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Realized volatility spillovers between energy and metal markets: a time-varying connectedness approach

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Abstract

This paper analyzes the degree of dynamic connectedness between energy and metal commodity prices in the pre and post-COVID-19 era, using the time-varying parameter vector autoregressive connectedness approach of Antonakakis et al. (J Risk Financ Manag 13(4):84, 2020). The results suggest that market interconnectedness increased slightly following the outbreak of COVID-19, although this increase was lower and less persistent than that observed after the Global Financial Crisis of 2008. Furthermore, we find that crude oil was the main net transmitter of shocks before COVID-19 while heating oil, gold, and silver were the main net transmitters of shocks during the COVID-19 pandemic. In contrast, natural gas and palladium were the main net receivers of shocks during the entire sample period, making these two commodities attractive hedging and safe haven options for investors during the pandemic. Overall, our results suggest that hedging and diversification opportunities decrease during crises. Furthermore, they indicate that accurate forecasts of the volatility of several commodities, such as natural gas and different metals, can be obtained by exploiting the information content of crude oil. However, they also reveal that crude oil lost its leading position as a net shock transmitter during the COVID-19 pandemic.

Keywords: Realized volatilities, Energy market, Metal market, TVP-VAR, Dynamic connectedness

JEL Classification: C32, C50, G15

Introduction

There is no doubt about the relevance of energy and precious and industrial metal commodities to the global economy. In addition to their roles as key inputs in production processes, they serve as effective hedging instruments against other financial assets, particularly during crises. Although each commodity market responds to specific shocks (Baffes and Nagle 2022), the financialization of commodities (Cheng and Xiong 2014) has been accompanied by stronger cross-market linkages and, thus, an increase in volatility spillovers among commodity markets (Mandacı et al. 2020; Bouri et al. 2021a, b; Shahzad et al. 2021). According to existing literature, the global crisis triggered an increase in the connectedness between commodity prices (Sari et al. 2010; Zhang and

Wei 2010; Ahmadi et al. 2016; Kang et al. 2017; Luo and Ji 2018; Umar et al. 2019, 2021; Zhang and Broadstock 2020; Jebabli et al. 2021; Farid et al. 2021; Lin and Su 2021; Hung 2021; Balcilar et al. 2021; Apergis et al. 2022; Huang et al. 2023; Zhang et al. 2023; Cunado et al. 2023), implying a reduction in diversification opportunities for investors. We pay particular attention to the volatility spillovers between energy and metal commodities before and after the Coronavirus disease of 2019 (COVID-19) pandemic, as this pandemic is one of the most important sources of uncertainty. A comparison of the degree of connectedness between energy and metal prices during the Global Financial Crisis (GFC) and the COVID-19 pandemic will also be interesting because of the distinct nature of the two crises. In the current energy transition process to lower carbon intensity, which is accompanied by a decreasing demand for fossil fuels and an increasing demand for the metals needed to build solar and wind infrastructure, this analysis of the volatility linkages between the commodity markets will also be useful for designing energy policies to facilitate this transition process.

COVID-19 originated in Wuhan City, China, in early December 2019 and was officially declared a global pandemic in March 2020 by the World Health Organization. It has been an outbreak of a new global health and economic crisis. Owing to the severity of the COVID-19 outbreak, its economic and financial impacts have been studied in comparison with those of the GFC that occurred in 2008 (Shehzad et al. 2020; Chen and Yeh 2021; Jebabli et al. 2021). For example, the stock market prices in the United States (S &P500), the United Kingdom (FTSE100), and China (CSI300) decreased by 14.9%, 21.4%, and 12.1%, respectively, from March 8 to March 18, 2020 (Chen and Yeh 2021), a decrease compared to that observed during the GFC of 2008 (International Monetary Fund 2020).

The energy and metal sectors have also been severely affected by the COVID-19 crisis because acute declines in energy and metal prices have been triggered owing to the collapse in energy and metal demand caused by economic lockdowns imposed in numerous countries to prevent the spread of the pandemic (Salisu et al. 2021). In parallel with the sharp decline in oil and metal prices due to the decrease in the demand for these products for industrial consumption, the COVID-19 crisis has had undeniable effects on financial markets and thus on the attractiveness of certain commodities as a potentially viable hedge strategy, which could substantially change the demand for energy or metal commodities for diversification purposes because of their lower volatility and correlation with other financial assets. Thus, oil prices declined by 85% between January 22 and April 21, 2020 (Wheeler et al. 2020) whereas copper and gold prices decreased by 14% and 2% in March and April 2020, respectively (Laing 2020). In contrast, during the post-COVID-19 period, the price indices of energy and metals increased by 111% and 71% between July 2020 and July 2021, respectively. These sharp movements in commodity prices have also significantly increased volatility. In this context, analyzing volatility spillovers among commodity prices has important policy implications. For example, the energy market's huge dependence on crude oil and its volatility can increase profit opportunities for investors in the clean energy sector (Hammoudeh et al. 2021). If this is the case, increases in crude oil volatility will be followed by a sizeable increase in the demand for metals (e.g., copper), favoring the energy transition away from fossil fuels to a clean energy system. Furthermore, periods of high uncertainty in the financial and oil markets are expected to increase the demand for assets for hedging purposes (Salisu et al. 2021).

