University of Pretoria
Department of Economics Working Paper Series

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Working Paper: 2021-80
November 2021

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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 TVP-VAR based connectedness approach of Antonakakis et al. (2020). The results suggest that market interconnectedness slightly increased 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 transmitter of shocks during the period prior to COVID-19 while heating oil, gold and silver became the main transmitters of shocks during the COVID-19 pandemic. On the contrary, natural gas and palladium have been the main receivers of shocks during the whole sample period, making these two commodities attractive hedging and safe-haven options for investors during the pandemic crisis. The implications of our findings for portfolio diversification and energy transition policies are discussed.

Keywords: Realized volatilities, energy market, metal market, TVP-VAR, dynamic connectedness.

JEL codes: C32, C50, G15.

1 Introduction

Since the Coronavirus disease 19 (COVID-19) was originated at Wuhan city of China in early December 2019 and it was officially declared to be a global pandemic in March 2020 by the World Health Organization (WHO), it has been the outbreak of a new global health and economic crisis. Due to the severity of the COVID-19 outbreak, its economic and financial impacts have been studied in comparison to those of the Global Financial Crisis (hereafter, GFC) occurred in 2008 (Shehzad et al., 2020; Chen and Yeh, 2021; Jebabli et al., 2021). For example, the stock market prices in the US (S&P500), in the UK (FTSE100) and in China (CSI300) dropped by a 14.9%, a 21.4% and a 12.1% from March 08 to March 18, 2020 (Chen and Yeh, 2021), a decrease comparable to that observed in 2008 (International Monetary Fund, 2020).

The energy and metal sectors have also been severely affected by the COVID-19 crisis, since it triggered acute declines in energy and metal prices due to the collapse in energy and metals demand caused by economic lockdowns imposed in numerous countries to prevent the spread of the pandemic (Salisu et al., 2021). In parallel to the sharp declines in oil and metal prices due to the decrease in the demand of 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 due to their lower volatility and correlation with other financial assets. In this sense, oil prices declined by 85% between January 22 and April 21, 2020 Wheeler et al. (2020), while copper and gold prices fell by a 14% and a 2% across March and April 2020, respectively (Laing, 2020). On the other hand, during the post COVID-19 time, the price indices of energy and metals rose by a 111% and 71%, respectively, between July 2020 and July 2021. These sharp movements in commodity prices have significantly increased the volatility of commodity prices as well. In this context, the analysis of the volatility spillovers among different commodity prices will have important policy implications. For example, the huge dependence of energy market on crude oil and its volatility could increase the 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 (i.e., copper) favoring the energy transition away from fossil fuels to a clean energy system. Furthermore, periods of high uncertainty in financial and oil markets are expected to increase the demand for assets for hedging purposes (Salisu et al., 2021).

According to the academic literature, global crisis trigger 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., 2021), implying a reduction in the diversification opportunities for investors. Zhang and Broadstock (2020), for example, find a significant increase in the connectedness degree in global commodity prices following the 2008 GFC, while Kang et al. (2017) also report that the volatility spillover across commodity markets become stronger after the GFC period. While the impact of the 2008 GFC on market connectedness has been widely examined, there is still scarce evidence on the degree of the market interconnectedness after the COVID-19 crisis. For example, Jebabli et al. (2021) find that the transmission across stock and energy markets during the COVID-19 crisis surpassed those observed during the GFC of 2008.

In this context, the objective of this paper is to analyze the degree of dynamic connectedness between energy and metal commodity prices in the pre- and post-COVID-19 era. Specifically, we will try to determine whether there has been an increase in the market interconnectedness, and hence, market risk, due to the pandemic outbreak. Furthermore, it will be interesting to establish whether the impact on market risk is similar or different to that observed during the GFC of 2008. Besides, it will allow us to understand how the diversification opportunities of investing in energy and metal commodities have changed since the beginning of the pandemic. Finally, our results will help investors and policy makers to understand the propagation mechanisms of realized energy and metal volatility.

