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Tail risk connectedness in the refined petroleum market: A first look at the impact of the COVID-19 pandemic☆

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ABSTRACT

This study provides a novel framework for analysing systematic tail risk transmission mechanisms by combining the Conditional Autoregressive Value-at-Risk (CAViaR) model with the recently developed Time-Varying Parameter Vector Autoregressive (TVP-VAR) based connectedness approach. We estimate dynamic spillovers across two crude oil (Brent and WTI) and four refined petroleum product (gasoline, heating oil, jet fuel and propane) prices from January, 17, 1997 to December 11, 2020. Results show that, both heating oil and kerosene are persistent net transmitters of shocks, signifying the important role of liquidity in the relevant markets. In addition, the role of either crude oil type appears to shift around 2009 following developments in the energy market. Overall, our findings suggest that, total connectedness are positively affected by major crisis episodes and that the recent COVID-19 pandemic appears to have the potential to propel both tail risk and exposure to losses to levels akin to those of the Global Financial Crisis of 2007–2008.

1. Introduction

In this study, we measure systematic tail risk spillovers between crude oil and refined petroleum products prices over the period 1997–2020. We propose the research hypothesis that tail risk connectedness between crude oil and refined petroleum products rises with major crisis episodes such as COVID-19. Tail risk connectedness facilitates the examination and assessment of spillovers stemming from extreme positive or negative events over time.

This study is associated with the literature on petroleum return (or volatility) spillovers (see, Atukeren et al., 2021; Asai et al., 2020; Dahl et al., 2020; Liu and Gong, 2020; Chatziantoniou et al., 2020; Mensi et al., 2020; Baruník et al., 2015). In addition, our study is also related to the broader strand of volatility spillovers literature (see, Atukeren et al., 2021; Dahl et al., 2020, and references therein). For instance, Atukeren et al. (2021) and Dahl et al. (2020) evaluate petroleum volatility spillovers predicating upon the index initially proposed by Diebold and Yilmaz (2009, 2012) and utilizing Granger causality and EGARCH models, respectively.

We are primarily motivated by the crude oil price dynamics developed during the COVID-19 pandemic when the US crude oil price of the benchmark West Texas Intermediate (WTI) futures fell into negative territory for the first time in its history closing at -$37.63/bbl (The Economist, 2020). We are also motivated by studies such as Asche et al. (2003) who emphasize the link between crude oil prices and prices of several refined petroleum products and further consider the possibility of integration among different refined petroleum markets. More recent studies, such as Ederington et al. (2019), provide a thorough overview of the linkages between crude oil prices and petroleum product prices.

In this regard, the extreme behaviour of crude oil prices in the light of the COVID-19 outbreak (Commodity Futures Trading Commission, 2020) has rekindled the interest regarding the impact sudden price drops have on refined petroleum product prices. Negative crude oil prices also draw the interest in the transmission mechanism of extreme volatility and tail risk spillover connectedness during periods of uncertainty in the markets of refined petroleum products. Only a few studies

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have addressed the adverse effects COVID-19 have on the dynamics between stock prices and energy variables (Abuzayed and Al-Fayoumi, 2021; Huang and Liu, 2021; Jebabli et al., 2021; Si et al., 2021; Zhang et al., 2021) or oil price volatility (Devpura and Narayan, 2020). Tail risk connectedness offers an indication of uncertainty-contagion within a network of variables, as it captures the transmission of greater exposure to losses. In this regard, utilizing a framework that analyses tail risk connectedness is crucial when investigating contagious effects across crude oil and refined petroleum product prices.

We contribute to the existing literature in various ways. First, considering that the COVID-19 pandemic has increased oil price volatility (see, Devpura and Narayan, 2020), we investigate, what is the specific impact of tail risk uncertainty in the crude oil market on the respective uncertainty in the market for refined petroleum products. Second, considering the possibility that refined petroleum markets are indeed integrated to some extent (see, Asche et al., 2003) we further examine, how tail risk uncertainty propagates across various refined petroleum products. In close relation to this point, by including (i) four petroleum refined products; that is, gasoline, heating oil, jet fuel and propane, and (ii) two popular crude oil types (i.e., Brent and WTI), we provide a broader picture of the relevant market interconnectedness. By contrast, most relevant studies have so far focused primarily on heating oil or gasoline prices (see, for example, Kaufmann and Laskowski, 2005; Baruník et al., 2015; Ederington et al., 2020). Third, we add to the relatively scarce strand of existing literature that measures tail risk connectedness, by combining, for the first time, two recently developed methods, namely, the Time-Varying Parameter Vector Autoregressive (TVP-VAR) Connectedness and the Conditional Autoregressive Value-at-Risk (CAViaR) methods. Finally, we make use of a dataset that runs throughout the period from January 1997 to December 2020 which is a sufficient period to thoroughly investigate the interaction among the variables of interest as (i) it incorporates a number of major geopolitical events – thereby, facilitating comparison of the effects of major events across time – and (ii) it offers an account for almost throughout 2020; that is, the whole year when the COVID-19 pandemic had a strong bearing on rising uncertainty in the economic environment.

Findings suggest that contagion is indeed a factor that drives developments in this network of variables. To put differently, we find evidence that greater exposure to tail risk and losses can be attributed to connectedness dynamics among the series of this study. Please note that, increased connectedness in this study implies that it is easier for greater exposure to losses in one commodity market to migrate and affect exposure to losses in other commodity markets. In turn, we provide evidence that connectedness increases with major crisis episodes and that the recent pandemic has the potential to leave an indelible mark in the respective markets of interest. Apparently, both heating oil and kerosene are persistent net transmitters of shocks into the system, while both gasoline and propane assume a persistent net receiving role. With reference to the COVID-19 pandemic period, averaged results show that all pairwise connectedness indices increase substantially while, dynamic connectedness measures reach unprecedented heights in the period marked by the COVID-19 outbreak. These findings are important for the relevant stakeholders to attain a better understanding of developments in the respective markets and to plan ahead considering potential exposure to losses.

We also test our findings for robustness. In particular, we estimate the underlying transmission mechanism on both the 2.5% and 10% CAViaR series. Overall, we find that our results and therefore their corresponding implications, hold across the different settings.

The remainder of the paper is organized as follows. In Section 2, we review the related literature on modelling refined petroleum prices and volatilities. We then look at the employed dataset in Section 3. In Section 4 we describe (i) the methodology of the CAViaR and (ii) the TVP-VAR based connectedness approach. Next, we set out and discuss empirical results in Section 5. Finally, Section 6 concludes the study.

2. Brief overview of the literature

Our study is closely related to the new strand of the literature which focuses on the economic effects of COVID-19 (see the novel survey by Padhan and Prabheesh, 2021, and references therein). Only few studies have addressed the adverse effects of COVID-19 on the dynamics between stock prices and energy variables (see, for example, Abuzayed and Al-Fayoumi, 2021; Huang and Liu, 2021; Jebabli et al., 2021; Si et al., 2021; Zhang et al., 2021) or oil price volatility (Devpura and Narayan, 2020). It should also be noted that the recent financialization of the market for oil (see, Silvennoinen and Thorp, 2013) has brought the market for oil closely together with financial markets. Hence, developments in each one of these markets has the potential to affect developments in the other.

With regard to the broader impact of COVID-19 on economic activity and financial markets, authors such as Abuzayed and Al-Fayoumi (2021) identify that the effect of oil price systemic risk on Gulf Cooperation Council stock market returns was significantly larger during COVID-19 than before the pandemic. Huang and Liu (2021) observe that the effect of COVID-19 on stock price crash risk is less severe for state energy owned enterprises than for non-state owned enterprises. Jebabli et al. (2021) evaluate the volatility spillovers between energy and stock markets during crisis periods. Their findings suggest that transmission of volatility during the COVID-19 pandemic crisis exceeded the levels that were recorded throughout the Global Financial Crisis of 2007–2008 (GFC, hereafter). Si et al. (2021) focus on the risk spillover effects of COVID-19 on the Chinese energy industry utilizing a high-dimensional and time-varying factor augmented VAR model. They observe that the net volatility spillovers of the pandemic period remain positive to all underlying energy sectors. Zhang et al. (2021) analyse the dynamic spillovers between energy and stock markets and document that COVID-19 had a significant positive impact on spillover effects.

