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Dynamic spillovers across precious metals and oil realized volatilities: Evidence from quantile extended joint connectedness measures☆

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ABSTRACT

This paper proposes a novel quantile vector autoregressive extended joint connectedness framework to examine realized volatilities spillovers between oil and precious metals commodities using daily data from May 1st, 2006 until June 18th, 2021. Our findings suggest that crude oil is the main net transmitter of shocks in the network across all quartiles. The dynamic total connectedness is heterogeneous over time and driven by economic events. Interestingly, we see that the higher the quartile the more pronounced the net transmission mechanisms of realized volatilities. Notably, the net total directional and pairwise connectedness measures illustrate in most cases similar dynamics.

1. Introduction

Precious metals have traditionally been considered to be one of the safest asset classes. According to the latest Gold Outlook 2021 (World Gold Council, 2021a), gold was one of the best-performing major assets of 2020, a year driven by a high-risk environment due to the COVID-19 pandemic, low interest rates, and a positive price momentum—especially in late spring and over summer. In addition, portfolio managers and investors have traditionally regarded gold as being the most effective commodity investment to generate a portfolio with a high reward-to-volatility ratio that outperforms commodities in low inflation periods. Moreover, a recent report by the World Gold Council (2021b) shows that gold deserves to be seen as a differentiated asset as it

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has historically benefited from superior absolute and risk-adjusted returns contrasted with other commodities over multiple time horizons and has been a more effective diversifier than other commodities (see, also, the survey by O'Connor et al., 2015, on the relevant role of gold in economics).

There are two seminal empirical studies that examine the role of gold as either a hedge or a safe haven: Baur and Lucey (2010) and Baur and McDermott (2010). Baur and Lucey (2010) show that gold can both be a hedge against stocks and a safe haven in extreme stock market conditions. Baur and McDermott (2010) also find that the same is true for the US and major European stock markets. Building on these early papers, a large body of empirical studies provides evidence of the hedging, the diversifying and the safe haven potential of gold and silver (see, for example, Hood and Malik, 2013; Beckmann et al., 2015; Bredin et al., 2015; Bekiros et al., 2017; Mensi et al., 2021b; Wang et al., 2021). More recently, authors such as Alqaralleh and Canepa (2022), Kinateder et al. (2021), Salisu et al. (2021) and Syuhada et al. (2021) point out the potential of gold and silver to serve as a safe haven during the COVID-19 pandemic.

Given the close association between gold and silver market developments and market stress, it is no surprise that a multitude of studies explore the nexus between precious metals and petroleum markets (Sujit and Kumar, 2011; Šimáková, 2011; Chang et al., 2013; Bampinas and Panagiotidis, 2015b; Raza et al., 2016; Chen and Xu, 2019; Kumar et al., 2020; Hung and Vo, 2021; Mensi et al., 2021b). Movements in both these markets are found to be connected, especially over the last decade. Therefore, understanding the volatility transmission mechanism between energy and precious metals[1] is crucial for investors, traders, and portfolio managers (see, for example, Zhang et al., 2021). In this context, the objective of this paper is to understand in detail the relationship between selected oil commodities (namely, oil and heating oil) and precious metals (namely, gold and silver) volatilities over time.[2]

One limitation of existing studies is that they do not allow the possibility for connectedness to vary across high and low volatility. It assumes that the relationship between oil and precious metals at the mean also holds for the entire conditional distributions. We relax this assumption to match what we observe. Evidence suggests that volatility transmission between crude oil, heating oil, gold, and silver exhibit a time-varying pattern, and this pattern is driven by economic events like the COVID-19 pandemic (Yıldırım et al., 2020; Farid et al., 2021; Mensi et al., 2021b). Nonetheless, when the response is different relative to the one revealed by the conditional mean estimator, then we need a unified framework that allows volatility connectedness to vary across high and low-volatility regimes

In addition to the empirical evidence supporting the modeling approach, our framework is also grounded in theories modeling contagion (Masson, 1998; Calvo, 2004; Allen and Gale, 2000) and herding behavior (aptly surveyed in Spyrou, 2013). These theories suggest that when rational traders are faced with the problem of incomplete information, the spillover of risk between markets increases. Naturally, in times of greater risks and uncertainty, this problem accentuates. Consequently, the degree of connectedness in such a period most likely differs from connectedness in tranquil financial market conditions. These theoretical underpinnings motivate us to study spillovers between energy and precious metals markets while accounting for varying degree of connectedness across time and different market conditions. We thus consider the entire conditional distribution using the QVAR approach together with extended joint connectedness.

Furthermore, investigating the dynamic volatility interrelationships across quantiles for gold, silver, crude oil, and heating oil is worthwhile. This is because the dynamics of each of these market segments are different. Gold and silver are precious metals, and can be argued to be governed by common dynamics. However, the existence of a stable cointegrating relationship between gold and silver prices is not always obvious and often unclear (Sami, 2021; Baur and Tran, 2014; Ciner, 2001; Escribano and Granger, 1998). There are significant periods when this relationship is weakened or broken (Lucey and Tully, 2006). Zhu et al. (2016) even show that the quantile behavior of cointegration between silver and gold prices differs across quantiles. Similar findings are for the relationship between crude oil and heating oil prices, which are both a part of the energy market. Kaufmann and Laskowski (2005) find that there is an asymmetric relationship between crude oil and heating oil prices. Ederington et al. (2021) also show that heating oil prices do not Granger-cause crude oil price movements. These results suggest that additional insights will be gained by separately exploiting the dynamic volatility interrelationships for each of these market segments.

In particular, this paper extends previous related studies on (i) volatility spillovers across commodities, precious metals, heating oil, and crude oil (see, Mensi et al., 2013; Balli et al., 2019; Bonato et al., 2020; Zhang et al., 2021); and (ii) volatility dynamics emphasizing the COVID-19 shock (see, Hung and Vo, 2021; Mensi et al., 2021b; Wei et al., 2021) by introducing a novel connectedness framework which combines quantile vector autoregressive (QVAR) models (White et al., 2015; Chatziantoniou et al., 2021) with the extended joint connectedness approach (Balcilar et al., 2021). The QVAR (White et al., 2015) provides the appropriate framework to study the dependencies across different quantiles with lower quantiles capturing low realized volatility periods and higher quantiles being indicative of expansions and of high realized volatility dynamics. Furthermore, by adopting the joint connectedness approach we refine the original procedure (Diebold and Yilmaz, 2012, 2014) by employing an improved normalization technique.

The contribution of this study to the literature on the nexus between volatility in precious metals and the petroleum market relates to the following points. First, we use a novel modeling approach that is capable of capturing volatility connectedness based

[1] As in previous related studies on spillover effects, we note that dynamic spillover across selected precious metals and oil realized volatilities is partially contaminated by the underlying sectoral connections. In our case, we try to overcome the underlying within sectoral connections examining alternative quantile connectedness.

[2] Though gold and silver are both precious metals, the short-run dynamics between these two assets appear to be different (Sami, 2021; Zhu et al., 2016; Baur and Tran, 2014; Ciner, 2001; Escribano and Granger, 1998). This is also the case for oil and heating oil prices (Kaufmann and Laskowski, 2005; Ederington et al., 2021). Hence, it is worthwhile to investigate the dynamic volatility interrelationships between each of these market segments.

on stages of low and high volatility. This provides deeper insights into volatility spillovers between precious metal and petroleum markets. This paper builds on the work of White et al. (2015) and Chatziantoniou et al. (2021) using a QVAR as well as the extended joint connectedness approach of Balcilar et al. (2021). We note that, Chatziantoniou and Gabauer (2021) show that the original estimation of connectedness by Diebold and Yilmaz (2009, 2012) exhibits certain interpretability issues. Utilizing Monte Carlo simulations, Chatziantoniou and Gabauer (2021) show that own-variance connectedness shares are always either larger than, or equal to cross-variance connectedness shares. What is more, the corrected connectedness measures that were introduced in the work by Chatziantoniou and Gabauer (2021), were initially adopted in a quantile connectedness framework by Chatziantoniou et al. (2021). In this regard, we extend all these efforts by combining, for the first time, the (corrected) quantile connectedness approach that was presented in Chatziantoniou et al. (2021) with the extended joint connectedness framework introduced in Balcilar et al. (2021)—which involves the adoption of a refined connectedness normalization technique that leads to more accurate results. Therefore, this is the methodological contribution of our paper. Second, compared to existing studies (Mensi et al., 2013; Benlagha and El Omari, 2021; Wei et al., 2021), we consider an extended data span that covers almost all existing waves of COVID-19 as it incorporates data from 2006 to 2021, and thereby provide more specific insights about the volatility nexus between selected petroleum and precious metals. Finally, our results have important implications for policymakers.

