\ \vdots & \vdots & \ddots & \vdots \\ a_{K1,t} & a_{K2,t} & \cdots & 0 \end{pmatrix} \] (14)
With absolute values of marginal effects as define below:

\[
 a_{ji,t} = \begin{cases} 
 |\frac{\partial Q^\tau(X_{j,t}^\tau | X_{-j,t}^\tau)}{\partial X_{i,t}^*}| X_{-j,t}^\tau = VaR_{-j,t}^\tau, & \text{if } j \neq i \\
 0, & \text{if } j = i 
\end{cases} 
\]  

(15)

We contend that \( a_{ji,t} \neq a_{ij,t} \) as risk spillovers are usually asymmetric. The above adjacency matrix identifies the weighted directed graph, incorporating the systemic risk of commodity markets.

### 3.3.4 Network analysis of spillover

Following the study of Diebold and Yilmaz (2012, 2014), we can measure various networks to further explore the systemic relevance of commodity markets.

We first measure the total directional connectedness, i.e., the sum of absolute marginal effects of all other commodities on \( j \) and \( I \), from commodity \( i \) at time \( t \) to commodity \( j \) at time \( t \) defined as:

\[
 C_{j \leftarrow i,t} = \sum_{i=1}^{K} a_{ji,t}  
\]  

(16)

\[
 C_{j \leftarrow ,t} = \sum_{j=1}^{K} a_{ji,t}  
\]  

(17)

Finally, Diebold and Yılmaz (2014) propose total net connectedness at time \( t \) as the sum of all absolute marginal effects:

\[
 C_t = \frac{1}{K} \sum_{i=1}^{K} \sum_{j=1}^{K} a_{ji,t}  
\]  

(18)

We use Systemic Network Risk Index (SNRI) to compute the tail connectedness of lower quantile for the whole system (Keilbar & Wang, 2021).

\[
 SNRI_t = \sum_{i=1}^{K} \sum_{j=1}^{K} (1+|VaR_{i,t}^\tau|) (1+|CoVaR_{j,t}^\tau|) a_{ji,t}  
\]  

(21)

The adjacency matrix is

\[
 \tilde{A}_t = \begin{pmatrix} 
 0 & \tilde{a}_{12,t} & \cdots & \tilde{a}_{1K,t} \\
 \tilde{a}_{21,t} & 0 & \cdots & \tilde{a}_{2K,t} \\
 \vdots & \vdots & \ddots & \vdots \\
 \tilde{a}_{K1,t} & \tilde{a}_{K2,t} & \cdots & 0 
\end{pmatrix}  
\]  

(22)

With elements given as:

\[
 a_{ji,t} = \begin{cases} 
 a_{ji,t} (1+|VaR_{i,t}^\tau|) (1+|CoVaR_{j,t}^\tau|), & \text{if } j \neq i \\
 0, & \text{if } j = i 
\end{cases} 
\]  

(23)

The adjusted adjacency matrix is the refined version of risk spillover and defines the level of incoming CoVaRs and outgoing VaRs.

However, the total connectedness determines the level of connectedness of the whole system regardless of the nature of individual nodes of the network. Keilbar and Wang (2021)
propose the improved version of VaR and CoVaR proxies of systemic risks and develop Systemic Fragility Index (SFI) and Systemic Hazard Index (SHI) to rank the relevancy of each commodity market in the system.

\[
SFI_{jt} = \sum_{i=1}^{K} (1 + |VaR_{i,j,t}^\tau|) \cdot a_{ji,t}
\]  

(19)

\[
SHI_{jt} = \sum_{j=1}^{K} (1 + |CoVaR_{j,i,t}^\tau|) \cdot a_{ji,t}
\]  

(20)

SFI represent the risk exposure of commodity j. It increases when VaR of commodity i increases and the adjacency weights pertaining to j are large. This naturally indicates that SFI increases during crises periods and distinguishes the commodities having high exposure to the tail risk.

On the other hand, SHI estimate the risk of commodity i contributes to the entire system. It is dependent on outgoing adjacency weights from i weighted by CoVaRs of the other commodities. Both SFI and SHI are commodity-specific. It is worth mentioning that this model takes into account asymmetries, which implies that the commodity with manifesting high tail risk may not essentially have a large impact on the system.

4 Results

4.1 VaR and CoVaR

To comprehend the impact of COVID-19 crisis on systemic risk of energy and other commodities, we perform the analysis in four steps. In the first step, for every firm, linear quantile regression is employed to estimate VaR. In the second step, CoVaR is estimated using network quantile regression. In recent literature, Abuzayed et al. (2021) used this approach to assess systemic risk of global stock markets. We use a sliding window estimation framework to address potential non-stationarity. The window size is 250 days, i.e., one year of daily returns). Following Keilbar and Wang (2021) and Härdle et al. (2016), the quantile level of \( \tau = 5\% \) is selected. As there is inverse relationship between density and variance of the error term, we may get the lesser reliable estimates if we select lower value for the quantile level. We show the results of these estimations in the shape of figures for each commodity for the sample period (Fig. 3).