Important volatility spillovers among commodity markets have been reported. For example, Zhang and Broadstock (2020) find a significant increase in the connectedness degree in global commodity prices following the GFC of 2008, while Kang et al. (2017) report that the volatility spillover across commodity markets became stronger after the GFC period. While the impact of the GFC on market connectedness has been widely examined, evidence on the degree of market interconnectedness after the COVID-19 crisis is scarce. Huang et al. (2023) investigate the dynamic volatility spillovers among energy commodities and financial markets, finding that the total volatility transmission pattern is prominently time-varying, with a peak reached during the outbreak of COVID-19 and a swift decline afterward. Bouri et al. (2021b) use high-frequency data to study dynamic connectedness among the realized volatility of 15 commodity futures, obtaining strong and moderate levels of volatility connectedness among energy and metals, a volatility connectedness which is time-varying and increases around the pandemic. Unlike the two previous studies, this study includes a longer sample period, which allows us to compare the total volatility connectedness between the GFC and the COVID-19 crisis. Jebabli et al. (2021) compare the volatility spillovers across energy and stock markets over the two crises and find that the transmission across stock and energy markets during the COVID-19 crisis surpassed those observed during the GFC of 2008, highlighting the differences between each of the two crisis on risk transmission. Conditional extreme value and copula methodologies have also been used to examine the dependence structure across financial variables (see, Bhatti and Nguyen 2012; Bhatti and Do 2019). For example, Zhang et al. (2023) find significant and greater spillovers among the clean energy, electricity, and energy metals markets under extreme quantile conditions, and obtain that COVID-19 is an important driver of spillover effects. Ghouse et al. (2023) investigate the spillover effects of the waves of the COVID-19 pandemic that affected the performance of the Islamic financial sector in Pakistan, finding an asymmetric effect of the pandemic on the financial sector in each wave.

In this context, the objective of this study is to analyze the degree of dynamic connectedness between energy and metal commodity prices in the pre- and post-COVID-19 eras. Specifically, we attempt to determine whether there has been an increase in market interconnectedness, and hence, market risk, due to the pandemic. Furthermore, we examine whether the impact on market risk is similar to or different from that observed during the GFC of 2008. With this aim, we use a full-fledged time-varying parameter vector autoregression (TVP-VAR) connectedness framework, as suggested by Antonakakis et al. (2020), to calculate the degree of dynamic connectedness through the considered period. This methodology was also used by Lin and Su (2021) to analyze connectedness in energy markets following the outbreak of COVID-19. The authors find a remarkable increase in the total connectedness in energy markets following the pandemic, while Rehman and Vo (2021) find a low-to-moderate level of integration among the three commodity classes (energy, precious metals, and industrial metals) during the period 2010–2020. Using the same methodology, Naeem et al. (2023) find that the pandemic was followed by a sharp increase in market volatility and financial market connectedness. We use daily annualized volatilities for several energy sources (crude oil, heating oil, and natural gas), precious metals (gold, silver, palladium, and platinum), and industrial metals (copper), which constitute a representative sample of the most traded energy and metal commodities, from January 4, 2006, to June 18, 2021, a long time series period that includes both the GFC and the COVID-19 outbreak. This allowed us to evaluate the hedging features of different commodities as a result of the COVID-19 pandemic. Additionally, in the context of clean energy transition, our sample includes oil and natural gas (represented in 2020 as 31.2% and 24.7% of the world's energy consumption, respectively) and copper, an industrial metal vital for the production of renewable energy resources (wind and solar technology or electronic vehicles, among others). In addition, it will allow us to understand how diversification opportunities for investing in energy and metal commodities have changed since the beginning of the pandemic. Finally, our results will help investors and policymakers understand the propagation mechanisms of realized energy and metal volatilities.

Our main results suggest that market interconnectedness, and market risk, has only slightly increased following the coronavirus outbreak. The results indicate that energy commodities (crude oil and heating oil) and precious metals (gold and silver) are the main shock transmitters, while other metals (copper and palladium) and natural gas are net shock receivers. It is important to highlight that the results indicate that while crude oil was the main transmitter of shocks in the period before COVID-19, it lost this position during the COVID-19 pandemic, and heating oil, silver, and gold became the new main transmitters of shocks during that period. Overall, our primary results suggest that diversification opportunities exist among commodities (Lahiani et al. 2021). Furthermore, they indicate that accurate forecasts of the volatility of several commodities, such as natural gas and different metals, can be obtained by exploiting the information content of crude oil. However, they also state that crude oil lost its leading position as a net transmitter of shocks during the pandemic.

The remainder of this paper is organized as follows: Section "Methodology" describes the methodology employed and Section "Empirical analysis" discusses the dataset and empirical results. Finally, we present our "Concluding remarks".

Methodology

We use a full-fledged TVP-VAR-based connectedness framework, as suggested by Antonakakis et al. (2020), to calculate the degree of dynamic connectedness in the relevant period. As explained in Antonakakis et al. (2020), this method overcomes certain shortcomings of the connectedness measures proposed by Diebold and Yılmaz (2012, 2014). In detail, this approach (i) captures potential parameter changes more accurately,[1] (ii) is less outlier sensitive, (iii) does not require an arbitrarily chosen rolling window size, and (iv) avoids the loss of observations in the calculation of the dynamic measures. Estimating this dynamic index allows us to infer how the risk market evolved throughout the sample period.

To investigate the time-varying linkages across realized energy and metal volatility, we estimate a TVP-VAR model with heteroscedastic variance-covariances.[2] Based on the

[1] Interested readers are referred to the Monte Carlo simulation in Antonakakis et al. (2020).

[2] As the detailed algorithm is beyond the scope of this study, interested readers are referred to Antonakakis et al. (2020).

Bayesian information criterion (BIC), we choose a TVP-VAR(1) model that can be mathematically formulated as follows:

$$\boldsymbol{y}_t = \boldsymbol{B}_t \boldsymbol{y}_{t-1} + \boldsymbol{\epsilon}_t \qquad \boldsymbol{\epsilon}_t \sim N(\boldsymbol{0}, \boldsymbol{\Sigma}_t) \tag{1}$$

$$vec(\boldsymbol{B}_t) = vec(\boldsymbol{B}_{t-1}) + \boldsymbol{v}_t \qquad \boldsymbol{v}_t \sim N(\boldsymbol{0}, \boldsymbol{S}_t) \tag{2}$$