Our findings suggest that crude oil is the main net transmitter of shocks in the network across all quartiles. We find significant time variation in dynamic total connectedness. We find several spikes in connectedness, particularly around the 2007–08 Global Financial Crisis, the recent oil-price crash, and the COVID-19 pandemic. Given the innovation of our approach, we find that higher quartiles are characterized by a more pronounced transmission of realized volatilities. Notably, the net total directional and pair-wise connectedness measures illustrate in most cases similar dynamics.

The remainder of the paper is organized as follows. Section 2 provides a brief overview of existing literature while Section 3 describes the empirical methods. Section 4 discusses the dataset and the empirical results while Section 5 highlights the implications of the study. Section 6 concludes the study.

2. Brief review of the literature

Previous empirical studies find relevant synchronization among different petroleum commodities prices and volatilities – i.e., crude oil and heating oil – (see, for example, Gong et al., 2021; Naeem et al., 2021). Similarly, precious metals commodities present highly co-movement in prices and volatilities (see, Bampinas and Panagiotidis, 2015a; Li and Lucey, 2017).

Our paper builds on a growing literature that studies the nexus between the volatility of petroleum and precious metal markets. Ewing and Malik (2013) are the first to empirically examine the volatility of gold and oil futures using GARCH models with structural breaks. Their results provide strong evidence of significant transmission of volatility between gold and oil returns when structural breaks in variance data are accounted for in the model.

Our paper extends on this evidence of volatility spillovers across these two markets (see, for example, Mensi et al., 2013; Bampinas and Panagiotidis, 2015a; Balli et al., 2019; Bonato et al., 2020; Uddin et al., 2020; Naeem et al., 2021; Zhang et al., 2021). Mensi et al. (2013) study the volatility transmission between the S&P 500 and different commodity prices using a VAR-GARCH model. They find that past shocks and volatility of the S&P 500 strongly influence the oil and gold markets. Bampinas and Panagiotidis (2015b) examine the relationship between oil and gold using linear, nonlinear and time-varying causality testing. Their evidence suggests that the nonlinear linkages between the oil and gold markets can be attributed to volatility spillover effects. Bonato et al. (2020) use intraday data and find strong evidence of bidirectional causality in the realized volatility between gold and oil markets which seems to be stemming from volatility jumps. Uddin et al. (2020) explore the characteristics of the risk spillover between the stock market and precious metals and oil. Their results suggest that the stock market influences oil and silver under both market downturns and upturns with an asymmetric tail dependence of the stock market with silver. Zhang et al. (2021) explore volatility spillovers among gold, stock market, bond market, and oil price. They find no significant spillovers from gold to either stocks or bonds, but there is a bidirectional spillover between gold and oil. Furthermore, Naeem et al. (2021) explore the extreme tail dependence between heating oil and green bonds using a time-varying optimal copula model obtaining an extreme negative tail dependence between green bonds and heating oil.

Within this literature, recent papers emphasize the spillovers between oil and precious metal volatilities during the COVID-19 pandemic (see, for example, Benlagha and El Omari, 2021; Hung and Vo, 2021; Mensi et al., 2021b; Wei et al., 2021). Benlagha and El Omari (2021) examine the effects of the COVID-19 pandemic on the dynamic connectedness between gold, oil, and stock markets. They report that the COVID-19 pandemic increased connectedness among oil, gold, and selected stock markets. Furthermore, they find that gold is a receiver of shocks from stock markets whereas oil is a transmitter of shocks during this outbreak. Hung and Vo (2021) investigate spillover effects between S&P 500, crude oil prices, and gold assets using both the spillover index and wavelet coherence. The results suggest that gold might play a prominent role as a safe haven during extreme stock and crude oil market movements. Mensi et al. (2021b) investigate the volatility transmission between oil and precious metals. Their empirical analysis shows that the conditional volatility of oil and precious metals heavily depends on previous shocks and conditional variances. Furthermore, Wei et al. (2021) study the effects of the pandemic on the long-term volatility and long-term correlation between gold and crude oil markets. The study by Wei et al. (2021) is a pioneering work that uses data from the infectious disease equity market volatility tracker. Their findings show that the infectious disease pandemic has a prominent positive impact on the long-run volatilities of both gold and crude oil markets, and this impact increases with the time lags of the infectious disease pandemic.

Nonetheless, existing studies do not provide any formal evidence that spillover connectedness between precious metals and petroleum markets is potentially a function of volatility regimes. That is, intuitively, during distressed financial market conditions, the degree of herding among investors rises and we would therefore expect volatility connectedness between petroleum and precious metal markets to increase. So far, there has been little evidence in support of such arguments. Mensi et al. (2021b) find time-varying patterns in the volatility transmission between crude oil and four precious metals. Their study highlights the importance of economic events like the COVID-19 pandemic in driving these variations. Similar results have been found in Farid et al. (2021). It follows that, to the best of our knowledge, we are the first to investigate spillover connectedness among petroleum and precious metal markets across time and quantiles. For this purpose, we introduce the novel quantile extended joint connectedness approach which improves the original VAR connectedness approach of Diebold and Yilmaz (2009, 2012) in several ways. First, results are more robust as QVAR models are less outlier sensitive than VAR models. Second, while the standard VAR model only allows for the investigation of mean connectedness dynamics, employing a QVAR model facilitates the examination of time-varying connectedness across different quantiles. Thus, this technique both improves our understanding and highlights the differences between low and high-volatility regimes; a fact that, offers crucial insights to portfolio risk managers and policymakers. Third, the quantile extended joint connectedness approach improves the normalization technique that is used for the generalized forecast error variance decomposition (Balcilar et al., 2021). Thus, the contribution of this paper is twofold. First, this paper introduces a new econometric approach that extends the connectedness literature and allows to model spillover measures across time, quantiles, and volatility regimes. Second, this paper fills the gap in the COVID-19 literature and the literature relating to the precious metals and petroleum markets by investigating the dynamic volatility interrelationships across quantiles for gold, silver, crude oil, and heating oil.

3. Methodology

3.1. QVAR connectedness approach

We employ the quantile connectedness approach proposed by Chatziantoniou et al. (2021) as well as Ando et al. (2022) to examine the quantile propagation mechanism across precious metal and energy realized volatilities. To compute all connectedness metrics, we first estimate a quantile vector autoregression, QVAR(p) (see, White et al., 2015) which can be outlined as follows[3]:

$$\boldsymbol{y}_t = \boldsymbol{\mu}(\tau) + \sum_{j=1}^{p} \boldsymbol{\Phi}_j(\tau)\boldsymbol{y}_{t-j} + \boldsymbol{u}_t(\tau) \tag{1}$$

$\boldsymbol{y}_t$ and $\boldsymbol{y}_{t-j}$ are $K\times 1$ dimensional endogenous variable vectors, τ is between $[0, 100]$ and represents the quantile of interest, p stands for the lag length of the QVAR model, $\boldsymbol{\mu}(\tau)$ is a $K\times 1$ dimensional conditional mean vector, $\boldsymbol{\Phi}_j(\tau)$ is a $K\times K$ dimensional QVAR coefficient matrix, and $\boldsymbol{u}_t(\tau)$ demonstrates the $K\times 1$ dimensional error vector which has a $K\times K$ dimensional variance–covariance matrix, $\boldsymbol{\Sigma}(\tau)$. To transform the QVAR(p) to its QVMA(∞) representation, we use Wold's theorem: $\boldsymbol{y}_t = \boldsymbol{\mu}(\tau)+\sum_{j=1}^{p} \boldsymbol{\Phi}_j(\tau)\boldsymbol{y}_{t-j} + \boldsymbol{u}_t(\tau) = \boldsymbol{\mu}(\tau) + \sum_{i=0}^{\infty} \boldsymbol{A}_i(\tau)\boldsymbol{u}_{t-i}(\tau)$.

In a next step, the H-step ahead Generalized Forecast Error Variance Decomposition (GFEVD) of Koop et al. (1996) and Pesaran and Shin (1998) is computed which demonstrates the impact a shock in series j has on series i:

$$\psi_{ij}^{gen}(H) = \frac{\boldsymbol{\Sigma}(\tau)_{ii}^{-1}\sum_{h=0}^{H-1}(\boldsymbol{e}_i'\boldsymbol{A}_h(\tau)\boldsymbol{\Sigma}(\tau)\boldsymbol{e}_j)^2}{\sum_{h=0}^{H-1}(\boldsymbol{e}_i'\boldsymbol{A}_h(\tau)\boldsymbol{\Sigma}(\tau)\boldsymbol{A}_h(\tau)'\boldsymbol{e}_i)} \tag{2}$$

$$gSOT_{ij}(H) = \frac{\psi_{ij}^{gen}(H)}{\sum_{j=1}^{K}\phi_{ij}^{gen}(H)}. \tag{3}$$

$\boldsymbol{e}_i$ indicates a zero vector with unity on the ith position.