We observe that both VaR and CoVaR pursue similar trends. In normal times, these measures show the movements within a given range. After the emergence of pandemic (March, 2020), both the risk measures explode pointing to increasing systemic risk in COVID-19 period. However, there are certain notable asymmetries in case of sampled commodities. First, the energy sector (except NGS) shows stability in terms of systemic risk before pandemic. Subsequent to COVID-19, several spikes are observed pointing to persistent instability. There is a noticeable gap between both the estimates (blue and red lines) and notice that CoVaR portrays comparatively higher systemic risk in case of most of the commodities in post-crisis period. The similar trend is detected in case of all the other commodity sectors, as the systemic risk substantially increased at the onset of pandemic. The energy and precious metals remained volatile during pandemic and the industrial metals, as well as agriculture sectors, reverted to pre-crisis position.
Fig. 3 Plot of Returns (black dots), VaR (blue line) and CoVaR estimated by neural network quantile regression (red line) for sampled commodities, $\tau = 5\%$
Fig. 3 continued
4.2 Risk spillover network

We perform the calculation of directional spillover effects for all the pairs of commodities for our prediction horizon. For this purpose, we use fitted VaRs and CoVaRs and employ the estimated values the neural network quantile regression. We obtain a weight-adjusted time-varying adjacency matrix. Our risk spillover network explains the time dynamics and cross-section of systemic risk. Figure 4 parts a and b show the evolution of the network in pre- and post-crisis periods respectively.

In pre COVID-19 period, moderate to high connectedness of commodities is evident within each sector. In addition, we notice low connectedness of energy commodities with the other sectors. A similar lower tail connectedness pattern is observed in the crisis period.
Moving forward, we visualize to the largest edges of the commodities markets by keeping the connections larger than the average of the top 100 risk spillovers of commodities market. The motivation is to improve the visibility of the figures and facilitate the analysis. For pre-crisis period, a close look at network diagram (Fig. 5 Part a) reveals that spillover effects within commodity groups are mostly symmetric (except industrial metals). This finding is in line with Caporin et al. (2021) who found a similar pattern for 12 commodities from energy, metals and grains categories. If commodity $i$ exhibits a large impact on commodity $j$, the converse is also likely. In case of energy sector, all the commodities are interconnected except NGS, which seems detached from the other commodities. For precious metals, we notice that PLD is not connected to any other commodity. Industrial metals portray a somewhat different picture as the spillover effects among the commodities are asymmetric. We may link this asymmetry to the mutual linkage of these commodities in global markets. There are unidirectional spillover effects of changes in COP on ZNC, NKL on COP and ZNC.
Fig. 5 Time average of risk spillover effects across commodity markets for different time periods. Note: This figure indicates the network connectedness among commodity markets. Panel (a) shows networks without thresholding, whereas Panel (b) shows network after thresholding. We only keep the connections larger than the average of the 100 largest individual pairwise connectedness.
on LED. The two metals namely ALM and TIN are not aligned to this network. However, the risk clusters are confined to each commodity group and there are no risk spillovers across commodity sectors. Nevertheless, the picture changes in crisis period. As Zhang and Broadstock (2020) observe, average connectedness among commodity markets rises during crisis period. There is higher (symmetric) connectedness among member commodities in each group and intragroup risk clusters get denser. Moreover, there are visible intergroup spillover effects that are mostly unidirectional. It is interesting to examine how volatility of different commodities is transmitted to energy returns. In respect of precious metals, the volatility in SLV returns is transmitted to WTI prices and PLD to UGS. For industrial metals, volatility in TIN and COP returns are passed on to GOL. In case of agriculture sector, SBOL and CRN are connected to HOL and CTN to GOL (Zhu et al., 2021). Therefore, during COVID-19 crisis period, commodities like Silver, Palladium, Tin, Copper, Soyabean Oil, Corn and Cotton transmit their volatility to different energy commodities. We link this finding with the increase in demand of these commodities in post-crisis period and resulting pressure on energy commodities.

4.3 Network risk measures

To estimate the systemic risk measures, we use the results from the previous steps. We first use the Systemic Network Risk Index (SNRI) to measure total systemic risk in the world commodities network for the sample period. The development of total systemic risk over time is displayed in Fig. 6. At the start of pandemic in March 2020, we notice an abrupt increase in systemic risk. We notice gradual stabilization after this peak, but still the total systemic risk remains well above the pre-crisis level.