where $\boldsymbol{y}_t$, $\boldsymbol{y}_{t-1}$ and $\boldsymbol{\epsilon}_t$ are $K \times 1$-dimensional vectors and $\boldsymbol{B}_t$ and $\boldsymbol{\Sigma}_t$ are $K \times K$-dimensional matrices. $vec(\boldsymbol{B}_t)$ and $\boldsymbol{v}_t$ are $K^2 \times 1$-dimensional vectors and $\boldsymbol{S}_t$ is a $K^2 \times K^2$ -dimensional matrix. As the dynamic connectedness approach of Diebold and Yılmaz (2012, 2014) relies on the Generalized Forecast Error Variance Decomposition (GFEVD) of Koop et al. (1996) and Pesaran and Shin (1998), it is necessary to transform the TVP-VAR into its time-varying parameter vector moving average (TVP-VMA) representation using the Wold representation theorem $\boldsymbol{y}_t = \sum_{h=0}^{\infty} \boldsymbol{A}_{h,t} \boldsymbol{\epsilon}_{t-i}$ where $\boldsymbol{A}_0 = \boldsymbol{I}_K$. The H-step-ahead GFEVD model explains the effect of a shock in series *j* on series *i*: This can be formulated as follows:

$$\phi_{ij,t}^{gen}(H) = \frac{\sum_{h=0}^{H-1} (\boldsymbol{e}_i' \boldsymbol{A}_{ht} \boldsymbol{\Sigma}_t \boldsymbol{e}_j)^2}{(\boldsymbol{e}_j' \boldsymbol{\Sigma}_t \boldsymbol{e}_j) \sum_{h=0}^{H-1} (\boldsymbol{e}_i' \boldsymbol{A}_{ht} \boldsymbol{\Sigma}_t \boldsymbol{A}_{ht}' \boldsymbol{e}_i)} \tag{3}$$

$$gSOT_{ij,t} = \frac{\phi_{ij,t}^{gen}(H)}{\sum_{k=1}^{K} \phi_{ik,t}^{gen}(H)} \tag{4}$$

where $\boldsymbol{e}_i$ is a $K \times 1$ dimensional zero vector with unity at the *i*th position. Because $\phi_{ij,t}^{gen}(H)$ denotes the unscaled GFEVD ($\sum_{j=1}^{K} \phi_{ij,t}^{gen}(H) \neq 1$), Diebold and Yılmaz (2009, 2012) suggested normalizing it by dividing $\phi_{ij,t}^{gen}(H)$ by the row sums to obtain the scaled GFEVD, $gSOT_{ij,t}$.

The scaled GFEVD is at the heart of the connectedness approach and is used to compute the total directional connectedness TO (FROM) of all series, from (to) series *i*. While TO total directional connectedness illustrates the effect series *i* has on all others, FROM total directional connectedness illustrates the impact that all series have on series *i*. These connectedness measures can be computed as:

$$S_{i \to \bullet,t}^{gen,to} = \sum_{j=1, i \neq j}^{K} gSOT_{ji,t} \tag{5}$$

$$S_{i \leftarrow \bullet,t}^{gen,from} = \sum_{j=1, i \neq j}^{K} gSOT_{ij,t}. \tag{6}$$

The difference between TO and FROM total directional connectedness results in the NET total directional connectedness of series *i* which determines its strength of series *i*:

$$S_{i,t}^{gen,net} = S_{i \to \bullet,t}^{gen,to} - S_{i \leftarrow \bullet,t}^{gen,from}. \tag{7}$$

If $S_{i,t}^{gen,net} > 0$ ($S_{i,t}^{gen,net} < 0$), series i is influenced (influenced by) all others more than by (influencing) them. Thus, it is considered a net transmitter (receiver) of shocks, indicating that series i is driving (driven by) the network.

The connectedness approach also provides further information on bilateral levels. The net pairwise directional connectedness highlights the bilateral net transmission of shocks between series i and j.

$$S_{ij,t}^{gen,net} = gSOT_{ji,t} - gSOT_{ij,t}. \tag{8}$$

If $S_{ij,t}^{gen,net} > 0$ ($S_{ij,t}^{gen,net} < 0$), series i dominates (is dominated by) series j implying that series i influences (is influenced by) series j more than it influences (influences) it.

The total connectedness index (TCI) is important because it represents the degree of network interconnectedness and, hence, market risk. Considering that the TCI can be calculated as the average total directional connectedness to (from) others, it is equal to the average amount of spillovers that one series transmits (receives) from all others. Chatziantoniou and Gabauer (2021) and Gabauer (2021) have shown that as the own variance shares are by construction always larger or equal to all cross variance shares the TCI is within $\left[0, \frac{K-1}{K}\right]$. To obtain a TCI that is within [0,1], which is the original definition, the TCI needs to adjust for its own variance share by

$$gSOI_t = \frac{1}{K-1}\sum_{i=1}^{K} S_{i\leftarrow\bullet,t}^{gen,from} = \frac{1}{K-1}\sum_{i=1}^{K} S_{i\rightarrow\bullet,t}^{gen,to}, \tag{9}$$

High (low) values indicate a high (low) market risk.

Finally, we calculate the pairwise connectedness index (PCI), which can be seen as the TCI at the bilateral level, illustrating the degree of interconnectedness between series i and j. This can be formulated as follows:

$$PCI_{ij,t} = 2\left(\frac{gSOT_{ij,t} + gSOT_{ji,t}}{gSOT_{ii,t} + gSOT_{ij,t} + gSOT_{ji,t} + gSOT_{jj,t}}\right), \qquad 0 \leq PCI_{ij,t} \leq 1. \tag{10}$$

This interpretation is identical to that of TCI.

Empirical analysis

Data description

We use up-to-date data on the daily realized volatility of returns for several energy (crude oil, heating oil, and natural gas), precious metals (gold, silver, platinum, and palladium), and industrial metal (copper) commodities covering the period 2006–2021 obtained from the Risk Lab. Risk Lab is maintained by Professor Dacheng Xiu at the Booth School of Business, University of Chicago (see Fig. 1). The data can be downloaded from the following internet page: https://dachxiu.chicagobooth.edu/#risklab. For an in-depth description of the data collection and the data transformations involved, the reader is referred to the Internet page of Risk Lab. Here, we briefly reproduce the key properties of the data. Risk Lab collects trades at the highest available frequencies. It then cleans the collected data in this manner based on the prevalent national best bid and offers