With a particular focus on COVID and the market for oil, Bourghelle et al. (2021) put forward the argument that the COVID-19 pandemic has had a tremendous impact on the market for oil and that it brought about two major developments (i.e., a reduction in global demand for oil and supply-side disputes between oil producing countries) that both resulted in increased oil price volatility. Besides, Devpura and Narayan (2020) also propose a connection between oil price volatility and COVID-19. Using hourly time-series data from July 2019 to June 2020, Devpura and Narayan (2020) show that COVID-19 has contributed to oil price volatility. Their results are robust to alternative measures of volatility and employment of controls for volatility. Furthermore, Zhang et al. (2021) documents that the COVID-19 outbreak has had a positive and weakly persistent effect on the volatility of oil stock prices considering the China national Petroleum share price index. In turn, Narayan (2020) provides evidence that when COVID-19 cases reach a certain threshold the effect of COVID-19 on oil prices becomes stronger and that it is negative oil price news that affect oil prices the most (again, after a certain threshold). With reference to the nature of the impact of the COVID-19 crisis per se, Gil-Alana et al. (2021) show that during the first months of the COVID-19 crisis the price of oil series is mean reverting, suggesting that any shocks should have only a transitory effect. Overall, we add to this strand of the literature which focuses on the impact of the COVID-19 pandemic on the market for oil, by considering contagion dynamics among a network of variables that consists of the tail risk series of two popular crude oil benchmarks, as well as, four refined petroleum products for a sample period characterized by major geopolitical, economic and other events — including the outbreak of the COVID-19 crisis.

On a final note, from a methods point of view, our work is related to the strand of the literature which discusses energy spillovers and price dynamics in the spirit of the seminal contribution by Diebold and Yilmaz (2009, 2012). An extensive discussion of dynamic connectedness methods is beyond the scope of this study; however, we should mention certain milestones relating to the development of connectedness studies

in general. In this regard, we start with the seminal work by Sims (1980) who introduced the Vector Autoregressive (VAR) model and the corresponding forecast error variance decompositions (FEVDs). In turn, Diebold and Yilmaz (2009, 2012) introduced elaborate ways to summarize FEVDs, in order to develop both their spillovers (i.e., predicating upon a Cholesky-type VAR) and connectedness (i.e., predicating upon a generalized VAR) empirical approach. In their work, Diebold and Yilmaz (2009, 2012) derive their dynamic results based on the typical rolling-windows technique. Nonetheless, the introduction of Bayesian time-varying parameter vector autoregressions (TVP-VAR) by authors such as Koop and Korobilis (2014) paved the path for the development of alternative ways to produce dynamic results. More recently Antonakakis et al. (2020) showed that dynamic connectedness measures based upon TVP-VARs are more accurate than rolling-window VAR retrieved results. With these methodological milestones in mind, in this present study we follow the above mentioned line of existing empirical research and we further extend the applications of said literature by considering tail risk connectedness (see, for example, Yang et al., 2020; Ji et al., 2018; Zhu et al., 2020; Peng et al., 2018; Du and He, 2015). In particular, our methodological approach of tail risk spillover is closely related to Zhang et al. (2020) who examine the systemic risk spillovers and connectedness in the sectoral tail risk network of Chinese stock market; Hanif et al. (2021) who evaluate tail dependence risk and spillovers between oil prices and food prices and Xu et al. (2021) who investigate the tail risk interconnectedness among cryptocurrencies. All these studies employ alternative approaches in order to measure extreme risk spillovers. With reference to the employed empirical methods, Zhang et al. (2020) use a conditional value at risk and single index model; Hanif et al. (2021) adopt a VaR and CoVaR methods while, Zhu et al. (2020) employ a high-dimensional non-parametric method to measure the extreme risk spillovers.

In retrospect, our paper extends previous related literature given our specific aim to evaluate the dynamic nexus between oil and refined petroleum product prices using (i) a measure of tail risk connectedness; (ii) relevant selected refined petroleum products and crude oil price variables; and (iii) a dataset that runs from January 1997 to December 2020 encompassing the initial stages of the pandemic.

3. Empirical data

We use weekly data of WTI (Cushing, OK WTI spot price FOB in USD per Barrel), Brent (Europe Brent spot price FOB in USD per Barrel), gasoline (New York Harbor conventional gasoline regular spot price FOB in USD per gallon), heating oil (New York harbor No. 2 heating oil spot price FOB in USD per gallon), kerosene (Gulf coast kerosene-type jet fuel spot price FOB in USD per gallon), and propane (Mont Belvieu, TX propane spot price FOB in USD per gallon). This dataset comprises two crude oil energy commodities (WTI and Brent) and four refined petroleum products prices (gasoline, heating oil, jet fuel and propane) over the period January 17, 1997 to December 11, 2020. The raw data has been collected from the U.S. Energy Information Administration.

Fig. 1 illustrates the 5% VaR tail risks which gives a first visual impression of the co-movements across the employed time series.

In a subsequent step, we compute the first log differences of the tail risk which can be interpreted as the changes in expected uncertainty. Table 1 reveals that the mean of all tail risk changes are negative except for propane. Additionally, all series are significantly right skewed, leptokurtic and non-normally distributed on the 1% significance level. Of main importance is also the fact that all series are stationary on the 1% significance level according to the Stock et al. (1996) unit-root test which indicates that all prerequisites of estimating a TVP-VAR model are met. Notably, we find that all unconditional correlations are positive meaning that a positive (negative) change in one variable is likely to occur with a positive (negative) change in another variable. Highest degree of correlation is observed across WTI, Brent, heating oil, and kerosene whereas the lowest correlations are observed with respect to propane and gasoline.

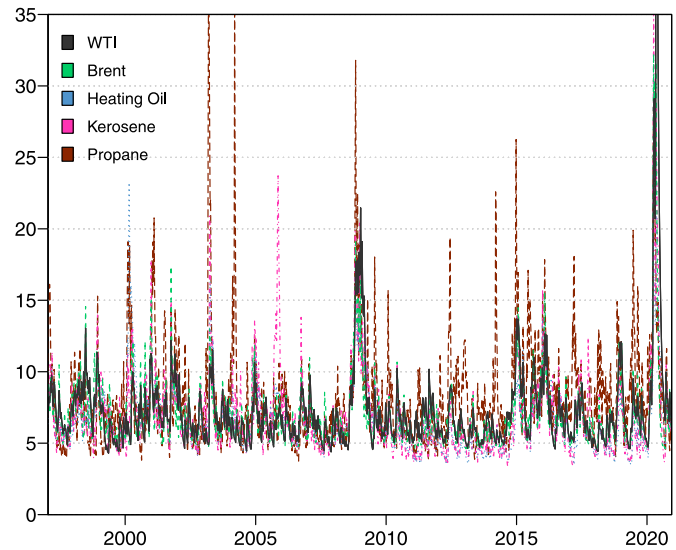

Fig. 1. Energy Price tail risk.
Notes: Results represent the 5% VaR using the asymmetric slope CAViaR model.

4. Methodology

4.1. Conditional Autoregressive Value-at-Risk (CAViaR)

Contrary to most existing approaches that measure Value-at-Risk (VaR) by estimating the distribution of the returns first and then by recovering its quantiles in an indirect way, we follow the asymmetric slope CAViaR approach proposed by Engle and Manganelli (2004) which estimates the VaR in a direct fashion. From our perspective this method is the most flexible among the three relevant options as the slope CAViaR approach allows for asymmetric effects which is not the case for either the symmetric absolute value or the indirect GARCH(1,1) approach. Furthermore, the asymmetric slope CAViaR model assumes that the VaR of a certain quantile follows an autoregressive process which can be mathematically formulated as follows:

$$f_{\alpha,t}(\beta) = \beta_0 + \beta_1 f_{\alpha,t-1}(\beta) + \beta_2 x^{+}_{t-1} + \beta_3 x^{-}_{t-1} \tag{1}$$

where $f_{\alpha,t}$ is the VaR at the α level – which in our case is equal to 5% – in period t, β_0 is the model constant, β_1 and $f_{\alpha,t-1}(\beta)$ are the weights of the lagged VaRs and the lagged VaRs, respectively while β_2 and β_3 represent the effects positive and negative returns have on the VaR, respectively.

4.2. TVP-VAR based connectedness approach

In the next step, we use the CAViaR changes as the basis for the TVP-VAR based connectedness approach to retrieve information about the energy price tail risk transmission mechanism. Hereby, we employ the same methodology as in Antonakakis et al. (2018, 2019, 2020).[1] In particular, we are estimating a TVP-VAR(1) as suggested by the Bayesian information criterion (BIC) which can be outlined as,[2]:

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

[1] We use the Minnesota shrinkage prior specification outlined in Koop and Korobilis (2010).

[2] For robustness purposes, we provide dynamic connectedness plots based upon the BIC (Schwarz, 1978) AIC (Akaike, 1974), and HQ (Hannan and Quinn, 1979) lag selection criteria in the online appendix. Results are qualitatively similar. However, we prefer the BIC given that Lütkepohl (1985), Koehler and Murphree (1988) and Granger and Jeon (2004) find suggestive evidence that the BIC specification achieves better forecasting performance compared to AIC.

Table 1
Summary statistics.