Furthermore, the total directional connectedness from all others to series i and the total directional connectedness to all others from a shock in series i representing how much the network influences series i and how much series i influences the predefined network, respectively, can be calculated as follows:

$$S_{i\leftarrow\bullet}^{gen,from}(H) = \sum_{j=1, i\neq j}^{K} gSOT_{ij}(H) \tag{4}$$

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

The difference between the TO and FROM connectedness measures of series i results in the net total directional connectedness of series i which is interpreted as the net influence series i has on the network,

$$S_{i}^{gen,net}(H) = S_{i\rightarrow\bullet}^{gen,to}(H) - S_{i\leftarrow\bullet}^{gen,from}(H) \tag{6}$$

If $S_{i}^{gen,net}(H) > 0$ ($S_{i}^{gen,net}(H) < 0$), series i drives (is driven by) others more than being influenced by (influencing) them. Therefore, series i is considered as a net transmitter (receiver) of shocks.

[3] As White et al. (2015) point out the QVAR model can also be called VAR for VaR (Value-at-Risk). This is caused by the fact that the dependent variables can be seen as VaRs of the employed time series as the qth quantile of the dependent variable depends on the series lagged values.

At the center of the connectedness framework is the total connectedness index (TCI) which highlights the degree of network interconnectedness and market risk. The TCI is equal to the average total directional connectedness from (to) others and is mathematically formulated as follows,

$$gSOI(H) = \frac{1}{K}\sum_{i=1}^{K} S^{gen,from}_{i\leftarrow\bullet}(H) = \frac{1}{K}\sum_{i=1}^{K} S^{gen,to}_{i\rightarrow\bullet}(H), \tag{7}$$

A high (low) TCI value indicates that the market risk is high (low).

Finally, the connectedness approach provides also information on the bilateral level. The net pairwise directional connectedness illustrates the bilateral power between series i and j,

$$S^{gen,net}_{ij}(H) = gSOT^{gen,to}_{ji}(H) - gSOT^{gen,from}_{ij}(H)(H). \tag{8}$$

If $S^{gen,net}_{ij}(H) > 0$ ($S^{gen,net}_{ij}(H) < 0$), series i dominates (is dominated) series j which means that series i influences (is influenced by) series j more than being influenced by it.

3.2. QVAR extended joint connectedness approach

As we mention in Section 1, this paper introduces a novel connectedness framework that combines QVAR models with the extended joint connectedness approach. In particular, the novel difference between the joint and the original connectedness is that the normalization method is derived from the popular R^2 goodness-of-fit measure.[4] $S^{jnt,from}_{i\leftarrow\bullet}(H)$ shows the impact all variables in the network have on series i. This can be mathematically formulated by:

$$\boldsymbol{\xi}_t(H) = \boldsymbol{y}_{t+H} - E(\boldsymbol{y}_{t+H}|\boldsymbol{y}_t, \boldsymbol{y}_{t-1}, \dots) = \sum_{h=0}^{H-1} \boldsymbol{A}_h \boldsymbol{\epsilon}_{t+H-h} \tag{9}$$

$$E(\boldsymbol{\xi}_t(H)\boldsymbol{\xi}'_t(H)) = \boldsymbol{A}_h \boldsymbol{\Sigma} \boldsymbol{A}'_h \tag{10}$$

$$S^{jnt,from}_{i\leftarrow\bullet}(H) = \frac{E(\xi^2_{i,t}(H)) - E[\xi_{i,t}(H) - E(\xi_{i,t}(H))|\epsilon_{\forall\neq i,t+1}, \dots, \epsilon_{\forall\neq i,t+H}]^2}{E(\xi^2_{it}(H))} \tag{11}$$

$$= \frac{\sum_{h=0}^{H-1} \boldsymbol{e}'_i \boldsymbol{A}_h \boldsymbol{\Sigma} \boldsymbol{M}_i (\boldsymbol{M}'_i \boldsymbol{\Sigma} \boldsymbol{M}'_i)^{-1} \boldsymbol{M}'_i \boldsymbol{\Sigma} \boldsymbol{A}'_h \boldsymbol{e}_i}{\sum_{h=0}^{H-1} \boldsymbol{e}'_i \boldsymbol{A}_h \boldsymbol{\Sigma} \boldsymbol{A}'_h \boldsymbol{e}_i} \tag{12}$$

where $\boldsymbol{M}_i$ is a $K \times K-1$ rectangular matrix that equals the identity matrix with the ith column eliminated, and $\epsilon\forall \neq i, t+1$ representing the $K-1$-dimensional vector of shocks at time $t+1$ for all series except series i.

In the next step, the joint total connectedness index is computed as follows,

$$jSOI(H) = \frac{1}{K}\sum_{i=1}^{K} S^{jnt,from}_{i\leftarrow\bullet}(H) \tag{13}$$

which is within zero and unity as opposed to the TCI of the originally proposed approach as pointed out by Chatziantoniou and Gabauer (2021) and Gabauer (2021).

An essential extension of Balcilar et al. (2021) is that multiple scaling factors are used to link $gSOT$ to $jSOT$:

$$\lambda_i(H) = \frac{S^{jnt,from}_{i\leftarrow\bullet,t}(H)}{S^{gen,from}_{i\leftarrow\bullet}(H)} \tag{14}$$

$$jSOT_{ij}(H) = \lambda_i(H) gSOT_{ij}(H) \tag{15}$$

This equality allows to calculate the total directional connectedness from variable i to all others, the net total directional and even the net pairwise directional connectedness by

$$S^{jnt,to}_{i\rightarrow\bullet}(H) = \sum_{j=1, i\neq j}^{K} jSOT_{ji}(H) \tag{16}$$

$$S^{jnt,net}_{j}(H) = S^{jnt,to}_{i\rightarrow\bullet}(H) - S^{jnt,from}_{\bullet\rightarrow i}(H) \tag{17}$$

$$S^{jnt,net}_{ij}(H) = jSOT^{jnt,to}_{ji}(H) - jSOT^{jnt,from}_{ij}(H). \tag{18}$$

4. Empirical results

In this paper, we use the realized volatility estimates based on 5-minute subsampled returns of the NYMEX light crude oil, NYMEX heating oil, COMEX gold, and COMEX silver futures, covering the period 2006–2021. All the daily realized volatility of

[4] For the detailed mathematical derivations interested readers are referred to the technical appendix of the original study of Lastrapes and Wiesen (2021).

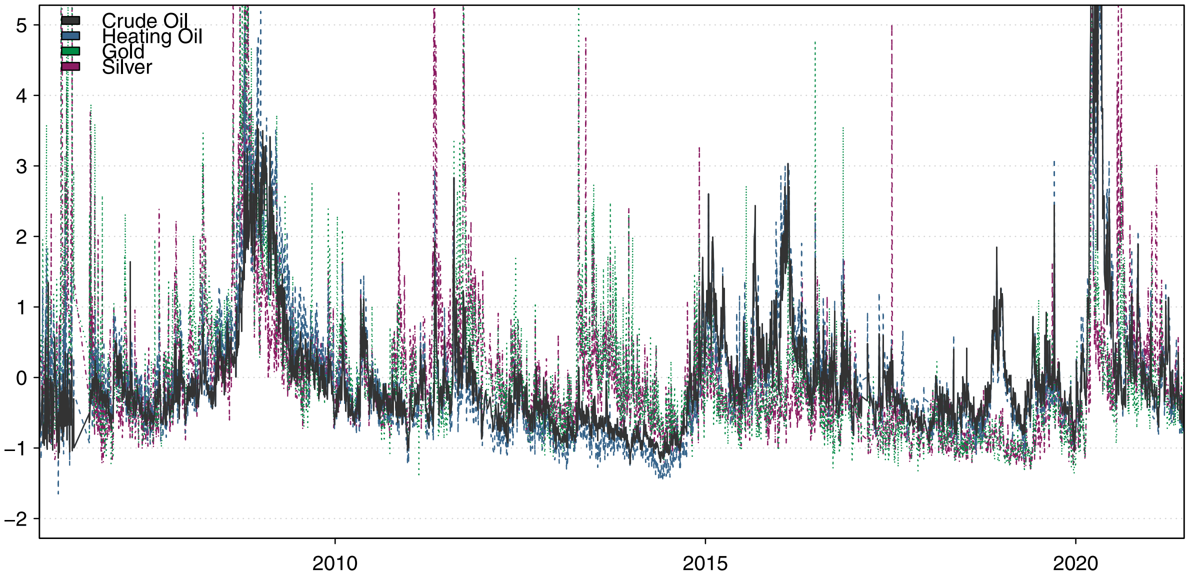

Fig. 1. Standardized realized volatility.

returns used in the analysis have been obtained from Risk Lab, maintained by Professor D. Xiu at Booth School of Business.[5] A detailed description of the methodology used to collect the data can be found in Xiu (2010) and Da and Xiu (2021). Risk Lab collects trades at their highest frequencies available. It cleans the data collected in this way based on the prevalent national best bid and offer that are available up to every second. The estimation procedure uses quasi-maximum likelihood estimates of volatility, building on moving-average models (see, Xiu, 2010; Da and Xiu, 2021).