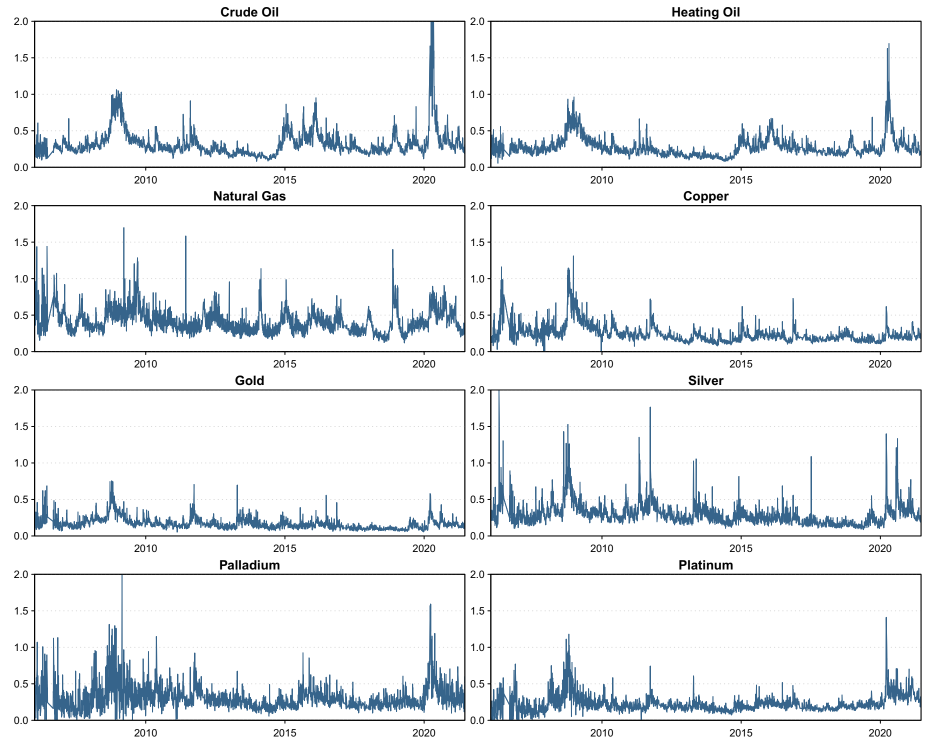

Fig. 1 Realized volatilities

that are available up to every second. Then, the realized volatility (RV) estimator of Xiu (2010) is used. The estimation procedure builds on moving average models and uses the quasi-maximum likelihood estimates of volatility. Nonzero returns of transaction prices are sampled up to their highest available frequency, where days with at least 12 observations are considered. We use realized volatility estimates based on 5-minute subsampled returns of NYMEX light crude oil, NYMEX heating oil No. 2, NYMEX natural gas, COMEX gold, COMEX high-grade copper, COMEX silver futures, NYMEX palladium, and NYMEX platinum futures. Note that these are the only publicly available robust estimates of realized volatility associated with the various commodities considered here. Volatility indicators were initially calculated from comparatively lower-frequency daily data (Bollerslev 1986), whereas the greater availability of high-frequency data extended the use of high-frequency volatility estimators. As explained by Lyócsa et al. (2021), volatility estimators based on high-frequency data are theoretically preferred (Andersen et al. 2001), and models using high-frequency data also provide superior performance (Andersen et al. 2007). Despite these advantages, the presence of market microstructure noise in high-frequency data complicates volatility estimation (Hansen and Lunde 2006). In this context, Xiu (2010) and Da and Xiu (2021) proposed the use of a quasi-maximum likelihood estimation of volatility with high-frequency data and showed that this estimator delivers a more desirable finite-sample performance than alternative non-parametric estimators.

Table 1 provides descriptive statistics for the daily volatilities of each of the eight commodities. We find that natural gas exhibits the highest mean volatility, followed by crude oil and palladium; these commodities also present the highest variances, suggesting that

Table 1 Summary statistics

	Crude oil	Heating oil	Natural gas	Copper	Gold	Silver	Palladium	Platinum
Mean	0.332	0.275	0.411	0.244	0.168	0.297	0.31	0.229
Variance	0.042	0.018	0.027	0.016	0.007	0.025	0.028	0.014
Skewness	4.847***	2.487***	1.616***	2.784***	2.352***	2.975***	2.340***	2.661***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Kurtosis	42.721***	12.187***	5.171***	11.613***	8.638***	15.606***	10.486***	12.124***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
JB	268663.762***	24255.651***	5205.988***	23221.302***	13542.539***	39051.474***	18460.757***	24544.847***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ERS	−6.694***	−5.529***	−4.429***	−7.011***	−5.191***	−9.587***	−11.443***	−6.323***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Q(20)$	21489.650***	21963.781***	13290.228***	19714.223***	15742.101***	12794.413***	6777.043***	13134.576***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Q^2(20)$	11714.631***	14952.371***	7831.009***	16963.601***	12407.747***	6003.273***	4022.247***	10190.779***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Pearson correlation coefficients								
Crude oil	1.00	0.79	0.31	0.36	0.27	0.27	0.28	0.36
Heating oil	0.79	1.00	0.33	0.38	0.28	0.27	0.27	0.34
Natural gas	0.31	0.33	1.00	0.23	0.25	0.26	0.19	0.22
Copper	0.36	0.38	0.23	1.00	0.42	0.41	0.32	0.31
Gold	0.27	0.28	0.25	0.42	1.00	0.68	0.31	0.37
Silver	0.27	0.27	0.26	0.41	0.68	1.00	0.33	0.39
Palladium	0.28	0.27	0.19	0.32	0.31	0.33	1.00	0.45
Platinum	0.36	0.34	0.22	0.31	0.37	0.39	0.45	1.00

***denotes significance at 1% significance level; Skewness: D'Agostino (1970) test; Kurtosis: Anscombe and Glynn (1983) test; JB: Jarque and Bera (1980) normality test; ERS: Stock et al. (1996) unit-root test; $Q(20)$ and $Q^2(20)$: Fisher and Gallagher (2012) weighted Portmanteau test statistics

they were the most volatile commodities in our sample during the study period. The correlation matrix in Table 1 shows a strong relationship between the following pairs of commodities: crude oil, heating oil, gold-silver, and palladium-platinum. These results suggest that the characteristics of energy and metal commodities for their industrial use are the main factors determining the degree of interconnection among commodities during the analyzed period. Based on the Jarque and Bera (1980) test, all series are significantly non-normally distributed, a result supported by the skewness and kurtosis test statistics. Furthermore, all the variables were significantly autocorrelated and exhibited autoregressive conditional heteroskedasticity (ARCH) errors. Thus, these results support the decision to model the volatility transmission mechanism between the energy and metal markets by applying a TVP-VAR model with time-varying variance-covariances.