	WTI	Brent	Heating oil	Kerosene	Propane	Gasoline
Mean	−0.004	−0.016	−0.003	−0.015	0.005	−0.027
Variance	128.901	219.440	124.453	334.753	503.003	584.067
Skewness	2.206***	1.590***	1.615***	1.208***	0.967***	0.661***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ex.kurtosis	10.811***	3.764***	4.237***	2.327***	1.361***	1.535***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
JB	7072.957***	1259.289***	1472.589***	583.805***	290.148***	212.853***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ERS	−8.155***	−5.061***	−5.151***	−6.225***	−2.664***	−6.250***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.008)	(0.000)
$Q(20)$	41.684***	52.573***	29.282***	46.692***	46.133***	121.262***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Q^2(20)$	36.581***	13.875	18.046**	12.194	14.286	48.069***
	(0.000)	(0.177)	(0.039)	(0.293)	(0.155)	(0.000)
	Kendall rank correlation coefficients					
	WTI	Brent	Heating oil	Kerosene	Propane	Gasoline
WTI	1.000***	0.532***	0.283***	0.261***	0.074***	0.203***
Brent	0.532***	1.000***	0.379***	0.360***	0.130***	0.265***
Heating.oil	0.283***	0.379***	1.000***	0.600***	0.212***	0.283***
Kerosene	0.261***	0.360***	0.600***	1.000***	0.203***	0.309***
Propane	0.074***	0.130***	0.212***	0.203***	1.000***	0.148***
Gasoline	0.203***	0.265***	0.283***	0.309***	0.148***	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; and ERS: Stock et al. (1996) unit-root test.

$$vec(\boldsymbol{B}_t) = vec(\boldsymbol{B}_{t-1}) + \boldsymbol{v}t \qquad \boldsymbol{v}t \sim N(\boldsymbol{0}, \boldsymbol{R}_t) \tag{3}$$

where $\boldsymbol{z}_t$, $\boldsymbol{z}_{t-1}$ and $\boldsymbol{u}_t$ are $k \times 1$ dimensional vectors, representing all tail risk series in t, $t-1$, and the corresponding error term, respectively. $\boldsymbol{B}_t$ and $\boldsymbol{S}_t$ are $k \times k$ dimensional matrices demonstrating the time-varying VAR coefficients and the time-varying variance–covariances whereas $vec(\boldsymbol{B}_t)$ and $\boldsymbol{v}t$ are $k^2 \times 1$ dimensional vectors and $\boldsymbol{R}_t$ is a $k^2 \times k^2$ dimensional matrix.

Since the concept of the generalized forecast error variance decomposition (GFEVD) introduced by Koop et al. (1996) and Pesaran and Shin (1998) is built upon the Wold representation theorem we have to transform the estimated TVP-VAR model into its TVP-VMA process by the following equality: $\boldsymbol{z}_t = \sum_{i=1}^{p} \boldsymbol{B}_{it}\boldsymbol{z}_{t-i} + \boldsymbol{u}_t = \sum_{j=0}^{\infty} \boldsymbol{A}_{jt}\boldsymbol{u}_{t-j}$.

The (scaled) GFEVD normalizes the (unscaled) GFEVD, $\psi^g_{ij,t}(H)$, so that each row would sum up to unity. Hence, $\tilde{\psi}^g_{ij,t}(H)$ represents the influence variable j exerts on variable i in terms of its forecast error variance share which is defined as the *pairwise directional connectedness from j to i*. This indicator is computed by,

$$\psi^g_{ij,t}(H) = \frac{S^{-1}_{ii,t}\sum_{t=1}^{H-1}(\boldsymbol{\iota}_i'\boldsymbol{A}_t\boldsymbol{S}_t\boldsymbol{\iota}_j)^2}{\sum_{j=1}^{k}\sum_{t=1}^{H-1}(\boldsymbol{\iota}_i\boldsymbol{A}_t\boldsymbol{S}_t\boldsymbol{A}_t'\boldsymbol{\iota}_i)} \qquad \tilde{\psi}^g_{ij,t}(H) = \frac{\psi^g_{ij,t}(H)}{\sum_{j=1}^{k}\phi^g_{ij,t}(H)}$$

with $\sum_{j=1}^{k}\tilde{\psi}^g_{ij,t}(H) = 1$, $\sum_{i,j=1}^{k}\tilde{\psi}^g_{ij,t}(H) = k$, H stands for the forecast horizon, and $\boldsymbol{\iota}_i$ corresponds to a selection vector with unity on the ith position and zero otherwise.

First, we look at the case where variable i transmits its shock to all other variables j, called total directional connectedness TO others, which is defined as

$$C^g_{i\to j,t}(H) = \sum_{j=1,i\neq j}^{k}\tilde{\psi}^g_{ji,t}(H) \tag{4}$$

Second, we calculate the shock variable i receives from variables j, called total directional connectedness FROM others, which is defined as

$$C^g_{i\leftarrow j,t}(H) = \sum_{j=1,i\neq j}^{k}\tilde{\psi}^g_{ij,t}(H) \tag{5}$$

By subtracting the total directional connectedness TO others from the total directional connectedness FROM others we obtain the NET total directional connectedness, which can be interpreted as the influence variable i has on the analysed network.

$$C^g_{i,t}(H) = C^g_{i\to j,t}(H) - C^g_{i\leftarrow j,t}(H) \tag{6}$$

The total connectedness index (TCI) calculates the market interconnectedness and is constructed by

$$C^g_t(H) = \frac{\sum_{i,j=1,i\neq j}^{k}\tilde{\psi}^g_{ij,t}(H)}{\sum_{i,j=1}^{k}\tilde{\psi}^g_{ij,t}(H)} = \frac{\sum_{i,j=1,i\neq j}^{k}\tilde{\psi}^g_{ij,t}(H)}{k}. \tag{7}$$

The main problem with this measure is that the interpretation of what really constitutes high interconnectedness is subjective. Based on Monte Carlo simulations Chatziantoniou and Gabauer (2021) have shown that the own variance shares are by construction always larger or equal to all cross variance shares which means that the TCI is within $[0, \frac{k-1}{k}]$ and not within $[0, 1]$. Hence, to improve interpretability the TCI should be adjusted as follows,

$$C^g_t(H) = \left(\frac{k}{k-1}\right)\frac{\sum_{i,j=1,i\neq j}^{k}\tilde{\psi}^g_{ij,t}(H)}{k} \tag{8}$$

$$= \frac{\sum_{i,j=1,i\neq j}^{k}\tilde{\psi}^g_{ij,t}(H)}{k-1} \qquad 0 \le C^g_t(H) \le 1. \tag{9}$$

Finally, Gabauer (2021) has shown that the TCI can be decomposed to the pairwise connectedness index (PCI) measuring the interconnectedness between two variables i and j:

$$C^g_{ijt}(H) = 2\left(\frac{\tilde{\psi}^g_{ij,t}(H) + \tilde{\psi}^g_{ji,t}(H)}{\tilde{\psi}^g_{ii,t}(H) + \tilde{\psi}^g_{ij,t}(H) + \tilde{\psi}^g_{ji,t}(H) + \tilde{\psi}^g_{jj,t}(H)}\right) \qquad 0 \le C^g_{ijt}(H) \le 1. \tag{10}$$

This metric ranges between $[0, 1]$ illustrating the degree of bilateral interconnectedness across variable i and j which is masked by the TCI.[3]

5. Empirical findings and discussion

In this section, we present and discuss connectedness results focusing on crisis episodes. We are particularly interested in the specific role that each source of energy played during recent episodes such as the GFC of 2007–08, the oil price collapse of 2014 but also, the recent COVID-19 pandemic and we try to identify potential similarities. The adopted framework allows for a detailed exposition of the underlying

[3] Estimation is done using the R software program and the package `ConnectednessApproach` by Gabauer (2022).

Table 2
Averaged connectedness table.

Pre-COVID-19 (COVID-19)	WTI	Brent	Heating oil	Kerosene	Propane	Gasoline	FROM others
WTI	39.69 (33.20)	23.53 (21.47)	13.87 (17.62)	11.89 (16.08)	1.94 (2.44)	9.08 (9.20)	60.31 (66.80)
Brent	22.07 (19.79)	38.43 (30.20)	14.49 (18.28)	12.30 (17.33)	2.68 (5.26)	10.04 (9.15)	61.57 (69.80)
Heating oil	12.84 (16.14)	14.21 (17.34)	37.13 (28.35)	23.78 (22.52)	3.90 (4.31)	8.15 (11.35)	62.87 (71.65)
Kerosene	10.90 (14.28)	12.39 (16.68)	24.71 (23.00)	38.29 (28.95)	4.01 (4.89)	9.69 (12.21)	61.71 (71.05)
Propane	3.47 (4.29)	5.16 (9.84)	7.30 (8.90)	7.13 (9.53)	73.14 (57.57)	3.81 (9.87)	26.86 (42.43)
Gasoline	11.36 (10.57)	13.63 (11.20)	11.91 (16.01)	12.50 (16.30)	3.27 (7.32)	47.32 (38.60)	52.68 (61.40)
TO others	60.64 (65.06)	68.92 (76.52)	72.28 (83.81)	67.60 (81.75)	15.80 (24.21)	40.78 (51.77)	TCI
NET spillovers	0.33 (−1.74)	7.35 (6.73)	9.40 (12.15)	5.89 (10.70)	−11.07 (−18.21)	−11.90 (−9.63)	65.20 (76.63)

Notes: Results are based on a TVP-VAR model with lag length of order one (BIC) and a 20-step-ahead generalized forecast error variance decomposition.