After measuring total systemic risk employing SNRI, we focus on firm-specific metrics. The first measure is Systemic Fragility Index (SFI). The commodities ranking high in terms of SFI have higher systemic risk exposure. We rank the sampled commodities in terms of SFI for both pre- and post-crisis periods and report the results in Table 5. In pre COVID-19 period, two food items namely CRN and LCTL stand as the two most fragile commodities. This finding is in line with Guhathakurta et al. (2020), who find agricultural commodities net receivers of risk except Wheat, Soybeans and Sugar. The next two such commodities are

Fig. 6 Time series of the SNRI
Table 5 Ranking of commodity markets according to average SFI for different periods

| Rank | Pre-COVID-19 | COVID-19 |
|------|--------------|----------|
|      | Symbol       | SFI      | Symbol       | SFI      |
| 1    | CRN          | 4.139    | GLD          | 4.293    |
| 2    | LCTL         | 4.013    | SLV          | 4.274    |
| 3    | PLD          | 3.964    | COP          | 4.050    |
| 4    | SLV          | 3.904    | ZNC          | 4.035    |
| 5    | ALM          | 3.818    | CRN          | 4.032    |
| 6    | COP          | 3.807    | NKL          | 3.987    |
| 7    | NGS          | 3.769    | CTN          | 3.978    |
| 8    | FEDR         | 3.766    | LCTL         | 3.939    |
| 9    | GLD          | 3.753    | PLT          | 3.918    |
| 10   | CTN          | 3.723    | PLD          | 3.902    |
| 11   | LED          | 3.722    | FEDR         | 3.835    |
| 12   | TIN          | 3.679    | TIN          | 3.827    |
| 13   | WHKN         | 3.666    | UGS          | 3.799    |
| 14   | PLT          | 3.664    | SOBN         | 3.756    |
| 15   | SOBN         | 3.591    | WTI          | 3.727    |
| 16   | NKL          | 3.573    | WHKN         | 3.712    |
| 17   | COF          | 3.571    | LED          | 3.674    |
| 18   | WHT          | 3.529    | HOL          | 3.662    |
| 19   | ZNC          | 3.470    | NGS          | 3.615    |
| 20   | HOL          | 3.460    | COF          | 3.587    |
| 21   | BRNT         | 3.453    | ALM          | 3.565    |
| 22   | SUGR         | 3.450    | BRNT         | 3.508    |
| 23   | GOL          | 3.439    | SBOL         | 3.491    |
| 24   | UGS          | 3.436    | GOL          | 3.487    |
| 25   | COC          | 3.354    | COC          | 3.469    |
| 26   | SBOL         | 3.350    | WHT          | 3.465    |
| 27   | WTI          | 3.349    | SUGR         | 3.380    |

This table reports average SFI over different time intervals.

Precious metals PLD and SLV. The most fragile energy commodity is NGS (ranked 7) as the other energy commodities rank very low in terms of SFI. In post COVID-19 period, two precious metals, i.e., GLD and SLV emerge as most fragile followed by two industrial metals COP and ZNC. Interestingly, NGS is now ranked 19th in terms of exposure to systemic index. Similarly, SFI of the other energy commodities is further reduced. The least fragile commodities in post COVID-19 world appear to be two important food commodities namely WHT and SUGR. The time graph of SFI for CRN and GLD (most fragile commodities in pre- and post-crisis periods) is displayed in Fig. 7. We observe a visible gap in SFI for both the commodities in pre COVID period except a short spike in Gold prices in October 2019. In post-crisis period, both commodities follow the similar pattern.
Moving ahead, we use Systemic Hazard Index (SHI) and report ranking of commodities with respect to their risk contribution to global commodities network (Table 6). In pre-COVID-19 period, four energy commodities (BRNT, HOL, WTI and UGS) are among top five commodities that contribute most to the systemic risk followed by Wheat, as represented by WHT (ranked 4) and WHKN (ranked 6). Interestingly, NGS (Natural Gas) is among the four commodities that are least contributing to systemic risk. The remaining commodities include TIN, SUGR and COC. During the crisis period, the results are not very different with the exception that HOL has highest SRI in post-crisis period and GOL is ranked fourth highest systemic risk factor. Figure 8 shows the time dynamics of SHI for BRNT and HOL, the two commodities with highest SRI in pre- and post-crisis periods respectively. As expected, the SRI of both commodities follows a similar trend.

The advantage of using both measures is that they enable us to differentiate between the commodities transmitting systemic risk and the commodities affected through systemic risk. Using this approach, the asymmetric nature of the systemic risk may be captured. For instance, in pre-COVID-19 period, WTI crude oil is least affected by systemic risk but it stands at number three in commodities that play important role in influencing systemic risk.