Table 2 shows the average connectedness measures among commodities before and during the COVID-19 pandemic, based on the TVP-VAR model. Market interconnectedness, measured as the percentage of the forecast error variance in each series of our system of commodities that can be attributed to innovations in all other series, increased from an average of 67.43% to an average of 68.12% during COVID-19, suggesting a slight increase in market risk following the COVID-19 pandemic outbreak, which is in line

Table 2 Averaged dynamic connectedness table

	Crude oil	Heating oil	Natural gas	Copper	Gold	Silver	Palladium	Platinum	FROM others
Crude oil	41.38 (46.02)	28.04 (34.76)	2.96 (3.10)	7.22 (4.72)	5.69 (4.52)	5.42 (3.20)	3.38 (0.92)	5.90 (2.76)	58.62 (53.98)
Heating oil	32.20 (35.80)	38.47 (44.48)	2.94 (3.70)	6.83 (4.70)	5.60 (4.57)	5.38 (3.13)	2.96 (0.94)	5.63 (2.68)	61.53 (55.52)
Natural gas	7.67 (9.63)	7.84 (19.42)	65.09 (50.51)	4.64(2.57)	4.51(6.42)	4.16(7.00)	2.61 (0.40)	3.47 (4.05)	34.91 (49.49)
Copper	11.48 (4.61)	8.79 (5.13)	2.22 (1.05)	40.71 (43.04)	11.70 (18.27)	11.23 (16.21)	5.69 (3.84)	8.18 (7.84)	59.29 (56.96)
Gold	7.60 (4.14)	5.82 (4.93)	2.63(0.78)	9.66 (16.05)	33.42 (32.28)	22.82 (25.15)	5.82 (4.24)	12.23 (12.43)	66.58 (67.72)
Silver	6.91 (2.74)	5.45 (3.52)	2.37 (1.38)	9.76 (13.20)	22.76 (23.41)	35.22 (35.30)	6.11 (3.91)	11.41 (16.54)	64.78 (64.70)
Palladium	7.34 (8.09)	5.76 (9.18)	2.20 (0.56)	9.44 (10.43)	10.07 (10.64)	10.11 (10.67)	40.51 (35.71)	14.58 (14.72)	59.49 (64.29)
Platinum	9.08 (4.00)	7.20 (4.55)	2.09 (1.64)	8.89 (8.69)	14.65 (15.48)	13.76 (21.97)	10.50 (7.89)	33.84 (35.79)	66.16 (64.21)
TO others	82.28 (69.01)	68.92 (81.49)	17.40 (12.22)	56.44 (60.36)	74.98 (83.30)	72.87 (87.33)	37.07 (22.14)	61.40 (61.02)	TCI
NET	23.66 (15.02)	7.39 (25.97)	−17.51 (−37.27)	−2.85 (3.39)	8.40 (15.59)	8.10 (22.63)	−22.42 (−42.15)	−4.77 (−3.18)	67.34 (68.12)

Results are based on a TVP-VAR model with a lag length of order one (BIC), $\kappa_1 = 0.99$, $\kappa_2 = 0.99$, and a 20-step-ahead generalized forecast error variance decomposition. Values in parentheses represent connectedness measures during the COVID-19 pandemic while others stand for the connectedness measures prior to the COVID-19 period

with the result that the global crisis triggers an increase in the connectedness between commodity prices (Zhang and Broadstock 2020; Kang et al. 2017). Furthermore, at the individual commodity level, the results suggest that crude oil was the only main transmitter of shocks before the COVID-19 period, transmitting 82.28% while receiving only 58.62%, leading to a net transmission of 23.66%. This result is in line with those obtained by Shahzad et al. (2021), who find unidirectional causality from energy to precious metal volatility. The second most relevant net transmitter of shocks is gold, with a net transmission equal to 8.40%, followed by silver (8.10%) and heating oil (7.39%).

Heating oil, silver, and gold became the main transmitters during the COVID-19 pandemic with net transmissions of 25.97%, 22.63%, and 15.59%, respectively, whereas crude oil transmitted only 15.02% of the shocks during this period. Compared to the pre-COVID-19 period, heating oil, silver, and gold doubled or nearly tripled their power, while crude oil lost approximately one-third and as a result lost its leading position as a net transmitter of shocks during the COVID-19 period. This is an interesting result as it suggests that precious and industrial metals are less immune to crude oil volatility during the pandemic. However, natural gas, palladium, and platinum have assumed a net receiving position, with palladium and natural gas being the main average net recipients of shocks during the periods prior to and during the COVID-19 outbreak.

As far as the averaged pairwise connectedness measures prior to and during the COVID-19 pandemic are concerned, these are displayed in Table 3. The main results show that the highest pairwise connectedness index is between crude oil and heating oil (86.97% and 87.89%) and between silver and gold (80.11% and 83.87%). That is, as in Diebold et al. (2017), the results suggest a clear clustering associated with commodity