Table 3
Averaged pairwise connectedness table.

Pre-COVID-19 (COVID-19)	WTI	Brent	Heating oil	Kerosene	Propane	Gasoline
WTI	100.00 (100.00)	73.99 (78.84)	51.88 (70.90)	45.34 (65.63)	9.37 (13.92)	38.03 (43.07)
Brent	73.99 (78.84)	100.00 (100.00)	55.69 (75.66)	49.09 (73.03)	13.73 (29.48)	43.60 (45.70)
Heating oil	51.88 (70.90)	55.69 (75.66)	100.00 (100.00)	78.58 (88.60)	18.97 (26.82)	38.74 (58.10)
Kerosene	45.34 (65.63)	49.09 (73.03)	78.58 (88.60)	100.00 (100.00)	18.51 (28.73)	41.26 (59.43)
Propane	9.37 (13.92)	13.73 (29.48)	18.97 (26.82)	18.51 (28.73)	100.00 (100.00)	11.50 (30.45)
Gasoline	38.03 (43.07)	43.60 (45.70)	38.74 (58.10)	41.26 (59.43)	11.50 (30.45)	100.00 (100.00)

Notes: Results are based on a TVP-VAR model with lag length of order one (BIC) and a 20-step-ahead generalized forecast error variance decomposition.

relations, considering dynamics not only at the aggregate but also, at the pairwise level between the variables included in the relevant network.

5.1. Averaged connectedness measures

First, we look into averaged results considering the entire sample period. To be more explicit, we consider both total averaged results (i.e., based on the total connectedness index) and pairwise averaged results (i.e., based on the pairwise connectedness index).

Table 2 reports averaged total results based on the TCI. Numbers in parentheses correspond to findings associated with the outbreak of the COVID-19 crisis period (i.e., in our study this period coincides with the first reported cases in the US starting in January 2020). According to these findings, averaged co-movement within this network of variables is rather moderate given that the relevant value of total connectedness is equal to 65.20% for the period before the outbreak of the crisis and 76.63% during the outbreak period. This practically implies that, on average, 65.20% (or 76.63% respectively) of the forecast error variance in each energy source can be attributed to developments in all other energy sources included in the network.

Nonetheless, connectedness within this network of variables is far from being negligible and in this regard, a careful investigation of the associated linkages might very well improve our understanding of the ensuing dynamics between the energy sources of interest. To put differently, considering that the connectedness measures of this study predicate upon tail risk captured by the asymmetric slope CAViaR method then, the investigation of the particular network of variables is rather insightful for identifying potential sources of uncertainty for these particular markets for energy.

Additional information that we get from Table 2 includes the distinction between net transmitting and net receiving energy sources whereby, heating oil – with 9.40% (12.15%) net contribution, is the main net transmitter of innovations within this network of variables, while gasoline and propane with −11.90% (−9.63%) and −11.07% (−18.21%) respectively, are the main recipients. It would also be instructive at this point to note that the main diagonal of Table 2 corresponds to own variable shocks and that these shocks typically correspond to the largest source of disturbance for each one of the variables included in the network.

In retrospect, looking at the values provided by Table 2, we notice that the value of the TCI substantially increased during the COVID-19 outbreak, reflecting to a great extent the increased uncertainty during the first months of the crisis. It is also worth noting that, during the COVID-19 outbreak own variable shocks (i.e., main diagonal values) substantially decrease, a fact that further highlights (i) the stronger association among variables during that period and (ii) the greater potential for contagion dynamic across the variables of the network.

In turn, Table 3 reports averaged (pairwise) results based on the PCI. In this respect, the PCI Table reports the averaged co-movement (i.e., ranging from 0 to 100%) between any two energy markets, for the whole sample period. As above, values in parentheses correspond to the COVID-19 outbreak period. Note also that, by construction, all elements on the main diagonal are equal to 1.

The advantage of the PCI Table is that it makes it easier to identify strong co-movements between specific pairs of energy markets and kerosene with value 78.58% (88.60%), WTI and Brent with value 73.99% (78.84%), as well as, heating oil and Brent with value 55.69% (75.66%). It is also worth noting that, off-diagonal elements of this Table are mirror-images of each other. Overall, findings are suggestive of strong co-movements not only within either the energy commodities or the refined petroleum products group but also, across the two groups that make up the network of variables of the study. With reference to the first months of the COVID-19 crisis we note that, all averaged pairwise connectedness indices increase substantially. It is worth noting that, in the first months of the crisis, the relationship between propane and gasoline nearly tripled while, that of propane and Brent more than doubled.

5.2. Dynamic connectedness measures

Before we continue discussing the dynamic connectedness measures, we would like to point out that in addition to the 5% CAViaR spillover dynamics, information regarding both the 2.5% and 10% CAViaR propagation mechanism is also included in each connectedness plot in order to highlight the robustness of our empirical results. Across all connectedness plots, it appears that CAViaR dynamics are quantitatively and qualitatively alike. To be more explicit, we observe similar troughs and peaks as far as dynamic total connectedness is concerned, and also similar net total and pairwise directional connectedness when it comes to co-movements and the magnitude of the transmission mechanism. This in turn implies that, the pattern regarding the net receiving/transmitting behaviour among different CAViaR series exhibits no disparities and therefore we conclude that both findings and ensuing implications.

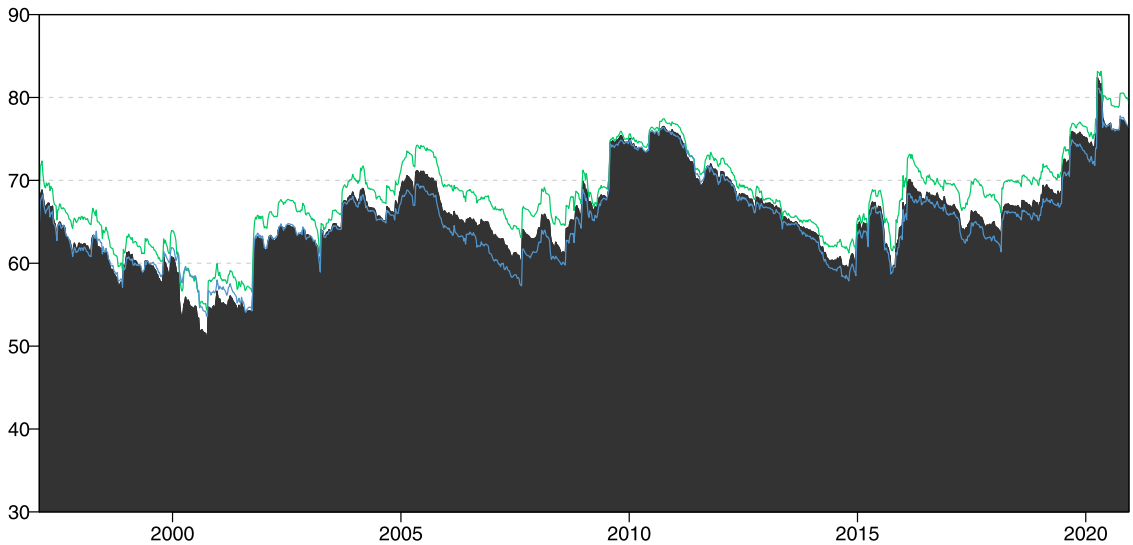

Fig. 2. Dynamic total connectedness.
Notes: Results are based on a TVP-VAR model with lag length of order one (BIC) and a 20-step-ahead generalized forecast error variance decomposition. Black area represents the findings based on the 5% VaR while the green and the blue line illustrate the results of the 10% and 2.5% VaR, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Despite that we obtain aggregated values of 65.20% (76.63%) for the corresponding total connectedness indices — which corresponds to a moderate co-movement of the variables of the network, we also proceed with a more granular approach to the effect that we are able to better understand the evolution of this co-movement across time. For example, it would be interesting to know whether the level of connectedness increased during specific crisis episodes or major events that transpired during the sample period of the study. To this end, we focus on the dynamic measures of connectedness offered by the employed method.

Starting with the dynamic TCI, results are presented in Fig. 2. This Figure illustrates the evolution of connectedness over time implying that analysis goes beyond averaged results that simply summarize linkages across variables.