Fig. 1 shows the standardized realized volatility for all four variables included in our network of study (i.e., crude oil, heating oil, gold, and silver). By way of example, the most significant spikes of crude oil standardized realized volatility are being observed around 2009, in the period between 2015 and 2016, around 2018, and then again at the beginning of 2020.

Table 1 presents the summary statistics of the employed series. We find that crude oil has the highest average realized volatility followed by silver, heating oil, and gold. The same holds for the variability of the series. Interestingly, all variables are significantly right-skewed, leptokurtic, and non-normally distributed. Additionally, we find that all variables are stationary, autocorrelated and exhibit ARCH errors at least on the 1% significance level. Finally, the unconditional Kendall τ correlation coefficients highlight that the highest co-movement occurs between crude oil and heating oil, followed by gold and silver. The correlations across the energy and precious metal series are positive and vary between 0.266 and 0.278. Thus, modeling the interrelationship employing a TVP-VAR model seems to be adequate.

4.1. Averaged connectedness results

We begin our analysis by presenting average realized volatility connectedness (or, spillover) measures. That is, the findings presented in Table 2 refer to average results across the entire period of study. Please note that we include results from three different quantiles (i.e., the 25th, 50th, as well as the 75th quantile) in order to ascertain whether extreme shocks have a more pronounced role to play regarding the linkages across the variables of our system of variables (or, network). Results are based on a QVAR model with a lag length of order 1 (i.e., according to the Bayesian Information Criterion) and a 20-step ahead generalized forecast error variance decomposition.[6]

It would be instructive to note that the elements in the main diagonal of Table 2 (i.e., irrespective of quantile) correspond to idiosyncratic (i.e., own-variable) shocks; while, off-diagonal elements, reflect the interaction across the four variables that we investigate. All figures in Table 2 are percentages and correspond to average connectedness values within the network. Note also that, Table 2 further incorporates the magnitude of the spillover shock each variable receives “FROM” others but also the magnitude of the spillover shock each variable contributes “TO” others. In turn, considering “Directional” values (i.e., both “FROM” and “TO”),

[5] For additional information regarding the database the reader is kindly directed to: https://dachxiu.chicagobooth.edu/#risklab.

[6] For robustness purposes, we have conducted a battery of QVAR models where the number of lags, forecast horizon, and the window-size vary. As shown in Figs. A.1, A.2, and A.3 all results appear to be qualitatively similar which underlines the robustness of our reported findings. Furthermore, Fig. A.4 illustrates the difference between our proposed approach and the quantile connectedness approach of Chatziantoniou et al. (2021) with respect to the TCI.

Table 1
Summary statistics.

	Crude Oil	Heating Oil	Gold	Silver
Mean	0.332	0.275	0.168	0.297
Variance	0.042	0.018	0.007	0.025
Skewness	4.847***	2.486***	2.353***	2.974***
	(0.000)	(0.000)	(0.000)	(0.000)
Kurtosis	42.709***	12.183***	8.647***	15.600***
	(0.000)	(0.000)	(0.000)	(0.000)
JB	268446.471***	24234.598***	13565.736***	39012.958***
	(0.000)	(0.000)	(0.000)	(0.000)
ERS	−6.019***	−6.269***	−6.747***	−6.810***
	(0.000)	(0.000)	(0.000)	(0.000)
$Q(10)$	12847.375***	12489.480***	9198.369***	7889.832***
	(0.000)	(0.000)	(0.000)	(0.000)
$Q^2(10)$	8145.447***	8714.840***	7329.678***	3957.809***
	(0.000)	(0.000)	(0.000)	(0.000)
Kendall's τ	Crude Oil	Heating Oil	Gold	Silver
Crude Oil	1.000	0.788	0.274	0.266
Heating Oil	0.788	1.000	0.278	0.266
Gold	0.274	0.278	1.000	0.683
Silver	0.266	0.266	0.683	1.000

Notes: ***,**,* denote significance at 1%, 5% and 10% significance level; Skewness: D'Agostino (1970) test; Kurtosis: Anscombe and Glynn (1983) test; JB: Jarque and Bera (1980) normality test; ERS: Elliott et al. (1996) unit-root test with constant; $Q(10)$ and $Q^2(10)$: Fisher and Gallagher (2012) weighted portmanteau test.

Table 2
Averaged dynamic connectedness table.

25*th*, 50*th*, 75*th*	Crude Oil	Heating Oil	Gold	Silver	FROM
Crude Oil	23.53, 30.25, 25.92	45.36, 48.02, 43.94	15.77, 11.24, 15.95	15.34, 10.49, 14.19	76.47, 69.75, 74.08
Heating Oil	51.97, 60.20, 57.02	16.34, 19.14, 12.88	15.92, 10.70, 15.13	15.77, 9.97, 14.97	83.66, 80.86, 87.12
Gold	18.79, 15.33, 22.80	16.12, 10.63, 17.23	26.25, 32.20, 25.37	38.84, 41.84, 34.61	73.75, 67.80, 74.63
Silver	17.53, 13.80, 19.73	15.54, 9.69, 15.63	39.04, 40.00, 34.96	27.89, 36.50, 29.68	72.11, 63.50, 70.32
TO	88.29, 89.33, 99.55	77.01, 68.34, 76.80	70.73, 61.94, 66.04	69.95, 62.30, 63.77	TCI
NET	11.83, 19.58, 25.47	−6.64, −12.52, −10.32	−3.01, −5.87, −8.59	−2.17, −1.20, −6.55	76.50, 70.48, 76.54

Notes: Results are based on a 250-days rolling-window QVAR model with lag length of order one (BIC) and a 20-step-ahead generalized forecast error variance decomposition. Each cell represents the result based upon the 25th, 50th and 75th quantile, respectively. The diagonal values represent the own-variance shares while the off-diagonal values represent cross-variance shares. FROM values highlight the influence all other variables j ($column$) have on variable i (row) while contrary the TO measures stand for the influence variable i ($column$) has on all other variables j (row). The difference between the TO and FROM measures results in the NET spillovers which if positive (negative) implies that variable i is a net transmitter (receiver) of shocks. The TCI describes the degree of network interconnectedness by the average TO or FROM values and hence ranges within zero and unity.

we may subsequently deduce if (on average) a variable is either a "NET" transmitter (i.e., positive sign) or a "NET" recipient (i.e., negative sign) of realized volatility spillover shocks within the network.

One of the main findings included in Table 2 is the value assumed by the total connectedness index (TCI), for the reason that, average total connectedness captured by the TCI, provides a first indication of the extent of co-movement among the four variables of interest. Specifically, we note that the TCI assumes the values of 76.50% (25th quantile), 70.48% (50th quantile), and 76.54% (75th quantile), respectively. In short, this implies that co-movement is very strong within the network (i.e., on average, connectedness assumes relatively large values). What is more, TCI measures suggest that 76.50% (25th quantile), 70.48% (50th quantile), and 76.54% (75th quantile) of the forecast error variance of each variable can be attributed to innovations in all other variables of the network. This finding further attests to our choice to investigate this specific network of variables, as apparently, all four variables are closely interrelated.

In turn, investigating both "directional" and "net" findings allows for the distinction between net transmitters and net recipients of shocks within the system. According to "Directional" findings presented in Table 2, crude oil is the main net transmitter of realized volatility connectedness shocks within the system contributing 88.29% (25th quantile), 89.33% (50th quantile) and 99.55% (75th quantile), respectively, "TO" all others. The corresponding "NET" findings for crude oil are: 11.83% (25th quantile), 19.58% (50th quantile), and 25.47% (75th quantile), respectively. In this regard, crude oil is (on average) the main net transmitter of realized volatility connectedness shocks within our network. In point of fact, crude oil is the only net transmitter within the network considering that all remaining "NET" figures for all other variables assume a negative sign. Furthermore, heating oil appears to be the main net recipient within the system (−6.64%, −12.52%, −10.32%), followed by gold (−3.01%, −5.87%, −8.59%) and silver (−2.17%, −1.20%, −6.55%).