Table 3 Averaged pairwise connectedness table

	Crude oil	Heating oil	Natural gas	Copper	Gold	Silver	Palladium	Platinum
Crude oil	100.00 (100.00)	86.97 (87.89)	19.47 (24.38)	37.91 (20.30)	31.75 (20.70)	29.06 (14.33)	24.13 (20.05)	35.01 (15.89)
Heating oil	86.97 (87.89)	100.00 (100.00)	20.58 (39.25)	35.21 (21.20)	29.50 (22.56)	27.65 (15.88)	21.77 (22.44)	32.81 (16.81)
Natural gas	19.47 (24.38)	20.58 (39.25)	100.00 (100.00)	13.35 (8.42)	15.22 (16.68)	13.68 (17.81)	9.90 (2.51)	12.52 (11.84)
Copper	37.91 (20.30)	35.21 (21.20)	13.35 (8.42)	100.00 (100.00)	45.68 (63.67)	44.54 (55.21)	32.85 (32.03)	39.71 (36.08)
Gold	31.75 (20.70)	29.50 (22.56)	15.22 (16.68)	45.68 (63.67)	100.00 (100.00)	80.11 (83.87)	36.95 (36.51)	59.72 (58.76)
Silver	29.06 (14.33)	27.65 (15.88)	13.68 (17.81)	44.54 (55.21)	80.11 (83.87)	100.00 (100.00)	36.79 (34.94)	56.15 (70.83)
Palladium	24.13 (20.05)	21.77 (22.44)	9.90 (2.51)	32.85 (32.03)	36.95 (36.51)	36.79 (34.94)	100.00 (100.00)	52.44 (49.19)
Platinum	35.01 (15.89)	32.81 (16.81)	12.52 (11.84)	39.71 (36.08)	59.72 (58.76)	56.15 (70.83)	52.44 (49.19)	100.00 (100.00)

Results are based on a TVP-VAR model with a lag length of order one (BIC), $\kappa_1 = 0.99$, $\kappa_2 = 0.99$, and a 20-step-ahead generalized forecast error variance decomposition. Values in parentheses represent connectedness measures during the COVID-19 pandemic while others stand for the connectedness measures prior to the COVID-19 period

groups (energy and precious metals). In other words, spillovers within markets appear to be stronger than those across markets, as in Jiang and Chen (2022). Natural gas has the lowest average pairwise connectedness with all other commodities. A closer look at the table suggests that the average pairwise connectedness measures between each energy commodity (crude oil, heating oil, and natural gas) and each metal commodity (copper, gold, silver, palladium, and platinum) were lower during the pandemic. That is, higher within-group connectedness and lower system-wide connectedness were found during the pandemic, suggesting lower diversification opportunities within each commodity group and higher diversification opportunities between energy and metal commodities during the second period. This suggests that precious and industrial metals were more immune to crude oil volatility during the pandemic.

While Tables 2 and 3 present the averaged connectedness measures over the full time period, Fig. 2 estimates the dynamic total connectedness across time, which is essential because averaged connectedness measures mask the evolution over time and whether the results are driven by economic or financial events.[3] According to the dynamic total connectedness, market risk increased and reached its first peak in 2009, coinciding with the GFC. Although marked interconnectedness also peaked in 2020, coinciding with the COVID-19 pandemic, it was lower and less persistent than that observed in 2009. This indicates that diversification opportunities were higher during the COVID-19 crisis than during the GFC, and seems to imply that policy responses during the pandemic were more effective than those during the financial crisis, as policymakers had experience utilizing unconventional monetary policies to reduce the credit crunch (Benmelech et al. 2020). It is interesting to note that while Jebabli

[3] As suggested by the reviewers, we have added the original vector autoregression (VAR) and quantile vector autoregression (QVAR) connectedness approach of Diebold and Yılmaz (2012) and Chatziantoniou et al. (2021) for robustness purposes, respectively. The dynamics appeared to be similar to the major difference in 2018. This difference can be explained by the fact that the TVP-VAR model adjusted for changes in Crude Oil and Natural Gas in 2018, whereas this effect appears not to be weighted less by the VAR and QVAR models.

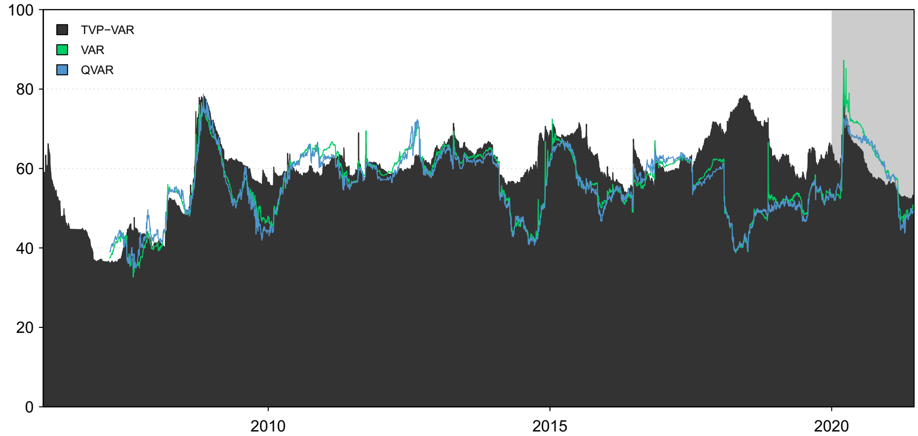

Fig. 2 Dynamic total connectedness. Notes: The black area represents dynamic total connectedness measures based on a TVP-VAR model with $\kappa_1 = 0.99$ and $\kappa_2 = 0.99$ while the green and blue line illustrates the dynamic total connectedness measures based on a 200-day rolling-window VAR (Diebold and Yılmaz 2012) and QVAR (Chatziantoniou et al. 2021) model, respectively. All models are estimated using a lag length of order one (BIC) and a 20-step-ahead generalized forecast error variance decomposition

et al. (2021) find a jump in volatility spillovers between the energy and stock markets during the COVID-19 crisis exceeding that observed during the GFC, our results suggest that the jump in volatility spillovers between energy and metal commodities during the COVID-19 crisis is lower and less than that during the GFC. Therefore, metal commodities seem to have acted as more effective hedging instruments during the recent pandemic.

In addition to these two peaks, the results seem to suggest that market connectedness also increased, coinciding with the Arab crisis in 2012, the European sovereign debt crisis of 2015, and 2018, the worst year since the GFC when almost 7 trillion USD was wiped off world stocks and emerging markets. These events are in line with the academic literature on connectedness, market risk, and global crises. We also observed a decline in total connectedness after the pandemic at the end of the sample period. This decline is consistent with the previous results (Lin and Su 2021; Huang et al. 2023).