Dynamic results suggest that, connectedness varies over time and is probably affected by major events that occur at specific points in time. In point of fact, we note that, over time, connectedness assumes values within a range from approximately 50% to a maximum that exceeds the 85% level. This is quite insightful considering that, connectedness, which in this study practically reflects the extent of uncertainty-contagion across energy sources, appears to be rising as a result of specific events. For instance, connectedness rises with the onset of the GFC of 2007–08, in the aftermath of the oil price collapse of 2014, while it also reaches new unprecedented peak-levels towards the end of our sample period which can be associated with the COVID-19 outbreak. The pronounced impact of the COVID-19 pandemic on the market for crude oil has also been reported by Zhang and Hamori (2021) who investigate frequency connectedness between COVID-19, crude oil and the capital market. In particular, Zhang and Hamori (2021) document that the impact of COVID-19 on the volatility of the crude oil market has actually surpassed that of the GFC 2007–08. Considering that volatility reflects riskiness, it is rather evident that the pandemic has had a pronounced impact on raising risk perception in energy markets. Besides, the negative impact of COVID-19 on the energy sector has also been reported by Jia et al. (2021) who provide evidence that the pandemic has had a profound negative impact on both demand and supply of crude oil. It can therefore be argued that the negative impact of the pandemic on the extent of volatility on refined petroleum products should also be considerable, considering the strong correlation between crude oil markets and refined petroleum products. For instance, Mensi et al. (2021) provide ample evidence on the strong correlation between crude oil and heating oil and report that particularly during the COVID-19 pandemic period, WTI contributed considerably to the forecast error variance of both heating oil and gasoline. In this regard, findings from the dynamic analysis echo previously reported findings and further highlight the importance of the dynamic investigation of the interrelations within the specific network. Overall, we could reach the conclusion that the dynamic TCI is able to capture the magnitude of the propagation of market uncertainty over time throughout the network under investigation.

We then turn to net dynamic results. These typically take the form of (i) net total results whereby, we are able to classify the variables of the study into either net transmitters or net receivers of market uncertainty shocks and (ii) net pairwise results whereby, we investigate the underlying dynamics between specific pairs within the network. Total net results are given by Fig. 3. A net transmitter of market uncertainty shocks is indicated by positive connectedness values.

Looking at the panels of Fig. 3 it becomes obvious that with reference to the refined petroleum products group, the picture is rather straightforward given that there appear to be two persistent transmitters (i.e., heating oil and kerosene) and two persistent receivers (i.e., propane and gasoline) of market uncertainty. That is, on net terms, these markets do not seem to assume a different role (i.e., at least not for a noteworthy interval) within the network with the passing of time. By contrast, the picture as regards the energy markets of WTI and Brent is not as clear considering that they switch between roles, with WTI acting as a strong net transmitter until early 2009 and Brent, acting mainly as a net transmitter of market uncertainty in the period that followed.

With regard to the importance of both heating oil and kerosene as net transmitters in the system, the transmission of greater exposure to losses stemming from these two commodities could be explained by the fact that both are rather characterized by reduced liquidity which makes trading in these assets more cumbersome. In turn, authors such as Uddin et al. (2018) report that investments in commodities characterized by illiquidity such as heating oil or ethanol are typically associated with greater exposure to losses. This is closely related to the work by Cho et al. (2019) who emphasize that illiquid commodities are usually accompanied by higher premiums demanded by hedgers and speculators. Finally, authors such as Adams and Gerner (2012) and Berghöfer and Lucey (2014) put forward the argument that companies that depend on kerosene such as airliners are faced with

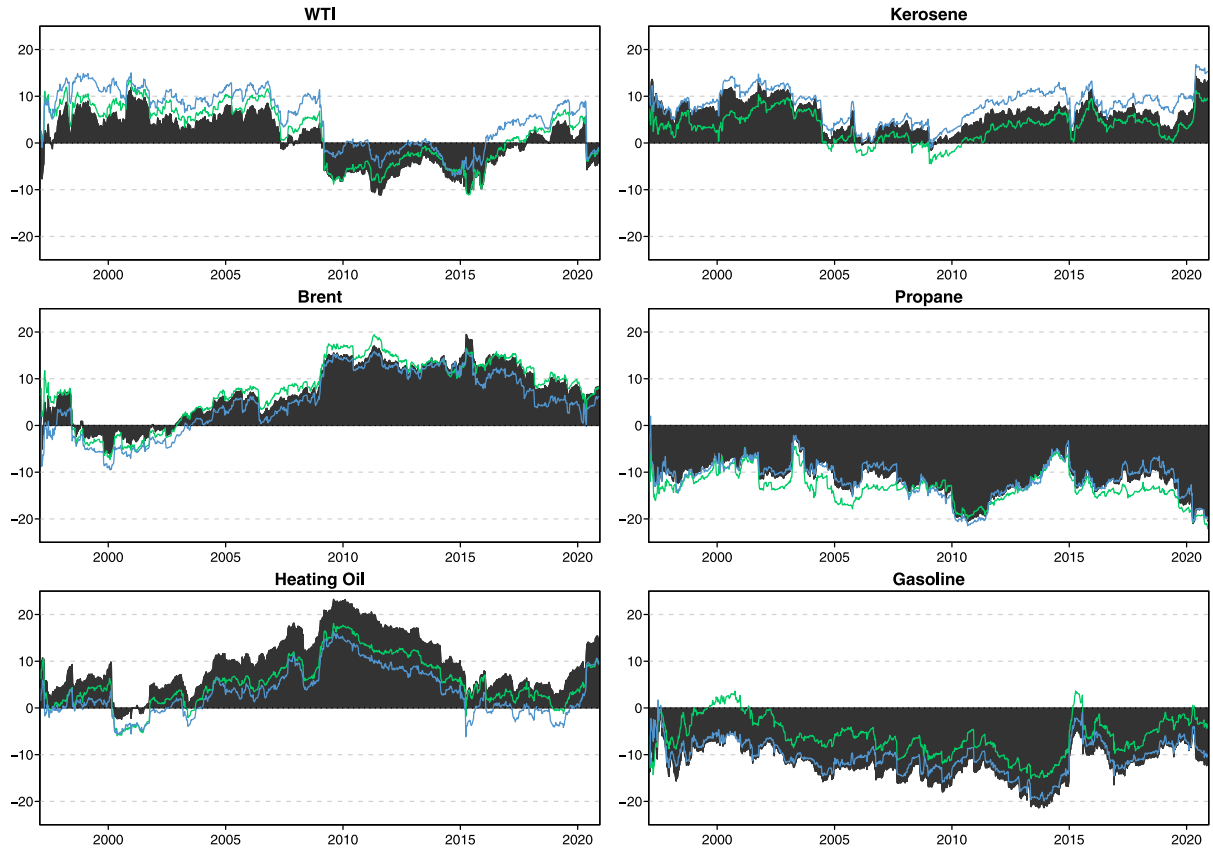

Fig. 3. Net total directional connectedness.
Notes: Results are based on a TVP-VAR model with lag length of order one (BIC) and a 20-step-ahead generalized forecast error variance decomposition. Black area represents the findings based on the 5% VaR while the green and the blue line illustrate the results of the 10% and 2.5% VaR, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

considerable illiquidity premia when trading in derivative markets. It follows that, liquidity seems to be a key force driving perception towards risk in derivative markets and therefore it stands to reason for commodities of reduced liquidity to act as major sources of risk contagion during turbulent times.

Turning to the two crude oil measures, apparently, the period around 2009 was a milestone for developments in the market for crude oil. Existing literature associated with the WTI-Brent price differential has already identified the period after 2008 and until at least 2015, as a period when WTI was trading at a substantial discount vis-a-vis Brent crude oil (see, inter alia, Caporin et al., 2019; Tian and Lai, 2019; Mastroeni et al., 2021). It follows that the shift in the role of each one of the respective crude oil measures around 2009 could be explained by notable developments in the market for crude oil (e.g., increased oil supply in the US as a result of extensive application of fracking and horizontal drilling) that greatly affected the balance between the two crude oil measures. Looking at either type of crude oil as a potential source of contagion of greater exposure to losses, we could document the following uncertainty factors. Starting with WTI, the US export ban was only lifted in 2015 while considerations were also present in connection with shipping constraints and existing pipeline infrastructure in the US (see among others, McRae, 2018; Agerton and Upton Jr., 2019). As far as Brent is concerned, a considerable depletion of oil reserves in the North Sea in recent years has probably been a major cause for concern (see, for example, Scheitrum et al., 2018; Tian and Lai, 2019).

Having identified some of the potential mechanisms that underpin the results of our study, it is worth looking deeper into the dynamics between pairs of variables across our network. To this end, net pairwise connectedness results are presented in Fig. 4. That is, in order to investigate the linkages between the variables of the network at greater length, we proceed with looking at dynamics between the variables of the network.

Notably, heating oil is a net transmitter for almost throughout the sample period vis-a-vis any other product and energy market. Interestingly enough, the net total behaviour of either WTI or Brent can actually be traced back to their net pairwise relation as evidentially, Brent transmits market uncertainty shocks to WTI in the years that followed 2009. What is more, Brent and WTI, in line with previous findings, both appear to mainly transmit to petroleum products with the exception of heating oil and kerosene. Finally, the relationship between propane and gasoline, which are the two main net recipients of the study is not very clear as both products appear to switch roles over time.