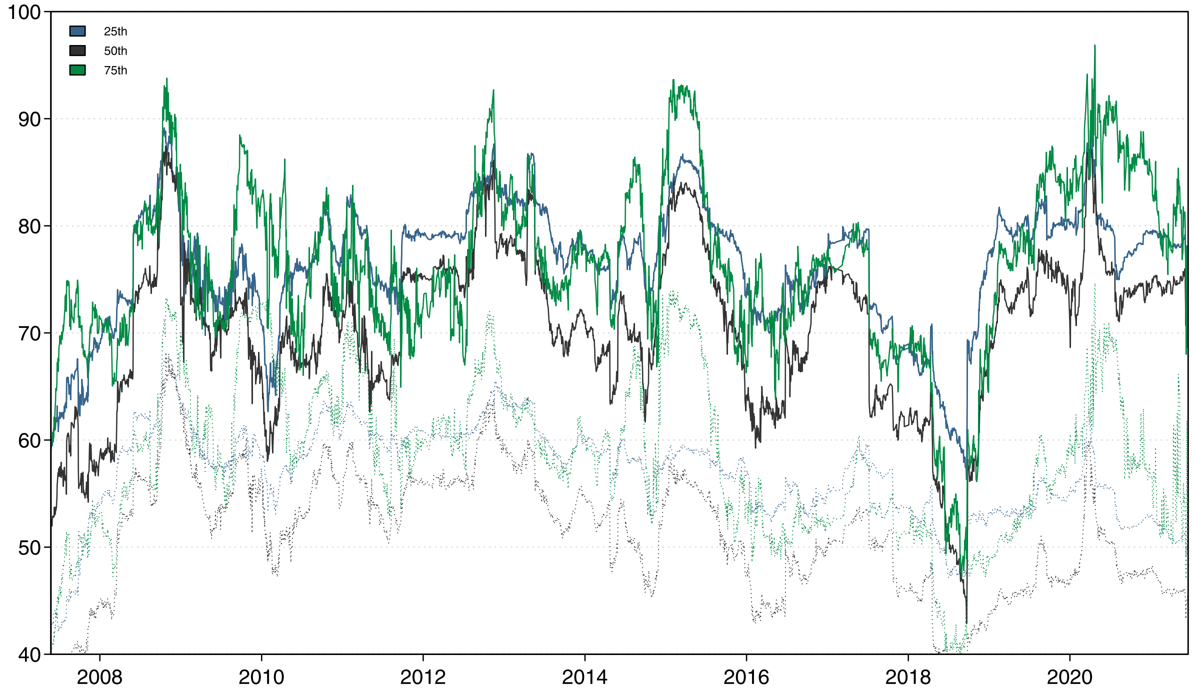

Fig. 2. Dynamic total connectedness.
Results are based on a 250-days rolling-window QVAR model with a lag length of order one (BIC) and a 20-step-ahead generalized forecast error variance decomposition. Dashed lines illustrate the results of the QVAR connectedness approach of Chatziantoniou et al. (2021).

The fact that crude oil is the main driver of volatility developments within this particular network of variables, is not dissociated from existing relevant literature. For instance, authors such as Mensi et al. (2021b) stress the strong correlation between WTI crude and heating oil and the contribution of the former to the volatility of the latter particularly during the period of the COVID-19 pandemic. Bouri et al. (2021), who also investigate volatility spillovers across energy and commodity futures markets report that crude oil is indeed a major transmitter of volatility shocks to a number of commodities including both gold and heating oil. In addition, Rehman et al. (2019) who investigate price dynamics between energy and other commodities provide evidence that crude oil prices have a strong and long-lasting negative impact upon both the market for gold and the market for silver. Besides, Guhathakurta et al. (2020) sustain that WTI crude oil is a main source of volatility for various metals markets (i.e., including gold and silver).

On a final note, average findings presented in Table 2 are not indicative of any major differences across quantiles. Nonetheless, it should be noted that crude oil becomes an all the more increasingly important net transmitter of realized volatility shocks in the network when shocks lie within the upper portion of the distribution (i.e., 19.58% “NET” connectedness for the 50th quantile and 25.47% for the 75th quantile, as opposed to only 11.83% for 25th quantile). The latter further suggests that big changes in the market for oil appear to have a more pronounced effect on the network of interest compared to smaller ones.

4.2. Dynamic total connectedness

However indicative average connectedness findings may be, they fail to capture the underlying dynamics of the period of study. That is, the average connectedness findings presented in the previous section, are actually “static” results that typically mask the unique effect on network connectedness exerted by major political, economic, or other events (e.g., the COVID-19 pandemic) that take place at specific points in time. In this regard, we proceed with our analysis by considering “dynamic” total connectedness results. These findings are illustrated in Fig. 2 and capture the evolution of the TCI across time and in the light of specific events. Note that the black line marks dynamic TCI at the 50% quantile, while the blue and the green lines delineate connectedness at the 25th and the 75th quantile respectively.

Prominent among our findings is the fact that the dynamic TCI assumes values within a range between approximately 40% and approximately 95% which is suggestive of the fact that connectedness within this network is time-varying and event-dependent. That is, major events of the period under investigation leave a unique mark upon the volatility dynamics of the network and affect the evolution of connectedness across time. Major milestones for dynamic TCI values include a peak around 2009, 2013, and again around 2015, a trough around 2018, as well as, a peak at the beginning of 2020. There are many major events that might have played a role in determining the magnitude of dynamic total connectedness, including the Global Financial Crisis (GFC) of 2007–08, the Syrian crisis which started in 2011 and peaked around 2015, the oil price collapse of 2014, the deterioration of trade relations between China and the US around 2018, as well as, the first stage of the COVID-19 pandemic at the beginning of 2020.

However, irrespective of events our main priority is to portray the extent to which these four commodity markets that we include in our study co-move across time. Apparently, with the exception of the trough period (i.e., around 2018) dynamic connectedness assumes relatively large values implying that these markets move closely together. In this regard, there is a strong potential for contagion dynamics to develop across these markets. One underlying mechanism and theoretical rationale for the presence of contagion is the herding behavior found in financial markets. When there is greater uncertainty, the magnitude of information spillovers from other related asset markets increases. This potentially explains the increased connectedness/spillover of risks between the four markets considered during the episodes of GFC and the recent COVID-19 pandemic.

Regarding the period of disentangling (i.e., the period of low connectedness levels), it is worth looking deeper into the literature regarding the recent trade conflicts between China and the US. Authors such as Chen et al. (2022) provide evidence that both gold and silver remained rather stable compared to other commodities during the 2018 trade dispute between China and the US, while gold was actually the most stable commodity of the period. Furthermore, Li and Lucey (2017) argue that political risk is key for periods when precious metals (i.e., including gold and silver) act as safe havens. In this respect, the disentangling that we observe around 2018 may be related to a more pronounced than usual role of precious metal markets as safe havens compared to energy commodities.

Looking at the dynamic results in Fig. 2 further facilitates a more effective comparison across the different quantiles. In particular, we note that the dynamic total connectedness at the third quartile tends to exhibit larger values compared to both the second and the first quartile. This is one advantage of our approach. It uncovers the variations across time and quartiles in the dynamic total connectedness between energy and precious metals markets.

What can further be evidenced by looking at the dynamic TCI across the different quartiles in Fig. 2 is that, the effect is not symmetric (i.e., the green and the blue lines do not fluctuate around approximately equal magnitudes across time). To put it differently, depending on the time interval under examination, it is either larger or small realized volatility shocks that lead to different market interconnectedness. For instance, it is rather evident that larger volatility shocks (i.e., the green line) result in higher levels of connectedness at the beginning of 2020 which coincides with the outbreak of the COVID-19 pandemic.

4.3. Net directional and net pairwise dynamic connectedness

We then turn to net directional and net pairwise dynamic connectedness findings. Results are given by Fig. 3 and Fig. 4, respectively. It should be noted that in line with the previous analysis, we present our findings for all three quartiles; that is, for the 25th quantile (i.e., blue line), the 50th quantile (i.e., black line) and the 75th quantile (i.e., green line), respectively. Furthermore, positive values on both Figures correspond to net transmitters, while negative values correspond to net recipients of realized volatility shocks. It would also be instructive at this point to note that, both directional and net pairwise spillovers—whereby, the variables of the network can be classified into either net transmitters or net recipients, largely reflect contagion dynamics. That is, this level of analysis shows how realized volatility shocks are being transmitted across our network with the passing of time. Variables (i) may shift between a net transmitting and a net receiving role depending on the time interval and (ii) may transmit (receive) in some quantiles (e.g. the 25th or the 75th) and receive (transmit) in others (e.g., the 50th) which would be indicative of the fact that the mere analysis of mean (or median) dynamics is not sufficient.

Findings illustrated in Fig. 3 suggest that the higher the quartile the more pronounced the net transmission mechanism. Furthermore, the net total directional and pairwise connectedness measures illustrate in most cases the same dynamics. We find that crude oil is persistently the main net transmitter of shocks while all other commodities in the network are rather net receivers of shocks. In point of fact, this holds irrespective of the quantile under investigation (although obviously, crude oil transmission exercises its strongest influence in the upper quantiles). All in all, based on the aforementioned analysis, the result regarding the net transmitting role of crude oil is rather anticipated.