To identify whether dynamic total connectedness comes from the short-term (1–5 days) or long-term (5–20 days), we decompose dynamic total connectedness into dynamic short- and long-term connectedness (Chatziantoniou et al. 2023). Figure 3 shows that most dynamics can be attributed to the short-term dynamics. Interestingly, short-term connectedness increased sharply around the GFC, the European sovereign debt crisis, and during 2018, which was the worst financial year since the GFC. Furthermore, long-term connectedness started to increase from 2016 to 2017 and at the beginning of 2020, which could be associated with increased crude oil volatility.

Furthermore, Fig. 4 shows that crude oil was the primary net transmitter of shocks during the GFC while heating oil, gold, and silver were the primary net transmitters of shocks during the pandemic outbreak. That is, crude oil lost its role as a leading transmitter of shocks during COVID-19, suggesting that the industrial metals market

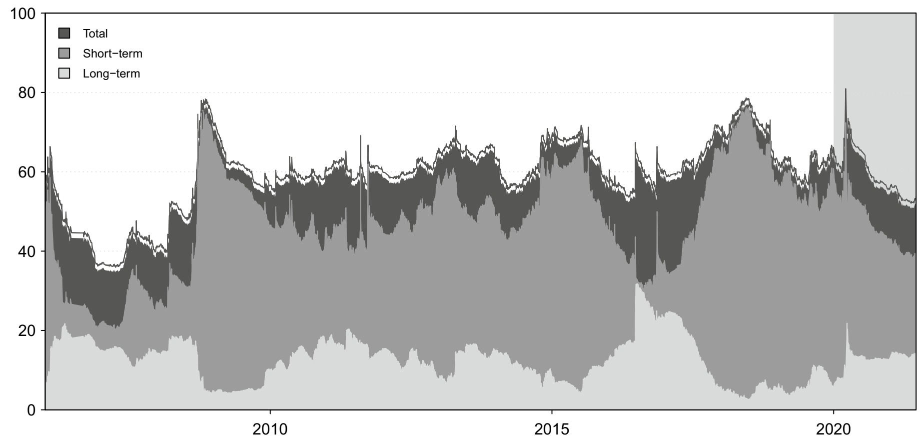

Fig. 3 Dynamic total, short-term and long-term connectedness. Notes: The black, dark grey and light gray areas represent the dynamic total, short-term (1–5 days), and long-term (5–20 days), respectively. The connectedness measures are based on the TVP-VAR frequency connectedness approach (Chatziantoniou et al. 2023) using a lag length of order one, $\kappa_1 = 0.99$, $\kappa_2 = 0.99$ and a 20-step-ahead generalized forecast error variance decomposition

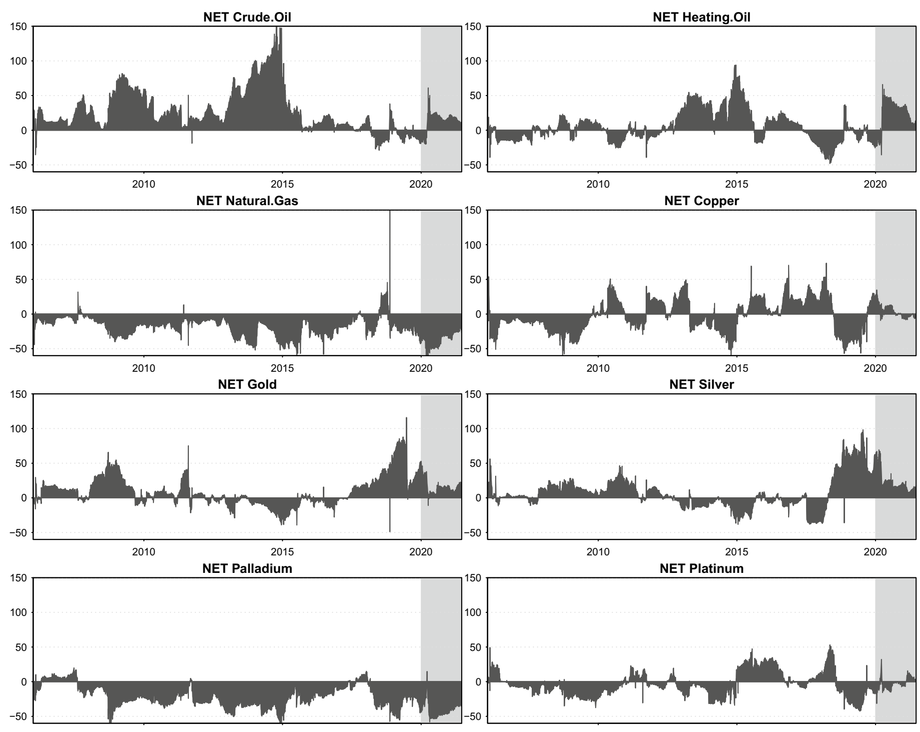

Fig. 4 Net total directional connectedness measures. Notes: The net total connectedness measures are based on a TVP-VAR model with a lag length of order one, $\kappa_1 = 0.99$, $\kappa_2 = 0.99$, and a 20-step-ahead generalized forecast error variance decomposition

is more immune to the high volatility observed in crude oil prices. However, it should be noted that crude oil increased in power at the beginning of 2008 and around 2012 (coinciding with the Arab Spring), and substantially decreased in 2015. During the COVID-19 outbreak, net transmission behavior increased again, which might be linked to crude oil oversupply and the subsequent price drop crude oil which reached the first time in history a negative price in April 2020. Furthermore, natural gas, palladium, and platinum are almost constant net shock receivers.