With reference to the magnitude of connectedness across pairs, in most cases net connectedness reaches considerable levels, particularly during crisis episodes. In addition, the impact from Brent, heating oil and kerosene appears to be rather strong particularly towards the end of the sample period indicating that the COVID-19 had a key part in shaping developments with regard to market uncertainty and contagion.

In the interests of consistency, we conclude the exposition of the findings of the study by looking at the evolution of pairwise co-movement over time as this is captured by the dynamic PCI index. Again, the advantage of this approach, is that we are immediately able to identify strong co-movement between specific pairs in the network and to further investigate how co-movement has changed in magnitude over time. In line with the static PCI, the dynamic PCI also assumes values between 0 and 1. Results are presented in Fig. 5.

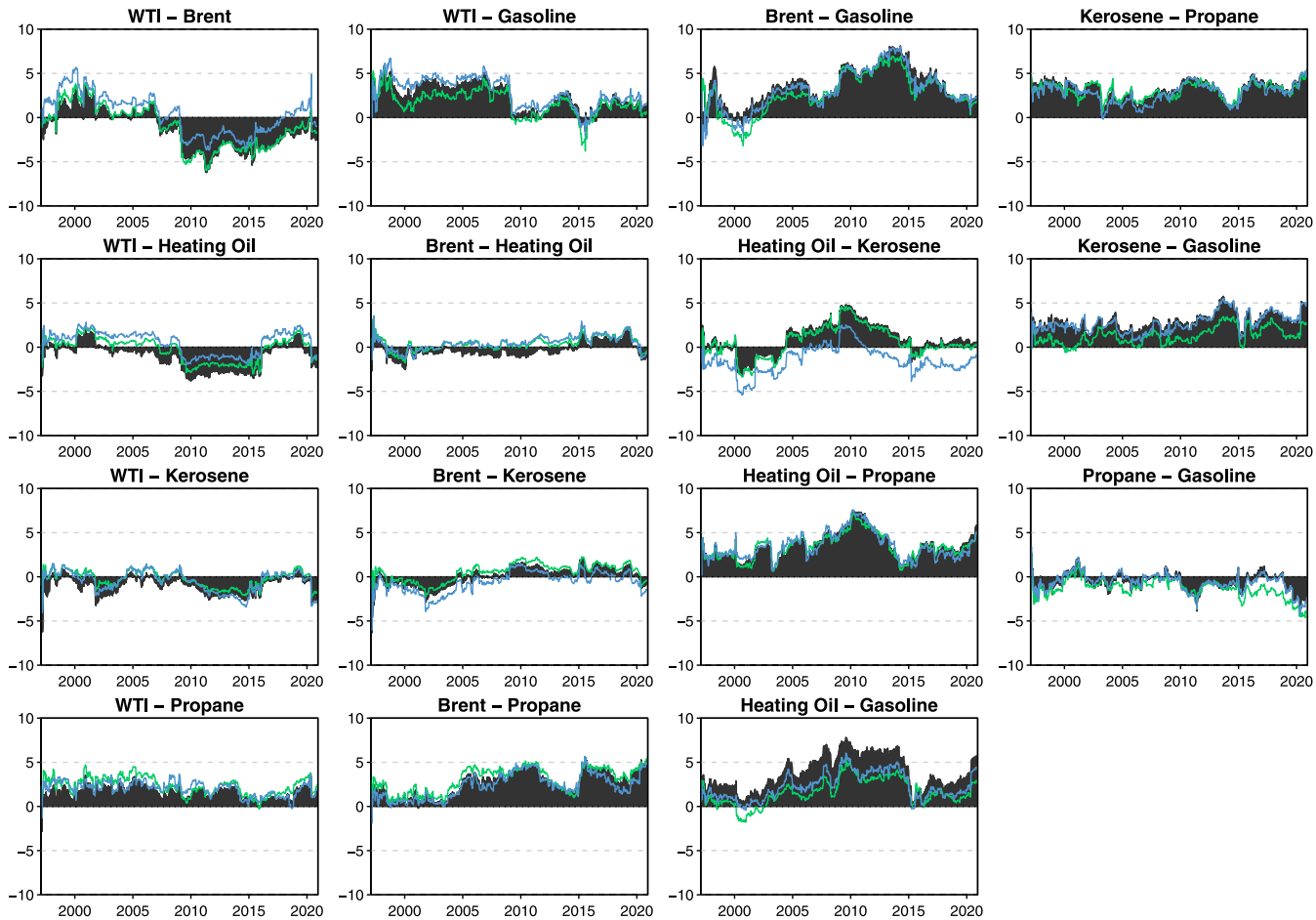

Fig. 4. Net pairwise directional connectedness.
Notes: Results are based on a TVP-VAR model with lag length of order one (BIC) and a 20-step-ahead generalized forecast error variance decomposition. Black area represents the findings based on the 5% VaR while the green and the blue line illustrate the results of the 10% and 2.5% VaR, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Looking at the panels of Fig. 5 we can draw certain conclusions. First, in some cases, such as WTI and Brent, or heating oil and kerosene, co-movement remains strong throughout the period of study. In other cases, such as, heating oil and propane, heating oil and gasoline or, Brent and gasoline, it is quite obvious that co-movement becomes stronger during crisis episodes such as the GFC of 2007–08 and the COVID-19 outbreak.

In conclusion, it is rather evident that co-movement between the variables of our network is strong and further amplifies during major episodes that severely affect economic activity. The market for energy as this is presented in this study which focuses both on energy commodities and refined petroleum products appears to be strongly interconnected and this could be a good measure of the extent to which uncertainty in some markets aggravates uncertainty in others. Further considering the results from the sample period of the study, the recent COVID-19 crisis outbreak, which has so far brought about, among other things, reduced levels of investment, also appears to have the potential to leave a strong mark on energy markets too.

6. Conclusion

In this study, we combine the asymmetric slope CAViaR approach initially introduced by Engle and Manganelli (2004) with a time-varying based connectedness approach (i.e., in the spirit of Antonakakis et al., 2020) in order to investigate uncertainty transmission in the market for refined petroleum products. In particular, we focus on heating oil, kerosene, gasoline and propane as four key products of the relevant market, while at the same time, we further consider the interaction of said products with two different types of crude oil; that is Europe Brent and US WTI. In this regard, this study investigates an important aspect of the market for refined petroleum products which is the transmission of greater exposure to losses following spillovers across the variables of the specific network. We focus on weekly data for the period between January 17, 1997 and December 11, 2020. In addition, we separate our sample between the period before the outbreak of COVID-19 and the period during the first months of the crisis.

Total averaged findings suggest that interconnectedness of tail events among the variables of the network can indeed explain developments in the market for refined petroleum products to a certain extent. Apparently, heating oil and kerosene emerge as the main net transmitters of the network, while both gasoline and propane clearly assume a net receiving role. What is more, heating oil appears to be strongly correlated not only with kerosene but also, with both crude oil measures. In turn, the dynamic investigation of interconnectedness among the variables of the network, which practically considers the evolution of tail connectedness across time, reveals that connectedness among the variables included in this study increases during all major events captured in the sample period. Notably, we find that, connectedness increases both at the onset of the GFC of 2007–08 and immediately after the oil price collapse in 2014 but also, in the beginning of the COVID-19 crisis which is being captured towards the end of our sample.