In the case of heating oil, results indicate that it has been a net receiver of shocks until 2016 while afterward its net transmission power has increased revealing periods of being a net transmitter of shocks among all three quartiles. Moreover, we find that during the period in which it assumes the net transmitting role, it clearly transmits more in the 75th quantile. These findings are more or less in line with existing literature. In their recent study of connectedness across popular energy commodities, Gong et al. (2021) show that both crude oil and heating oil are net transmitters of volatility spillover shocks to other energy futures markets and further argue that the transmitting character of heating oil is gradually increasing starting approximately in 2007. Furthermore, Iqbal et al. (2022) investigate a group of energy and agricultural commodities and maintain that although heating oil has from time to time-shifted between the net transmitting and the net receiving role; together with crude oil, it acted as a consistent net transmitter of volatility spillovers during the period of the COVID-19 pandemic.

In the case of the precious metals markets, gold has been a net transmitter of shocks between 2011 and 2014, while silver has been on the transmitting end between 2011 and 2013 (i.e., for approximately the same period). In every other respect, they both have mainly been net receivers of shocks with only a few exceptions whereby they transmitted more than they received. Authors such as Umar et al. (2021) maintain that gold and silver are much more highly correlated (i.e., they exhibit a higher degree of connectedness) compared to other precious metals markets. This point could be useful in understanding why in our study we obtain similar results regarding the connectedness dynamics of these two markets (i.e., across time and quantiles).

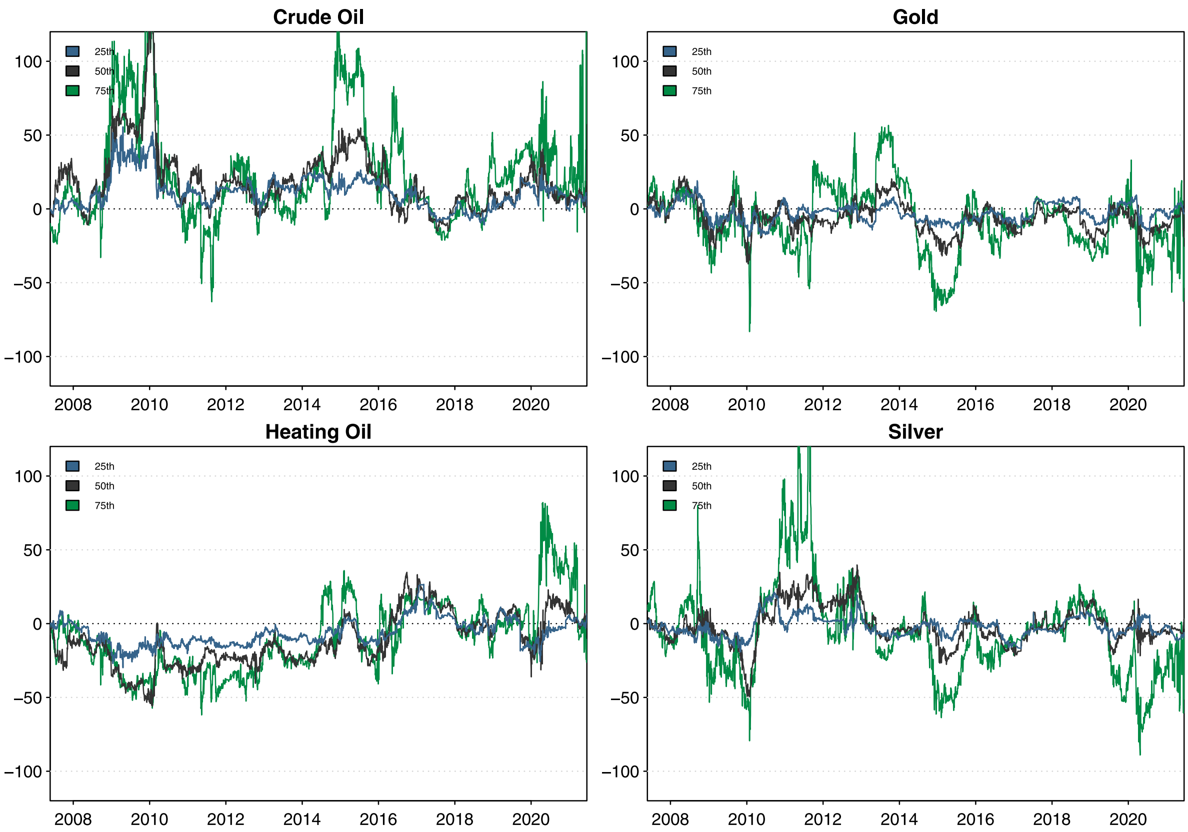

Fig. 3. Net Total Directional Connectedness.
Results are based on a 250-days rolling-window QVAR model with a lag length of order one (BIC) and a 20-step-ahead generalized forecast error variance decomposition.

Net pairwise dynamic connectedness is given by Fig. 4. These findings offer a more detailed view of directional connectedness findings presented above.

We note that, on a bilateral level, crude oil dominates all other variables for most of the time period of analysis with only a few exceptions (e.g., it receives volatility shocks from silver between 2011 and 2012 and also from heating oil around 2018 and in the beginning of 2020). The omnipotence of crude oil as a net transmitter within a network of petroleum futures markets has been recorded in the work by Jena et al. (2022). In this regard, it is not surprising that in our study crude oil is a rather persistent net transmitter of volatility vis-à-vis heating oil.

It is worth mentioning at this point that, in their investigation on psychological factors that affect precious metals markets, Lucey and O'Connor (2016) emphasize that 2011 was a year marked with high volatility for both the gold and the silver market. Furthermore, Pan (2018) in his study of bubble periods for precious metals markets, identifies two such periods for the market for silver; that is, the period between January-July 2008 and the period from November 2009 to January 2013. Silver also transmits to both heating oil and gold in the same period, but then gradually assumes a rather net-receiving role. This period aside, heating oil is therefore primarily a net transmitter of volatility shocks vis-à-vis the two precious metals markets. Overall, the pairwise transmission of shocks between gold and silver is more dynamic over time. We see that silver and gold markets are both net receivers and transmitters of shocks over the sample period.

5. Implications and extensions

This paper combines a quantile connectedness model in the spirit of Chatziantoniou et al. (2021) with the extended joint connectedness approach of Balcilar et al. (2021).

This novel approach appeals to macro-financial economists interested in modeling returns and volatility interlinkages across asset classes such as energy, precious metals, stocks, bonds, and foreign exchange markets. Understanding the spillover of risks in asset returns is a central area of research in the macro-finance literature. And using our approach in this area can provide valuable insights into how connectedness of risks varies across time and the conditional distribution of the asset return. Our approach also