This paper contributes to the extant literature in several ways. First, we use a full-fledged time-varying parameter vector autoregressive (TVP-VAR) based connectedness framework as suggested by Antonakakis et al. (2020) to calculate the degree of dynamic connectedness through the considered time period. As explained in Antonakakis et al. (2020), this method overcomes certain shortcoming of the connectedness measures proposed by Diebold and Yılmaz (2012, 2014). The estimation of this dynamic index will allow us to infer how the risk market has evolved through the whole sample period. This methodology was also used by Lin and Su (2021) to analyze the connectedness in energy markets following the outbreak of the COVID-19. The authors find a remarkable increase in the total connectedness in energy markets following the pandemic while on the contrary, Rehman and Vo (2021) find a low to moderate level of integration among three commodity classes (energy, precious metals and industrial metals) during the period 2010-2020. Second, we use daily annualized volatilities for several energy (crude oil, heating oil, natural gas), precious metals (gold, silver, palladium, platinum) and industrial metals (copper) from 2006 to 2020. This allows us to evaluate the hedging features of different commodities as a result of the COVID-19 pandemic. Additionally, in the context of the clean energy transition, our sample includes oil and natural gas (which represented in 2020 a 31.2% and a 24.7% of the world energy consumption) and copper, an industrial metal vital for the production of renewable energy resources (wind and solar technology or electronic vehicle, among others). Finally, we add to the emerging literature which examines the impact of COVID-19 on financial markets.

Our main results suggest that the market interconnectedness, and hence, market risk has only slightly increased following the coronavirus outbreak. As far as the propagation mechanisms of realized energy and metal volatility are concerned, the results indicate that energy commodities (crude oil and heating oil) and precious metals (gold and silver) are the main transmitters of shocks, while other metals (copper, palladium) and natural gas are the net receivers of shocks. It is important to highlight that the results indicate that while crude oil was the main transmitter of shocks in the period prior to 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 main results suggest that diversification opportunities still exist among the different commodities (Lahiani et al., 2021).

The remainder of the paper is structured as follows. Section 2 describes the employed methodology, Section 3 discusses the dataset and empirical results. Finally, Section 4 contains some concluding remarks.

2 Methodology

To investigate the time-varying linkages across realized energy and metal volatility, we estimate a TVP-VAR model with heteroscedastic variance-covariances[1]. Based upon the Bayesian information criterion (BIC), we have chosen a TVP-VAR(1) model which 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 vector 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 while $\boldsymbol{S}_t$ is a $K^2 \times K^2$ dimensional matrix. As the dynamic connectedness approach of Diebold and Yılmaz (2012, 2014) rests on the Generalised Forecast Error Variance Decomposition (GFEVD) of Koop et al. (1996)

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

and Pesaran and Shin (1998), it is required to transform the TVP-VAR to its TVP-VMA representation by 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 models explains the impact a shock in series j has on series i. This can be formulated by,

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

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

where $\boldsymbol{e}_i$ is a $K \times 1$ dimensional zero vector with unity on its ith position. As the $\phi_{ij,t}^{gen}(H)$ stands for the unscaled GFEVD ($\sum_{j=1}^{K}\phi_{ij,t}^{gen}(H) \neq 1$), Diebold and Yılmaz (2009, 2012) suggested to normalize 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 used to compute the total directional connectedness TO (FROM) all series from (to) series i. While the TO total directional connectedness illustrates the effect series i has on all others, the FROM total directional connectedness illustrates the impact all series have on series i. These connectedness measures can be computed by,

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

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

The difference between the TO and the FROM total directional connectedness results in the NET total directional connectedness of series i which determines the 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 influencing (influenced by) all others more than being influenced by (influencing) them and thus is considered as a net transmitter (receiver) of shocks indicating that series i is driving (driven by) the network.

The connectedness approach also provides further information on the bilateral level. 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 being influenced by (influencing) it.

The total connectedness index (TCI) is relevant as 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 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 which is within [0,1] - which has been the original definition - the TCI needs to adjust for the own variance share by,

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

A high (low) value indicates high (low) market risk.

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

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

The interpretation is identical to the TCI.