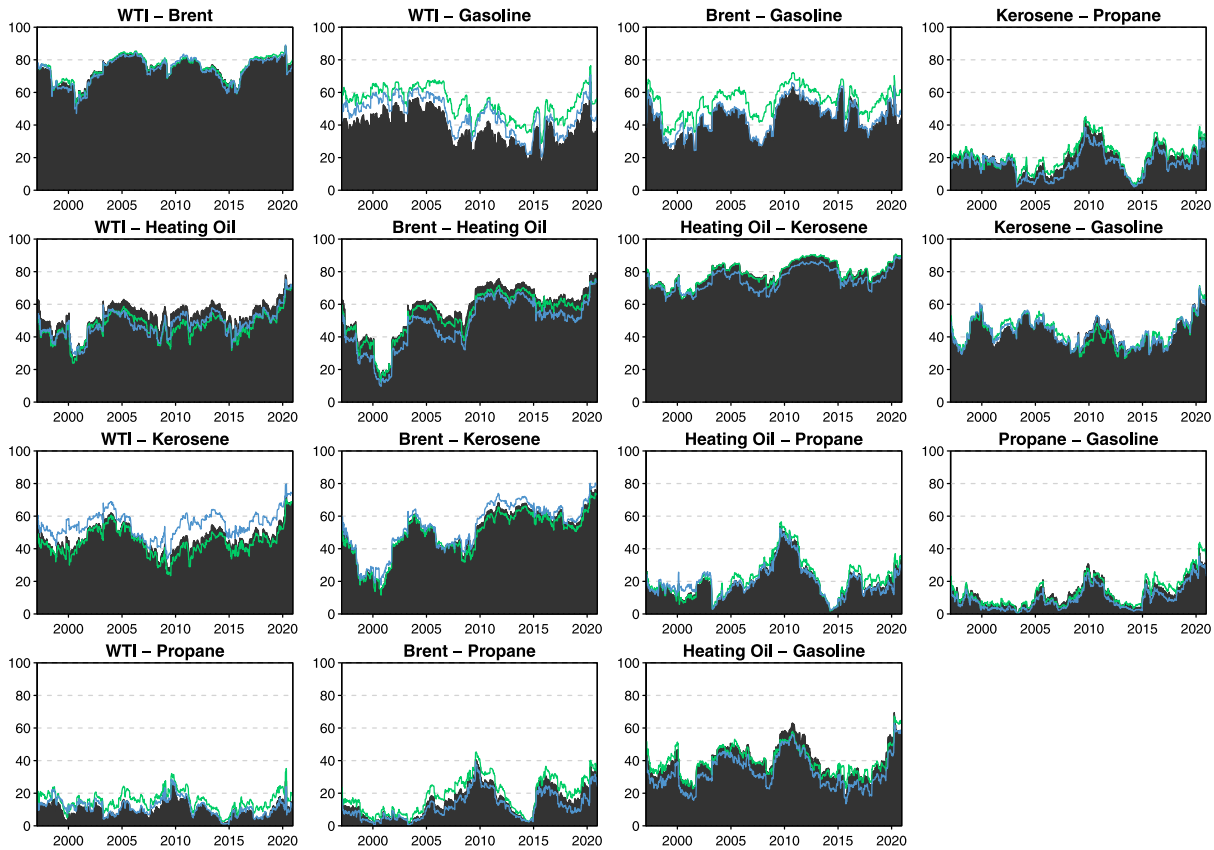

Fig. 5. Dynamic pairwise connectedness.
Notes: Results are based on a TVP-VAR model with lag length of order one (BIC) and a 20-step-ahead generalized forecast error variance decomposition. Black area represents the findings based on the 5% VaR while the green and the blue line illustrate the results of the 10% and 2.5% VaR, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

In point of fact, the magnitude of connectedness during the beginning of the COVID-19 appears to be similar to connectedness levels during the GFC of 2007–08. In this regard, we provide some preliminary evidence that the impact from the COVID-19 crisis on the particular energy market can in fact reach very high levels. It follows that, during periods of increased connectedness, increased risk and greater exposure to losses in one market, can lead to greater exposure to losses in other markets.

With reference to dynamic connectedness findings, it is evident that both heating oil and kerosene are rather persistent (i.e., throughout the sample period) transmitters of tail uncertainty to either gasoline or propane. The omnipotence of the former in the market for refined petroleum products can be viewed through the prism of liquidity whereby, illiquid commodities such as heating oil and kerosene are typically associated with higher premiums demanded not only by hedgers but also by speculators in the relevant markets. On a final note, we observe that around 2009 there was a remarkable shift in the role of the two crude oil measures. More particularly, while prior to 2009 WTI crude oil was a dominant net transmitter of tail uncertainty to all other variables of the network, in the years that followed, it clearly assumed a net receiving role. The reverse was true for Brent crude oil which became a dominant net transmitter of tail uncertainty in the period after 2009. We opine that, these findings could be explained by developments in the US energy market which include, among others, lifting the export ban in the US and adopting fracking and shale production. It follows that, investigating different measures of crude oil by focusing, for example, on price differentials, is key in identifying factors of risk in the respective markets.

The limitations of the study involve making use of more different types of refined petroleum products, processing a higher frequency dataset, and employing alternative connectedness approaches (see, Baruník et al., 2016; Baruník and Křehlík, 2018; Gabauer, 2020; Lastrapes and Wiesen, 2021; Balcilar et al., 2021), as well as, TVP-VAR frameworks (see, Koop and Korobilis, 2013; Del Negro and Primiceri, 2015; Petrova, 2019).

Avenues for further research include the investigation of the frequency Brent-WTI relationship as it might be of great importance for investors to know the short, medium and long-term transmission mechanism across those two variables. This directly leads to the second potential future research avenue that deals with the risk and portfolio management of energy prices. Among the many options, a prominent technique that could be linked to this research is to generate dynamic portfolios by minimizing the VaR.

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.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.eneco.2022.106051.

References

Abuzayed, B., Al-Fayoumi, N., 2021. Risk spillover from crude oil prices to GCC stock market returns: New evidence during the COVID-19 outbreak. North Am. J. Econ. Finance 101476.

Adams, Z., Gerner, M., 2012. Cross hedging jet-fuel price exposure. Energy Econ. 34 (5), 1301–1309.

Agerton, M., Upton Jr., G.B., 2019. Decomposing crude price differentials: Domestic shipping constraints or the crude oil export ban? Energy J. 40 (3), 155–172.

Akaike, H., 1974. A new look at the statistical model identification. IEEE Trans. Automat. Control 19 (6), 716–723.

Anscombe, F.J., Glynn, W.J., 1983. Distribution of the kurtosis statistic b2 for normal samples. Biometrika 70 (1), 227–234.

Antonakakis, N., Chatziantoniou, I., Gabauer, D., 2020. Refined measures of dynamic connectedness based on time-varying parameter vector autoregressions. J. Risk Financial Manag. 13 (4), 84.

Antonakakis, N., Gabauer, D., Gupta, R., 2019. International monetary policy spillovers: Evidence from a time-varying parameter vector autoregression. Int. Rev. Financ. Anal. 65, 101382.

Antonakakis, N., Gabauer, D., Gupta, R., Plakandaras, V., 2018. Dynamic connectedness of uncertainty across developed economies: A time-varying approach. Econom. Lett. 166, 63–75.

Asai, M., Gupta, R., McAleer, M., 2020. Forecasting volatility and co-volatility of crude oil and gold futures: Effects of leverage, jumps, spillovers, and geopolitical risks. Int. J. Forecast. 36 (3), 933–948.

Asche, F., Gjølberg, O., Völker, T., 2003. Price relationships in the petroleum market: an analysis of crude oil and refined product prices. Energy Econ. 25 (3), 289–301.

Atukeren, E., Çevik, E.I., Korkmaz, T., 2021. Volatility spillovers between WTI and Brent spot crude oil prices: An analysis of Granger causality in variance patterns over time. Res. Int. Bus. Finance 101385.

Balcilar, M., Gabauer, D., Umar, Z., 2021. Crude oil futures contracts and commodity markets: New evidence from a TVP-VAR extended joint connectedness approach. Resour. Policy 73, 102219.

Baruník, J., Kocenda, E., Vácha, L., 2015. Volatility spillovers across petroleum markets. Energy J. 36 (3), 309–329.

Baruník, J., Kočenda, E., Vácha, L., 2016. Asymmetric connectedness on the US stock market: Bad and good volatility spillovers. J. Financial Mark. 27, 55–78.

Baruník, J., Křehlík, T., 2018. Measuring the frequency dynamics of financial connectedness and systemic risk. J. Financ. Econom. 16 (2), 271–296.

Berghöfer, B., Lucey, B., 2014. Fuel hedging, operational hedging and risk exposure - evidence from the global airline industry. Int. Rev. Financ. Anal. 34, 124–139.

Bourghelle, D., Jawadi, F., Rozin, P., 2021. Oil price volatility in the context of COVID-19. Int. Econ. 167, 39–49.

Caporin, M., Fontini, F., Talebbeydokhti, E., 2019. Testing persistence of WTI and brent long-run relationship after the shale oil supply shock. Energy Econ. 79, 21–31.

Chatziantoniou, I., Degiannakis, S., Delis, P., Filis, G., 2020. Forecasting oil price volatility using spillover effects from uncertainty indices. Finance Res. Lett. 101885.

Chatziantoniou, I., Gabauer, D., 2021. EMU risk-synchronisation and financial fragility through the prism of dynamic connectedness. Q. Rev. Econ. Finance 79, 1–14.

Cho, S., Ganepola, C.N., Garrett, I., 2019. An analysis of illiquidity in commodity markets. J. Futures Mark. 39 (8), 962–984.

Commodity Futures Trading Commission, 2020. Interim staff report trading in NYMEX WTI crude oil futures contract leading up to, on, and around April 20, 2020.

D'Agostino, R.B., 1970. Transformation to normality of the null distribution of g1. Biometrika 679–681.

Dahl, R.E., Oglend, A., Yahya, M., 2020. Dynamics of volatility spillover in commodity markets: Linking crude oil to agriculture. J. Commod. Mark. 20, 100111.

Del Negro, M., Primiceri, G.E., 2015. Time varying structural vector autoregressions and monetary policy: A corrigendum. Rev. Econom. Stud. 82 (4), 1342–1345.