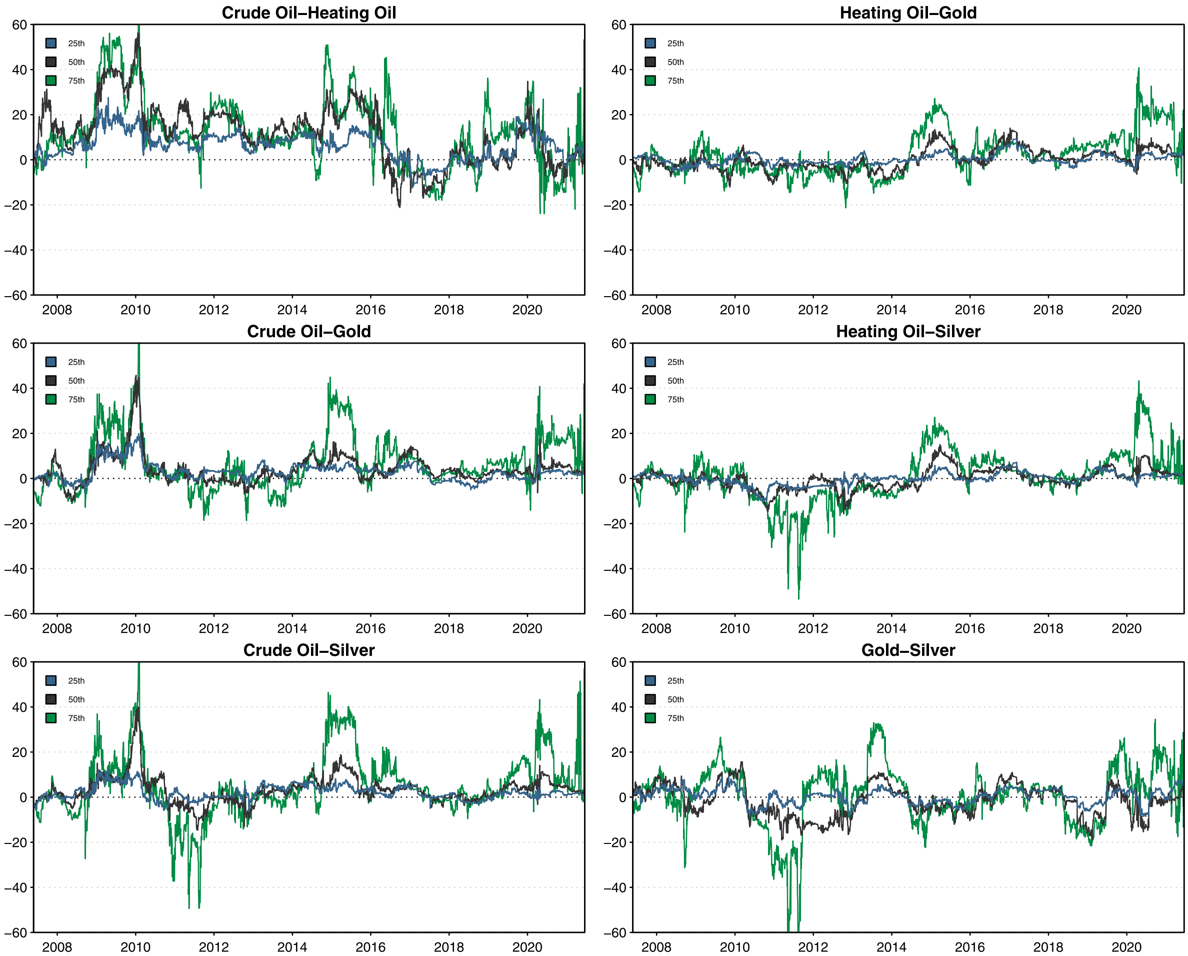

Fig. 4. Net Pairwise Directional Connectedness.
Results are based on a 250-days rolling-window QVAR model with a lag length of order one (BIC) and a 20-step-ahead generalized forecast error variance decomposition.

extends the recent research on risk spillovers (Tiwari et al., 2022); tourism volatility (Lee et al., 2022); volatility forecasting (Liu et al., 2021); and impact of oil supply shocks (Cai et al., 2022).

To put things into perspective, connectedness practically captures co-movement within a network of variables. In addition, the relevant spillover and connectedness measures, as initially described in the work by Diebold and Yilmaz (2009, 2012) can be very useful in distinguishing between net transmitters and net receivers of shocks (i.e., in this paper, we focus on volatility shocks) during periods marked by important geopolitical, economic or other events (e.g., the COVID-19 outbreak). In turn, the very fact that, in the light of certain events, some variables transmit, while others receive (on net terms), can be indicative of the fact that co-movement within the network varies with time—conditioned upon specific events. The latter, allows for mapping and classifying, for example, variables according to their response to specific events across time and offers useful insights regarding the potential response of these variables to similar events in the future.

It follows that from a portfolio diversification point of view, when the variables within the network are tradable assets then, including both net transmitters and net receivers within a portfolio of investments will subsequently improve portfolio diversification. In point of fact, the added value from considering connectedness for improving portfolio diversification has been reported by many authors (see, among many others, Antonakakis et al., 2019; Maitra et al., 2021; Mensi et al., 2021a; Jain et al., 2022). Bear in mind though that, periods characterized by very strong connectedness among the variables in the network are rather indicative of fewer diversification opportunities. It should also be noted that in the work by Broadstock et al. (2022)—who investigate a network of variables consisting of both green and conventional bonds, the authors introduce the minimum connectedness portfolio (MCoP) construction technique, which predicates upon minimizing pairwise connectedness and fares equally well compared to traditional techniques such as the minimum variance (MVP), the minimum correlation (MCP) or the minimum risk parity (RPP) portfolio approaches.

What is more, in this paper we consider refined quantile connectedness measures; that is, we take into account both the measurement adjustment introduced in Chatziantoniou and Gabauer (2021) and the refined normalization technique presented in Balcilar et al. (2021). More importantly, (i.e, irrespective of the aforementioned adjustments that lead to more accurate results) looking into the quantiles per se, offers potential investors a more detailed picture of the underlying dynamics. That is, a very common approach amongst portfolio managers interested in diversifying risk is the mean risk-return approach. Our results suggest though that, average risk-return dynamics are not always representative of market developments. Apparently, connectedness dynamics vary across quantiles, and therefore mean measures do not reflect the actual workings of market activity. In line with the analysis presented in White et al. (2015) we consider tail dependence directly—instead of just making assumptions about tail dynamics on the basis of some mean and volatility approach.

In this respect, extreme shocks (i.e., either low-volatility or high-volatility shocks) produce different results compared to average volatility shocks. As clearly evidenced in Fig. 2, connectedness appears to be stronger at the tails of the distribution throughout the period of study. We note for example that, during the early months of 2020 (i.e., the COVID-19 outbreak) connectedness assumes larger values for both the 75th (green line) and the 25th (blue line) quantiles, implying that during that particular period connectedness is more intense following extreme shocks (on either side of the distribution). What is more, the fact that during that period, connectedness was stronger for the 75th quantile practically implies that, the market maintained that this was in fact a high-volatility period. At the same time, highly volatile periods can be associated with market downturns (i.e., the bear market). Therefore, in line with authors such as Wang et al. (2016) and Jena et al. (2022) we also posit that the extent of interrelation within a network of variables greatly depends on changing market conditions (i.e., on the state of the market).

With this in mind, we may then ascertain what is the position of each variable during the high-volatility period at the beginning of 2020. By way of example, in Fig. 3, we notice that in early 2020, both crude oil and heating oil are net transmitters, while both gold and silver are net receivers of shocks; implying that, there could be diversification benefits from including all these assets in the portfolio. As earlier mentioned, diversification opportunities arise when connectedness is rather weak within the network. In early 2020 though, connectedness was strong in a period characterized by increased volatility. Despite that, we see that the variables in the network assume different positions (i.e., as either net transmitters or net receivers); a fact which in turn allows for diversification opportunities—despite the increased connectedness of the period. To put it differently, given the role of each market examined in this study—in the light of specific events, hedging could be possible by assuming different positions in the respective markets. Gold and silver, in particular, could act as invaluable hedges during periods of increased volatility.

Along a similar vein, results show that across all quantiles, crude oil is the main net transmitter of shocks in the network. Thus, from a diversification point of view, it would rather be imperative to hold crude oil in the portfolio as it would most likely provide a significant hedge against uncertainty. Note also that, investing in precious metals – gold and silver – can be an important inflation hedge, as precious metals are considered to be safe-haven assets. Overall, our study suggests that hedging objectives need to be modified according to the prevailing uncertainty level in financial markets.

As far as policymakers are concerned, they are often interested in preventing and controlling the spreading of risk across asset classes. Our results indicate that irrespective of financial conditions, monitoring volatility in the crude oil market would particularly be effective, considering potential spillovers of uncertainty from the crude oil to the precious metals markets. In this regard, specific regulatory policies aiming to curtail large swings in the oil market would have desirable regulatory effects. In addition, policymakers purport to contain contagion risk and foster greater stability in the market, particularly during very turbulent periods such as the outbreak of the COVID-19 crisis. A careful examination of our results with regard to the time-varying character of spillovers among the variables of the network could provide valuable insights toward achieving this goal. Consider, for example, a policymaker aspiring for financial stability. Understanding the source of volatility in precious metal markets could be instrumental. As previously mentioned, at the onset of the COVID-19 pandemic, volatility reached high levels and the market for crude oil transmitted considerably to both precious metal markets. It follows that policy efforts to contain volatility in the crude oil market during turbulent times could also contain volatility in the market for precious metals.

6. Concluding remarks

In this paper, we proposed a novel quantile vector autoregressive extended joint connectedness framework to study realized volatility spillovers between petroleum and precious metals commodities. The selected daily realized volatility series were crude oil, heating oil, gold, and silver for a period from 2006 to 2021. The empirical methods employed in this study allowed both for identifying potential deviations from mean connectedness dynamics (i.e., quantile-specific analysis) and for estimating more accurate connectedness measures (i.e., application of the extended joint connectedness approach).

Findings showed that crude oil was the main net transmitter of shocks across all quartiles (i.e., the 25th, 50th, and 75th quantile), while heating oil, gold, and silver were the primary net receiver of shocks. Interestingly enough, crude oil increased its strength as net transmitter across all quartiles, heating oil became a strong transmitter in the upper quantiles following the outbreak of the COVID-19 pandemic, while precious metals gradually became stronger net receivers of volatility shocks. Furthermore, we showed that the net total directional volatility connectedness in crude oil, heating oil, gold, and silver market varied across time and quantiles. We identified important periods when there was considerable deviation across quantiles for both net transmissions (e.g., during the period between 2014 and 2016 and early 2020, crude oil and heating oil transmit more in the upper quantile) and net receiving dynamics (e.g., following the outbreak of the COVID-19 pandemic, gold and silver receive more in the upper quantile).

With regard to implications for investors, the observed differences in connectedness dynamics across the different quartiles of the study, suggest that portfolio managers should not solely focus on mean risk-return models when formulating relevant diversification strategies; as apparently, mean measures do not always reflect the actual workings of market activity. In turn, policy implications are more likely associated with price stability in commodity markets, as according to the findings of our study extreme changes in both crude and heating oil appear to have a rather strong impact on the network under investigation, particularly in recent months.