3 Empirical analysis

To achieve the objective of our study, we use up to date data on the daily realized volatility of returns for several energy (crude oil, heating oil, natural gas), precious metals (gold, silver, platinum, palladium) and industrial metals (copper) commodities covering the period 2006-2020 obtained from obtained from Risk Lab. Risk Lab is maintained by Professor Dacheng Xiu at Booth School of Business, University of Chicago (see, Figure 1). The data is downloadable from the following internet page: https://dachxiu.chicagobooth.edu/risklab. For an in-depth description of the data collection and the involved data transformations, a reader is referred to the internet page of Risk Lab. Here, we only reproduce very briefly some key properties of the data. Risk Lab collects trades at their highest frequencies available. It then 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 for realized volatility follows Xiu (2010). The estimation procedure uses quasi-maximum likelihood estimates of volatility, building on moving-average models. Nonzero returns of transaction prices are sampled up to their highest frequency available, where days with at least 12 observations are considered. For our analysis, we use the realized volatility estimates based on 5-minute subsampled returns of the NYMEX light crude oil, NYMEX heating oil No. 2, and 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 for realized volatility associated with the various commodities considered here.

[INSERT FIGURE 1 AROUND HERE]

As customary for empirical analysis, Table 1 renders some descriptive statistics for the daily volatilities of each of the eight commodities. Essentially, we find that natural gas exhibit the highest mean volatility, followed by crude oil and palladium, while these commodities also present the highest variances, suggesting that they have been the most volatile commodities in our sample during the considered period. The correlation matrix presented in Table 1 shows the high relationship between the following pairs of commodities: crude oil-heating oil, gold-silver, and palladium-platinum. These results seem to suggest that the characteristics of the energy and metal commodities for their industrial use are the main factor determining the degree of interconnection among the commodities during the analyzed period. Based on the Jarque and Bera (1980) test, all series are significantly non-normally distributed, a result which is supported by the skewness and kurtosis test statistics. Furthermore, all variables are significantly autocorrelated and exhibit ARCH errors. Thus, these results support the decision of modeling the volatility transmission mechanism between energy and metal markets applying a TVP-VAR model with time-varying variance-covariances.

[INSERT TABLE 1 AROUND HERE]

Table 2 shows the averaged connectedness measures among the commodities prior to and during the COVID-19 pandemic based upon the TVP-VAR model. The market interconnectedness, measured as the percentage of the forecast error variance in each of the 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 the COVID-19, suggesting a slight increase in the market risk following the COVID-19 pandemic outbreak, which is in line with the result that global crisis trigger 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 has been the only main transmitter of shocks prior to the COVID-19 period, transmitting a 82.28% while receiving only 58.62% leading to a net transmission of 23.66%. The second most relevant net transmitter of shocks is gold with only a third of the crude oil transmission equal to 8.40% followed by silver (8.10%) and heating oil (7.39%).

Heating oil, silver and gold have become the main transmitters during the COVID-19 pandemic with a net transmission of 25.97%, 22.63% and 15.59%, respectively, while 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 trippled its power while crude oil lost around one-third and hence, lost its leading position as net transmitter of shocks during the COVID-19 period. On the other hand, natural gas, palladium and platinum have assume 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.

[INSERT TABLE 2 AROUND HERE]

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 within 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 the commodity groups (energy, precious metals). It is also worth mentioning that natural gas presents the lowest averaged pairwise connectedness with all the other commodities. A closer look at the table suggests that the averaged pairwise connectedness measures between each of the energy commodities (crude oil, heating oil and natural gas) with each of the metal commodities (copper, gold, silver, palladium, platinum) were lower during the pandemic than prior to it. That is, a higher within group connectedness and a lower system-wide connectedness was found during the pandemic, suggesting lower diversification opportunities within each of the commodity groups and higher diversification opportunities between energy and metal commodities during the second period.