Devpura, N., Narayan, P.K., 2020. Hourly oil price volatility: The role of COVID-19. Energy Res. Lett. 1 (2), 13683.

Diebold, F.X., Yilmaz, K., 2009. Measuring financial asset return and volatility spillovers, with application to global equity markets. Econ. J. 119 (534), 158–171.

Diebold, F.X., Yilmaz, K., 2012. Better to give than to receive: Predictive directional measurement of volatility spillovers. Int. J. Forecasting 28 (1), 57–66.

Du, L., He, Y., 2015. Extreme risk spillovers between crude oil and stock markets. Energy Econ. 51, 455–465.

Ederington, L.H., Fernando, C.S., Hoelscher, S.A., Lee, T.K., Linn, S.C., 2019. A review of the evidence on the relation between crude oil prices and petroleum product prices. J. Commod. Mark. 13, 1–15.

Ederington, L.H., Fernando, C.S., Lee, T.K., Linn, S.C., Zhang, H., 2020. The relation between petroleum product prices and crude oil prices. Energy Econ. 105079.

Engle, R.F., Manganelli, S., 2004. CAViaR: Conditional autoregressive value at risk by regression quantiles. J. Bus. Econom. Statist. 22 (4), 367–381.

Gabauer, D., 2020. Volatility impulse response analysis for DCC-GARCH models: The role of volatility transmission mechanisms. J. Forecast. 39 (5), 788–796.

Gabauer, D., 2021. Dynamic measures of asymmetric & pairwise connectedness within an optimal currency area: Evidence from the ERM I system. J. Multinatl. Financial Manag. 100680.

Gabauer, D., 2022. Package 'ConnectednessApproach'. R package version 1.0.0.. https://CRAN.R-project.org/package=ConnectednessApproach.

Gil-Alana, L.A., Monge, M., et al., 2021. Crude oil prices and COVID-19-persistence of the shock. Energy Res. Lett..

Granger, C., Jeon, Y., 2004. Forecasting performance of information criteria with many macro series. J. Appl. Stat. 31 (10), 1227–1240.

Hanif, W., Hernandez, J.A., Shahzad, S.J.H., Yoon, S.-M., 2021. Tail dependence risk and spillovers between oil and food prices. Quart. Rev. Econ. Finance 80, 195–209.

Hannan, E.J., Quinn, B.G., 1979. The determination of the order of an autoregression. J. R. Stat. Soc. Ser. B Stat. Methodol. 41 (2), 190–195.

Huang, S., Liu, H., 2021. Impact of COVID-19 on stock price crash risk: Evidence from Chinese energy firms. Energy Econ. 101, 105431.

Jarque, C.M., Bera, A.K., 1980. Efficient tests for normality, homoscedasticity and serial independence of regression residuals. Econom. Lett. 6 (3), 255–259.

Jebabli, I., Kouaissah, N., Arouri, M., 2021. Volatility spillovers between stock and energy markets during crises: A comparative assessment between the 2008 Global Financial Crisis and the Covid-19 pandemic crisis. Finance Res. Lett. 102363.

Ji, Q., Liu, B.-Y., Zhao, W.-L., Fan, Y., 2018. Modelling dynamic dependence and risk spillover between all oil price shocks and stock market returns in the BRICS. Int. Rev. Financ. Anal. 101238.

Jia, Z., Wen, S., Lin, B., 2021. The effects and reacts of COVID-19 pandemic and international oil price on energy, economy, and environment in China. Appl. Energy 302, 117612.

Kaufmann, R.K., Laskowski, C., 2005. Causes for an asymmetric relation between the price of crude oil and refined petroleum products. Energy Policy 33 (12), 1587–1596.

Koehler, A.B., Murphree, E.S., 1988. A comparison of the Akaike and Schwarz criteria for selecting model order. J. R. Stat. Soc. Ser. C. Appl. Stat. 37 (2), 187–195.

Koop, G., Korobilis, D., 2010. Bayesian Multivariate Time Series Methods for Empirical Macroeconomics. Now Publishers Inc.

Koop, G., Korobilis, D., 2013. Large time-varying parameter VARs. J. Econometrics 177 (2), 185–198.

Koop, G., Korobilis, D., 2014. A new index of financial conditions. Euro. Econ. Rev. 71, 101–116.

Koop, G., Pesaran, M.H., Potter, S.M., 1996. Impulse response analysis in nonlinear multivariate models. J. Econometrics 74 (1), 119–147.

Lastrapes, W.D., Wiesen, T.F., 2021. The joint spillover index. Econ. Model. 94, 681–691.

Liu, T., Gong, X., 2020. Analyzing time-varying volatility spillovers between the crude oil markets using a new method. Energy Econ. 87, 104711.

Lütkepohl, H., 1985. Comparison of criteria for estimating the order of a vector autoregressive process. J. Time Series Anal. 6 (1), 35–52.

Mastroeni, L., Mazzoccoli, A., Quaresima, G., Vellucci, P., 2021. Decoupling and recoupling in the crude oil price benchmarks: An investigation of similarity patterns. Energy Econ. 94, 105036.

McRae, S., 2018. Crude Oil Price Differentials and Pipeline Infrastructure. Technical report, National Bureau of Economic Research.

Mensi, W., Al-Yahyaee, K.H., Vo, X.V., Kang, S.H., 2020. Dynamic spillover and connectedness between oil futures and European bonds. North Am. J. Econ. Finance 101342.

Mensi, W., Rehman, M.U., Vo, X.V., 2021. Dynamic frequency relationships and volatility spillovers in natural gas, crude oil, gas oil, gasoline, and heating oil markets: Implications for portfolio management. Resour. Policy 73, 102172.

Narayan, P.K., 2020. Oil price news and COVID-19—Is there any connection? Energy Res. Lett. 1 (1), 13176.

Padhan, R., Prabheesh, K., 2021. The economics of COVID-19 pandemic: A survey. Econ. Anal. Policy 70, 220–237.

Peng, C., Zhu, H., Guo, Y., Chen, X., 2018. Risk spillover of international crude oil to China's firms: Evidence from granger causality across quantile. Energy Econ. 72, 188–199.

Pesaran, H.H., Shin, Y., 1998. Generalized impulse response analysis in linear multivariate models. Econom. Lett. 58 (1), 17–29.

Petrova, K., 2019. A quasi-Bayesian local likelihood approach to time varying parameter VAR models. J. Econometrics 212 (1), 286–306.

Scheitrum, D.P., Carter, C.A., Revoredo-Giha, C., 2018. WTI And brent futures pricing structure. Energy Econ. 72, 462–469.

Schwarz, G., 1978. Estimating the dimension of a model. Ann. Statist. 461–464.

Si, D.-K., Liu, Y., Xu, X., Fang, Y., 2021. The risk spillover effect of the COVID-19 pandemic on energy sector: Evidence from China. Energy Econ. 105498.

Silvennoinen, A., Thorp, S., 2013. Financialization, crisis and commodity correlation dynamics. J. Int. Financial Mark. Inst. Money 24, 42–65.

Sims, C.A., 1980. Macroeconomics and reality. Econometrica 1–48.

Stock, J., Elliott, G., Rothenberg, T., 1996. Efficient tests for an autoregressive unit root. Econometrica 64 (4), 813–836.

The Economist, 2020. American crude oil has fallen to less than nothing.

Tian, H.-Z., Lai, W.-D., 2019. The causes of stage expansion of WTI/Brent spread. Pet. Sci. 16 (6), 1493–1505.

Uddin, G.S., Hernandez, J.A., Shahzad, S.J.H., Hedström, A., 2018. Multivariate dependence and spillover effects across energy commodities and diversification potentials of carbon assets. Energy Econ. 71, 35–46.

Xu, Q., Zhang, Y., Zhang, Z., 2021. Tail-risk spillovers in cryptocurrency markets. Finance Res. Lett. 38, 101453.

Yang, Y., Ma, Y.-R., Hu, M., Zhang, D., Ji, Q., 2020. Extreme risk spillover between chinese and global crude oil futures. Finance Res. Lett. 101743.

Zhang, H., Chen, J., Shao, L., 2021. Dynamic spillovers between energy and stock markets and their implications in the context of COVID-19. Int. Rev. Financ. Anal. 77, 101828.

Zhang, W., Hamori, S., 2021. Crude oil market and stock markets during the COVID-19 pandemic: Evidence from the US, Japan, and Germany. Int. Rev. Financ. Anal. 74, 101702.

Zhang, W., Zhuang, X., Wang, J., Lu, Y., 2020. Connectedness and systemic risk spillovers analysis of Chinese sectors based on tail risk network. North Am. J. Econ. Finance 54, 101248.

Zhu, B., Lin, R., Liu, J., 2020. Magnitude and persistence of extreme risk spillovers in the global energy market: A high-dimensional left-tail interdependence perspective. Energy Econ. 89, 104761.