5 Conclusion

The commodities serve as a key input to production activity across the globe and a major output of many emerging economies. The fluctuations in demand/supply patterns of commodities strongly affect common business cycles. Consequently, the measurement of connectedness (central to risk measurement and management) of commodities in real time is of special relevance for designing of policy requiring real-time monitoring. Undoubtedly, COVID-19 pandemic unsettled the existing demand/supply patterns of global commodity markets. Therefore, this study assesses the systemic risk of global commodities network in pre- and post-crisis periods for the purpose of better policy advisory and effective portfolio risk management. We adopt neural network quantile regression approach to perform the estimations in view of nonlinear interconnectedness of global commodities network and their complex
Table 6  Ranking of commodity markets according to average SHI for different periods

| Rank | Pre-COVID-19 | COVID-19 |
|------|--------------|----------|
|      | Symbol | SHI | Symbol | SHI |
| 1    | BRNT | 4.987 | HOL | 5.240 |
| 2    | HOL | 4.802 | BRNT | 5.211 |
| 3    | WTI | 4.760 | WTI | 4.957 |
| 4    | WHT | 4.440 | GOL | 4.599 |
| 5    | UGS | 4.395 | UGS | 4.553 |
| 6    | WHKN | 4.366 | WHKN | 4.373 |
| 7    | GLD | 4.261 | SLV | 4.352 |
| 8    | SLV | 4.252 | WHT | 4.296 |
| 9    | CRN | 4.004 | PLT | 4.235 |
| 10   | SOBN | 3.973 | GLD | 4.233 |
| 11   | COP | 3.876 | COP | 4.119 |
| 12   | GOL | 3.766 | SOBN | 4.110 |
| 13   | LCTL | 3.519 | CRN | 4.092 |
| 14   | PLT | 3.494 | FEDR | 4.016 |
| 15   | FEDR | 3.467 | LCTL | 3.965 |
| 16   | ZNC | 3.368 | ZNC | 3.625 |
| 17   | SBOL | 3.172 | PLD | 3.553 |
| 18   | NKL | 3.165 | SBOL | 3.528 |
| 19   | LED | 2.997 | NKL | 3.454 |
| 20   | PLD | 2.883 | TIN | 3.284 |
| 21   | CTN | 2.834 | ALM | 3.249 |
| 22   | ALM | 2.832 | CTN | 3.129 |
| 23   | COF | 2.817 | LED | 3.120 |
| 24   | TIN | 2.715 | SUGR | 2.927 |
| 25   | SUGR | 2.670 | NGS | 2.625 |
| 26   | NGS | 2.593 | COF | 2.553 |
| 27   | COC | 2.305 | COC | 2.534 |

This table reports average SHI over different time intervals.

dependency channels. Our findings point to the surge in systemic risk of global commodities network in post COVID-19 period. There are visible spillover effects within commodity markets that are mostly unidirectional. The metals like Gold, Silver, Copper and Zinc are found to be most affected by pandemic while the least fragile commodities are Wheat and Sugar. The energy commodities appear to contribute most to the systemic risk.

There are certain policy implications of these results:

First, in the wake of COVID-19, policymakers should evaluate the implications of the theory of comparative advantage and redesign their preferences regarding production and consumption patterns. It had been experienced during pandemic that there can be unforeseen restrictions on physical mobility leading to supply/demand disparities. Hence, the economic policies should be restructured.
Second, our findings identify certain commodities that are detached from the global commodities network during normal and crisis periods. Investors can use this information to effectively hedge their portfolios for different investment horizons.

Third, we provide the details of systemically fragile commodities. Investors seeking high returns may use commodities ranking high in terms of SFI to earn abnormal profits. Similarly, the regulators of countries producing highly systemically fragile commodities may take preventive measures to protect their commodities in extreme times. The risk-averse investors may invest in commodities ranking low in SFI to protect their investments.

Fourth, the commodities with high SHI rank are safe havens and risk-averse investors can include these commodities in their portfolios in order to increase their probability of lower tail risk.

Fifth, as our results reflect, there is extremely high contribution of energy commodities to the systemic risk of global commodities network. Given the hazards of excessive usage of fossil fuels on the environment, policymakers should focus on alternate energy sources. Our suggestion is in light of the resolve of major industrial powers during the recent COP 26 Climate change conference that carbon emissions should be reduced to zero by the year 2050. It is also essential to mitigate the increase in systemic risk arising out of energy commodities.

This research can be extended by adding other commodity groups, like soft commodities, to the sample. The researchers may extend the sample period and assess the systemic risk of global commodities network across past crisis periods to investigate the similarities/divergencies among different crises.

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