Discussion

Interesting results were obtained from the empirical analysis. In line with previous literature, jumps in total connectedness among commodity markets were detected coinciding with stress or uncertainty periods, such as those observed during the GFC or the COVID-19 pandemic (increases in total connectedness were also detected coinciding with the Arab crisis in 2012 or the European sovereign debt crisis in 2015). This implies that hedging and diversification opportunities decrease during crises. Despite the previous general results, it is worth mentioning the main differences we detected in the degree of total connectedness and volatility transmission patterns between the GFC and the coronavirus pandemic. Our analysis suggests that market interconnectedness increased slightly following the outbreak of COVID-19, although this increase was lower and less persistent than that observed after the Global Financial Crisis of 2008. Our results also reveal that crude oil lost its leading position as a net transmitter of shocks during the COVID-19 period, suggesting that metal commodities were less vulnerable to crude oil volatility during the recent pandemic. The significant drop in oil prices at the beginning of the pandemic could be responsible for this change in the connectedness between energy and metal commodities based on the idea that price increases (inflation) are a transmission mechanism between energy and metal commodities. Oil price increases lead to inflation, which, in turn, leads to an increase in the demand for metals (i.e., gold) to hedge inflation. Furthermore, while oil price increases can affect the metals industry by increasing production costs, oil price decreases may not cause such a drop in production costs. Analyzing the possible asymmetric effects of oil price changes on total connectedness constitutes an area for future research. In addition, as quantitative easing measures were undertaken to revive the economy, equity markets rebounded quickly and were driven by technological stocks owing to lockdown measures and work-from-home requirements (Yousaf et al. 2023). Hence, the sharp connectedness in the volatility of commodity markets due to higher trading of these assets as a means of providing alternative hedging and diversification opportunities to the conventional financial market did not persist following the peak of the COVID-19 pandemic in March 2020 (Bouri et al. 2021b).

Concluding remarks

This study examines the degree of dynamic connectedness between energy and metal commodity prices in the pre- and post-COVID-19 eras using up-to-date daily data on energy (crude oil, heating oil, and natural gas), precious metals (gold, silver, palladium, and platinum), and industrial metals (copper) from 2006 to 2021. The results are obtained using a fully-fledged time-varying parameter vector autoregressive (TVP-VAR) model, as suggested by Antonakakis et al. (2020), which overcomes certain shortcomings of the connectedness measures proposed by Diebold and Yılmaz (2012, 2014). The analysis of volatility spillovers between the energy and metal markets is essential in light of the recent COVID-19 pandemic and the transition from fossil fuels to renewable energies, as this transition will require an increase in the demand for metals, such as copper (World Bank 2020; International Energy Agency 2021). A comparison of the degree of connectedness between energy and metal commodities during the Global Financial Crisis and the coronavirus pandemic is also interesting because of the distinct nature of each crisis.

The main conclusions are as follows: First, we find that the average market interconnectedness, and hence market risk, increased only slightly following the outbreak of COVID-19. Dynamic connectedness increased from an average of 67.43% to an average of 68.12% during COVID-19. When dynamic total connectedness measures are considered, we find that market interconnectedness increased and reached its highest peak in 2009, coinciding with the GFC. This index also reached another peak in 2021, which coincides with the Arab crisis, in 2015 marking the European sovereign debt crisis, in 2018 illustrating the worst year on the financial market since the GFC and in 2020 when the COVID-19 pandemic emerged. These events are in line with the academic literature on connectedness, market risk, and global crises (Zhang and Wei 2010; Ahmadi et al. 2016; Kang et al. 2017; Umar et al. 2019, 2021; Tan et al. 2021), implying that accurate forecasts of the volatility of several commodities, such as natural gas or different metals, can be obtained by exploiting the information content of crude oil. Second, based on the same dynamic analysis, the results suggest that the increase in market connectedness and market risk was lower and less persistent during the COVID-19 outbreak than during the GFC. This result has relevant policy implications, because it suggests that policy responses during the pandemic were more effective than those during the financial crisis (Benmelech et al. 2020; Wei and Han 2021). It also indicates that diversification opportunities were higher during the COVID-19 crisis than during the GFC, with the former being more of a health crisis and affecting lower-income groups, who are not major players in financial markets, more strongly.[4]

Third, regarding the average pairwise connectedness measures before and during the COVID-19 pandemic, the main results show that the highest pairwise connectedness index is between crude oil and heating oil and between silver and gold, indicating a clear clustering associated with commodity groups (energy, precious metals). This result supports Diebold et al. (2017) and Jiang and Chen (2022). Moreover, the average pairwise connectedness measures between each energy commodity (crude oil, heating oil, and natural gas) and each metal commodity (copper, gold, silver, palladium, and platinum) were lower during the pandemic than before.

Fourth, at the individual commodity level, the results indicate that crude oil was the main transmitter of shocks before the COVID-19 period, transmitting 23.66%, while heating oil, silver, and gold were the main transmitters during the COVID-19 pandemic, transmitting 25.97%, 22.63%, and 15.59%, respectively. In other words, crude oil lost its role as a leading transmitter of shock during COVID-19. However, natural gas, palladium, and platinum assumed a net receiving position, with palladium and natural gas as the main net recipients of shocks during the periods prior to and during the COVID-19 outbreak.

Finally, in the context of the energy market's high dependence on crude oil, the relatively lower connectedness between the energy market (crude oil, natural gas, and

[4] See: https://www.imf.org/external/pubs/ft/fandd/2021/06/inequality-and-covid-19-ferreira.htm.

heating oil) and industrial metals (copper) found during the most recent period suggests an increase in the immunity of the industrial metals market to the high volatility observed in the energy market, especially in crude oil prices.

Our results tend to suggest that volatility spillovers are time-varying, defining the evolution of the riskiness of the traded assets; the associated weights in the portfolio of investors would need to take account of this fact and put more emphasis on assets that drive risks rather than the receivers.

Abbreviations

ARCH	Autoregressive conditional heteroskedasticity
COVID-19	Coronavirus disease of 2019
GFC	Global Financial Crisis
GFEVD	Generalized Forecast Error Variance Decomposition
PCI	Pairwise connectedness index
QVAR	Quantile vector autoregression
RV	Realized volatility
TCI	Total connectedness index
TVP-VAR	Time-varying parameter vector autoregression
TVP-VMA	Time-varying parameter vector moving average
VAR	Vector autoregression

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Author contributions
All the authors were involved in the research that led to the article and its writing. All the authors have read and approved the final version of the manuscript.

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Availability of data and materials
All the data is downloadable from the following internet page: https://dachxiu.chicagobooth.edu/#risklab. The authors confirm that data will be made available on reasonable request.

Declarations

Competing interests
We declare that we have no competing financial interests or personal relationships that may have influenced the work reported in this study.

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