[INSERT TABLE 3 AROUND HERE]

While Tables 2 and 3 present averaged connectedness measures over the full time period,

Figure 2 estimates the dynamic total connectedness index across time which is essential as averaged connectedness measures mask the evolution over time and whether results are driven by economic or financial events. According to the dynamic total connectedness, we find that the market risk increased and reached its first peak in 2009, coinciding with the GFC. Although the marked interconnectedness also showed a peak in 2020 coinciding with the COVID-19 pandemic, this peak is lower and less persistent than that observed in 2009. That is, it indicates that diversification opportunities have been higher during the COVID-19 crisis than during the GFC, and it seems to imply that policy responses during the pandemic were more effective than those during the financial crisis (Benmelech and Tzur-Ilan, 2020). Besides those two peaks, 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 which was the worst year since the GFC when almost 7 trillion USD has been wiped off world stocks and emerging markets. Those events are in line with the academic literature on connectedness, market risk and global crisis.

[INSERT FIGURE 2 AROUND HERE]

Furthermore, Figure 3 shows that crude oil was the main net transmitter of shocks during the GFC, while heating oil, gold and silver were the main net transmitters of shocks during the pandemic outbreak. That is, crude oil lost its role as a leading transmitter of shocks during the COVID-19, which might suggest that the industrial metal market is more immune to the high volatility observed in crude oil prices. Still, it should be noted that crude oil increased its power at the beginning of 2008, around 2012 (coinciding with the Arab sprint) and substantially decreased in 2015. During the COVID-19 outbreak, its net transmission behavior increased again which might be linked to the crude oil oversupply and the subsequent price drop in WTI that reached first time in history a negative price in April, 2020. Furthermore, we find that natural gas, palladium and platinum are almost constantly net receivers of shocks.

[INSERT FIGURE 3 AROUND HERE]

4 Concluding remarks

This paper examines the degree of dynamic connectedness between energy and metal commodity prices in the pre and post COVID-19 era, using up to date daily data on energy (crude oil, heating oil, natural gas), precious metals (gold, silver, palladium, platinum) and industrial metals (copper) from 2006 to 2020. The results are obtained using a fully-fledged time varying parameter vector autoregressive (TVP-VAR) version, as suggested by Antonakakis et al. (2020), which overcomes certain shortcoming of the connectedness measures proposed by Diebold and Yılmaz (2012, 2014).

The main results are the following. First, we find that averaged market interconnectedness, and hence market risk, has only slightly increased following the outbreak of COVID-19. In fact, the dynamic connectedness increased from an average of 67.43% to an average of 68.12% during the 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, while this index also reached another peak in 2021 which coincides with the Arab crisis, in 2015 marking the European sovereign debt crisis, 2018 illustrating the worst year on the financial market since the GFC and in 2020 when the COVID-19 pandemic emerged. Those events are in line with the academic literature on connectedness, market risk and global crisis (Zhang and Wei, 2010; Ahmadi et al., 2016; Kang et al., 2017; Umar et al., 2019, 2021; Tan et al., 2021). Second, and based on the same dynamic analysis, the results also suggest that the increase in market connectedness, or market risk, was lower and less persistent during the COVID-19 outbreak than during the GFC. This result has relevant policy implications, since it seems to suggest that policy responses during the pandemic were more effective than those during the financial crisis (Benmelech and Tzur-Ilan, 2020; Wei and Han, 2021). It also indicates that diversification opportunities were higher during the COVID-19 crisis than during the GFC.

Third, and as far as the averaged pairwise connectedness measures prior to and during the COVID -19 pandemic are concerned, 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 the commodity groups (energy, precious metals). This result supports the finding of Diebold et al. (2017). Moreover, the averaged pairwise connectedness measures between each of the energy commodities (crude oil, heating oil and natural gas) with each of the metal commodities (copper, gold, silver, palladium, platinum) were lower during the pandemic than prior to it.

Fourth, and at the individual commodity level, the results indicate that crude oil has been the main transmitter of shocks prior to the COVID-19 period, transmitting 23.66%, while heating oil, silver and gold have been the main transmitters during the COVID-19 pandemic by transmitting 25.97%, 22.63% and 15.59%, respectively. That is, crude oil lost his role as a leading transmitter of shocks during the COVID-19. On the other hand, natural gas, palladium and platinum have assumed a net receiving position with palladium and natural gas being the main net recipients of shocks during the periods prior to and during the COVID-19 outbreak.