Despite its rich contribution, our study has some limitations. In the present study, we do not explicitly disentangle the underlying mechanisms that derive spillovers in the system. In this regard, uncovering the information transmission mechanism between oil and precious metals volatility could be the focal point of future research. Another direction in which researchers can extend the present analysis is by statistically modeling the impact of policy on connectedness measures relating to crude oil and precious metals volatility that we report in this study.

Avenues for further research might also include adding different classes of commodities (e.g., agricultural or industrial) and looking into the quantile dynamics of a larger system. Furthermore, conducting portfolio analysis in light of extreme shocks in some of the markets of this network might also be an option.

CRediT authorship contribution statement

Juncal Cunado: Conceptualization, Writing – original draft, Methodology, Writing – review & editing. **Ioannis Chatziantoniou:** Conceptualization, Writing – original draft, Methodology, Writing – review & editing. **David Gabauer:** Software, Validation, Writing – review & editing. **Fernando Perez de Gracia:** Conceptualization, Writing – original draft, Methodology, Writing – review & editing. **Marfatia Hardik:** Conceptualization, Writing – original draft, Methodology, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix

See Figs. A.1–A.4.

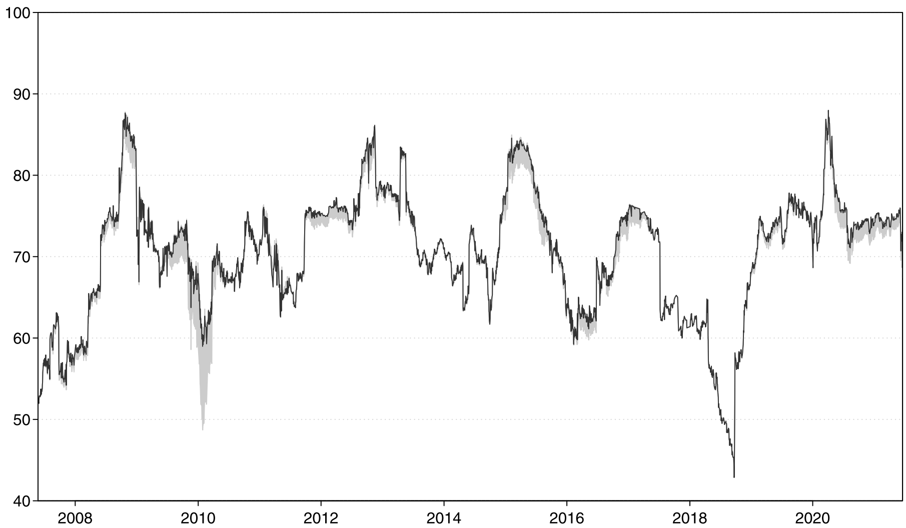

Fig. A.1. TCI sensitivity using different forecast horizons.
Results are based on a 250-days rolling-window QVAR(τ = 0.5) model with a lag length of order one (BIC) and different generalized forecast error variance decompositions. The forecast horizons range between 5 and 30 days.

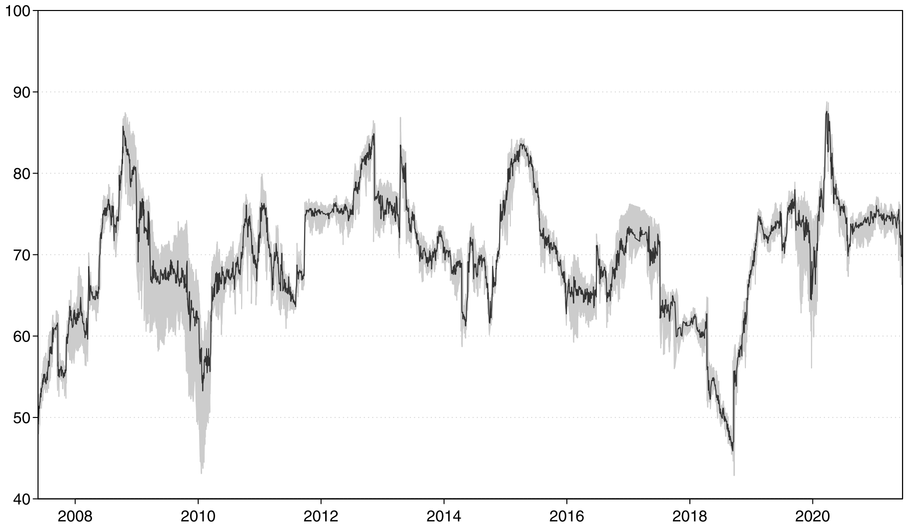

Fig. A.2. TCI sensitivity using different QVAR lag lengths.
Results are based on a 250-days rolling-window QVAR(τ = 0.5) model with different lag lengths and a 20-step-ahead generalized forecast error variance decomposition. The lag length varies between 1 and 5.

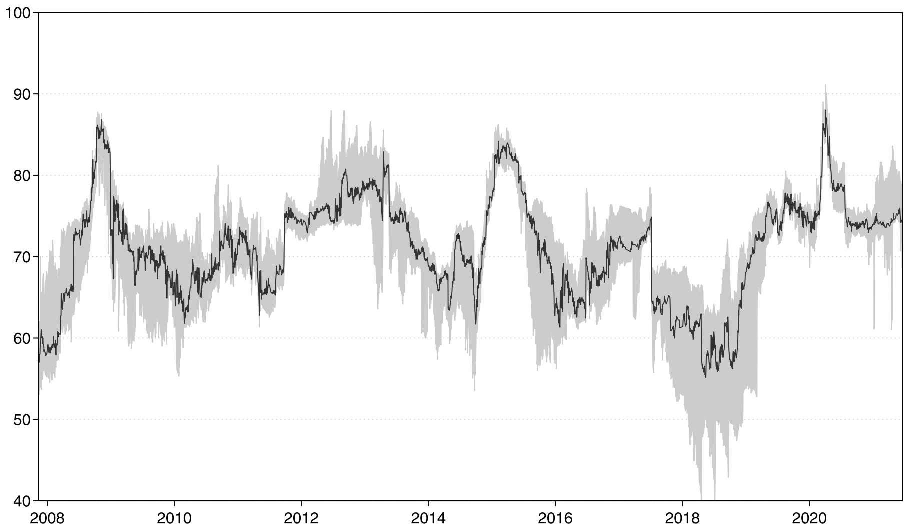

Fig. A.3. TCI sensitivity using different window sizes.
Results are based on different rolling-window QVARs(τ = 0.5) model with a lag length of order one (BIC) and a 20-step-ahead generalized forecast error variance decomposition. The window sizes are 150, 200, 250, 300, and 350.

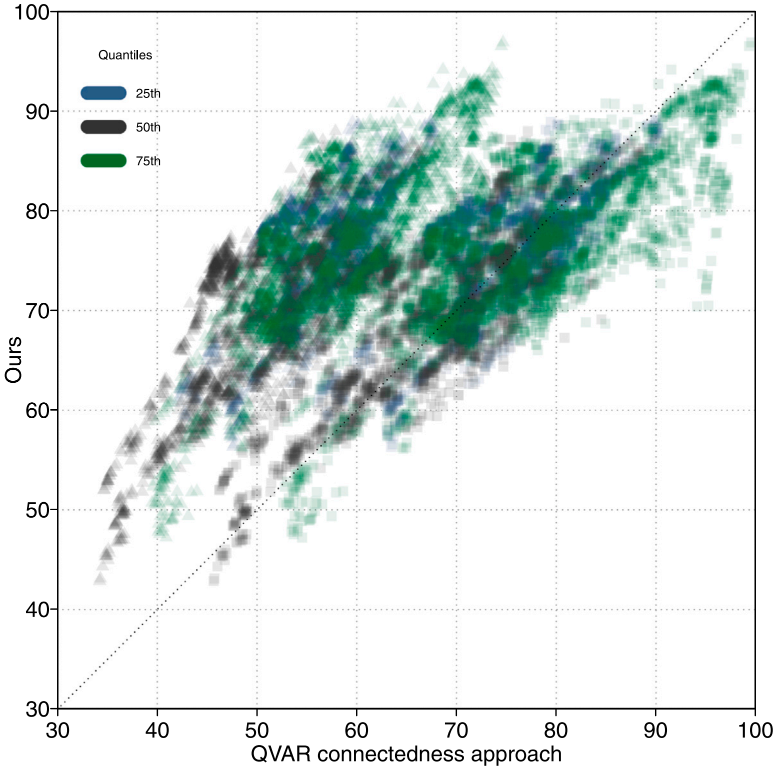

Fig. A.4. TCI comparison.
Results are based on a 250-days rolling-window QVARs(τ = 0.5) model with a lag length of order one (BIC) and a 20-step-ahead generalized forecast error variance decomposition. Triangles represent the QVAR connectedness approach of Ando et al. (2022) while squares represent the QVAR connectedness approach with the corrected TCI outlined in Chatziantoniou et al. (2021).

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