Finally, and in the context of the high dependence of energy market on crude oil, the relatively lower connectedness between energy market (crude oil, natural gas, heating oil) and industrial metals (copper) found during the most recent period seems to suggest an increase in the immunity of the industrial metal market to the high volatility observed in the energy market, especially in crude oil prices.

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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)
	Crude Oil	Heating Oil	Natural Gas	Copper	Gold	Silver	Palladium	Platinum
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

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)

Notes: Results are based on a TVP-VAR model with 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 the COVID-19 period.

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)

Notes: Results are based on a TVP-VAR model with 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 the COVID-19 period.

Figure 1: Realized volatilities

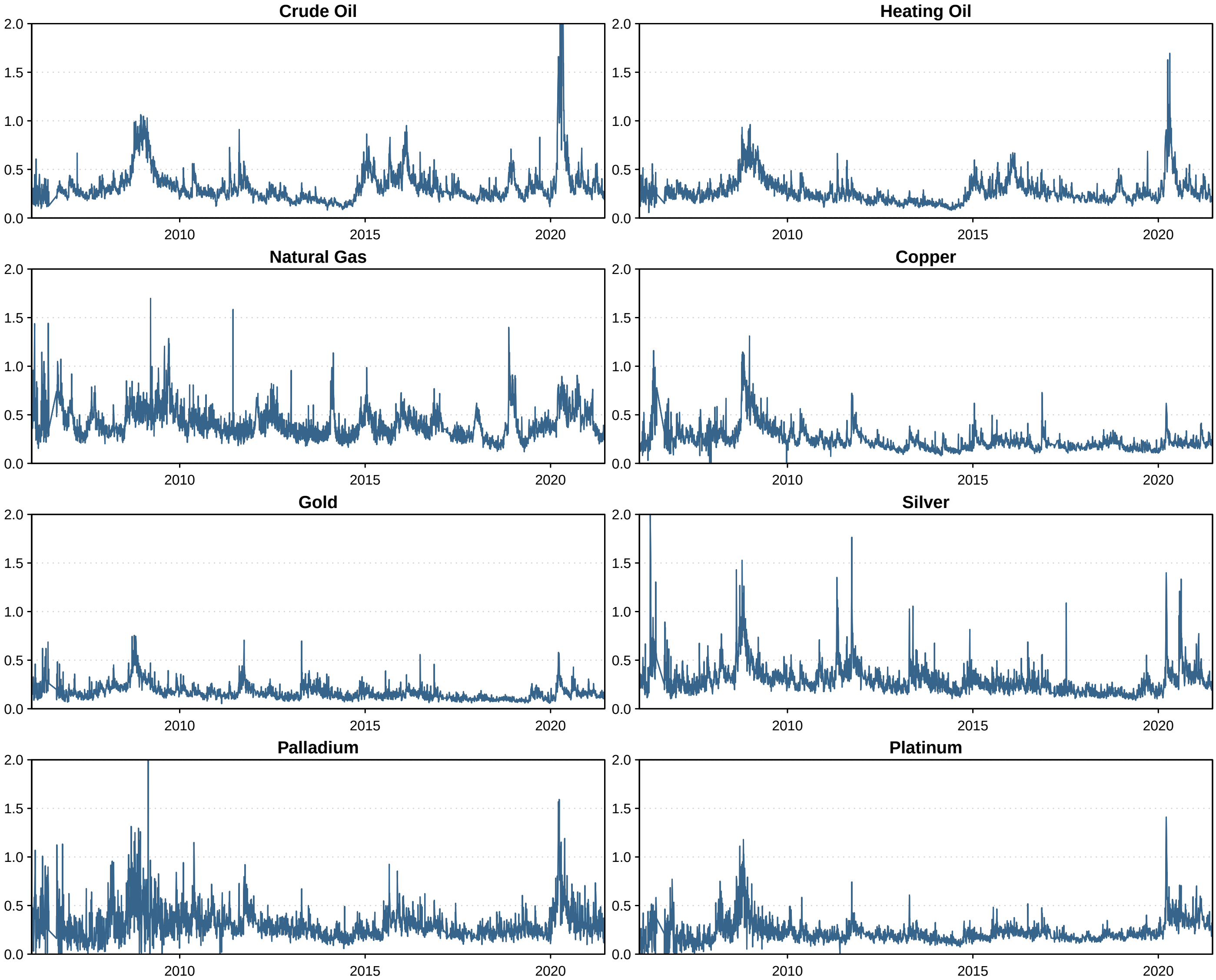

Figure 2: Dynamic total connectedness

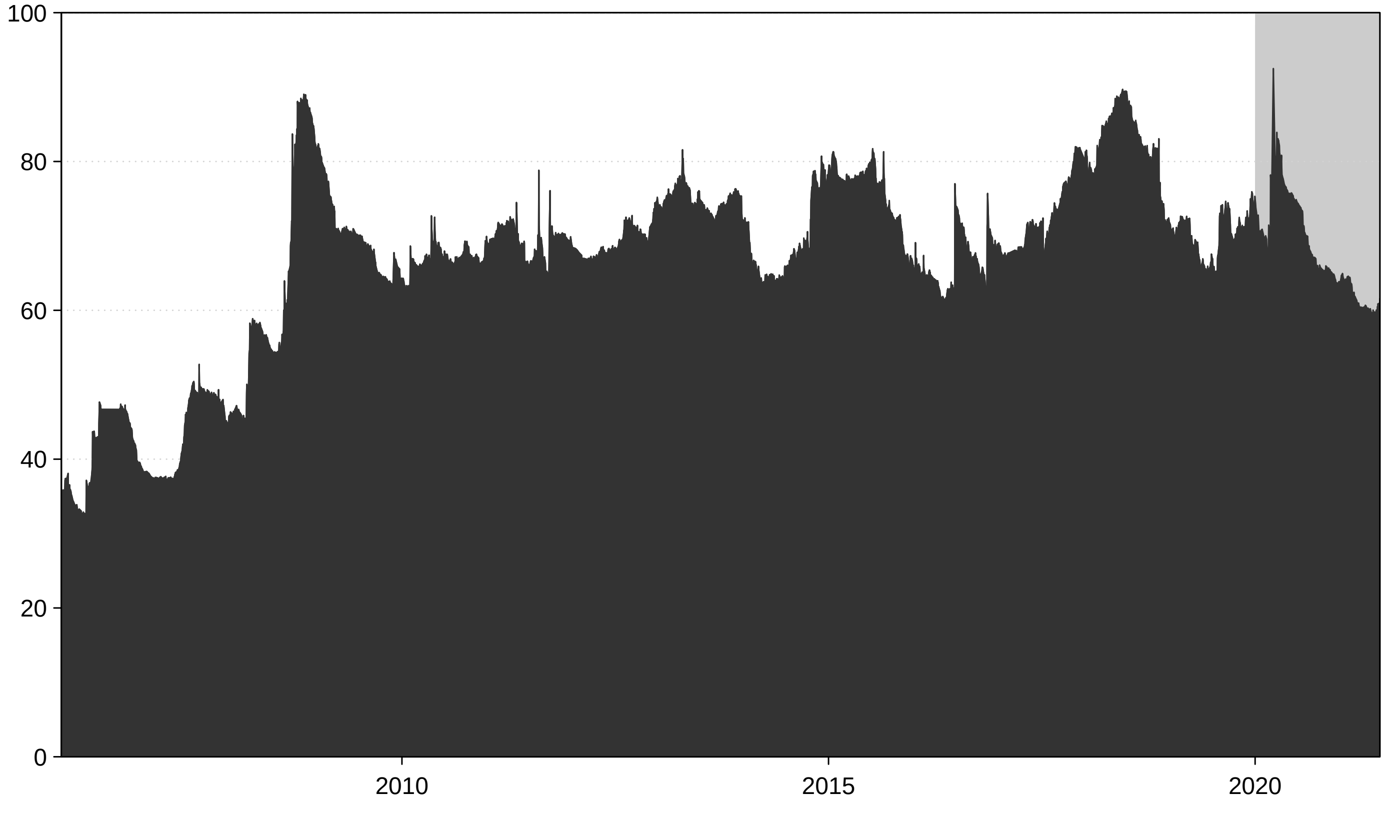

Figure 3: Net total directional connectedness measures