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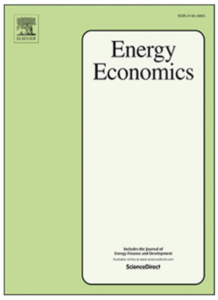

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Abstract

Exploring the dynamic behaviour of commodity market tail risk connectedness during the negative WTI pricing event

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Abstract

Using a TVP-VAR analytical framework, this study explores the change and persistence of the dynamic connectedness of international energy and carbon credit markets. The overall destabilisation effects that have been sourced within recent political and epidemiological events, and the subsequent consequences of shocks such as the negative WTI pricing event, have the potential to be quite disruptive to the continued growth and development of several regional oil markets. Results are presented via a comprehensive analysis of the dynamics of extreme risk spillovers for particular commodity pairs. In particular, WTI and Brent crude oil are found to have transmitted significant tail uncertainty shocks to other energy markets. However, Shanghai crude oil and carbon credit markets typically function as shock absorbers. The remaining energy-related commodities also primarily function as tail uncertainty receivers. Further incorporating EGARCH-based robustness testing procedures, testing for significant market connectedness shocks that manifest within international energy markets adds further validity to the results. Specifically, results relating to the substantial rebalancing of information to Shanghai crude oil futures and EUA carbon futures merit special consideration, as dynamic interactions strengthen evidence supporting their continued maturation into significant international markets. These findings are particularly interesting to policymakers and market participants who use such products to hedge against and diversify regional oil market fluctuations.

Keywords: TVP-VAR; Dynamic Connectedness; Oil Markets; EGARCH; Negative Valuation.
JEL Classification: C01; C58; C22.

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Using a TVP-VAR analytical framework, this study explores the change and persistence of the dynamic connectedness of international energy and carbon credit markets. The overall destabilising effects generated by recent political and epidemiological events, and the subsequent consequences of shocks such as the negative WTI pricing event, have the potential to be disruptive to the continued growth and development of several regional oil markets. Results are presented via a comprehensive analysis of the dynamics of extreme risk spillovers for particular commodity pairs. In particular, WTI and Brent crude oil are found to have transmitted significant tail uncertainty shocks to other energy markets. However, Shanghai crude oil and carbon credit markets typically function as shock absorbers. The remaining energy-related commodities primarily function as tail uncertainty receivers. Further, by incorporating EGARCH-based robustness procedures, tests for significant market connectedness within international energy markets adds further validity to the results. Specifically, results relating to the substantial rebalancing of information to Shanghai crude oil futures and EUA carbon futures merit special consideration, as dynamic interactions strengthen evidence supporting their continued maturation into significant international markets. These findings are particularly interesting to policymakers and market participants who use such products to hedge against and diversify regional oil market fluctuations.

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1. Introduction

In the period since early 2020, international energy markets have experienced multiple black swan events in the form of the worldwide COVID-19 pandemic and the Russia-Ukraine war [Neely, 2022, Kyriazis et al., 2022]. Subsequently, such events have manifested in a range of rare events, such as a significant negative pricing event in WTI crude oil markets Corbet et al. [2020], the implementation of price caps, international sanction packages, and the broad restriction of oil trading across many geographical regions [Girardone, 2022], and the continued growth and necessity to generate more rapid transitions to renewable sources of energy to reduce reliance on fossil fuels [Ahonen et al., 2022, Conlon et al., 2022]. The combination of such incidents has generated an environment through which dynamic interconnectivity between energy markets has changed significantly. Through the use of a TVP-VAR methodological structure, this research specifically investigates the change, and persistence of such change, of the dynamic connectedness of international energy markets, along with the market for EUA carbon credits, as has been previously used as a measure of carbon market price performance [Ashok et al., 2022]. Robustness testing procedures are developed through the use of an EGARCH-methodological structure. Such research is particularly important when attempting to not only understand the dynamics of international energy markets but to specifically understand how governments, policy-makers, and market participants can efficiently overcome the many geographical, political, and environmental risks and challenges to which they have been confronted.

While considering the interactions between crude oil markets and other energy variants, such as gasoline and gasoil, the broad destabilisation effects that have been sourced within recent political and epidemiological events have also had the potential to be quite disruptive to the continued growth and development of several new or emerging regional oil markets. This is particularly important to consider, as significant progress has been observed in recent times with the development of the Shanghai Futures Exchange (ShFE) Corbet et al. [2022a], which has allowed investors to trade based on different regional supply and demand dynamics than more traditional energy markets, for example, those dominated by WTI, and Brent crude oil. Brent crude oil has been broadly observed as a valuation barometer for crude oil across Europe, the Middle East and Africa. Previous attempts to develop such regional markets in Singapore, Japan and Dubai have struggled with liquidity issues; however, the continued growth of the ShFE comes in part from the growth of regional markets in Asia/Pacific (APAC), Europe, Middle East and Africa (EMEA), and the Americas (AMERS), and the provision of new arbitrage and hedging opportunities including tailored protection opportunities for Chinese-based refineries. Specifically, ShFE is the world's first RMB-dominated crude oil futures product. The following research further considers the development of such regional markets and the specific influence that recent black swan events have had.

Finally, specific regional differentials of dynamic connectedness offer particularly rich information surrounding both the behaviour and response to the COVID-19 pandemic, particularly as market participants revise their regional economic expectations in anticipation of the perceived probability of success of safety measures designed to restrict the contagion effects of the COVID-19 pandemic.[1]

To ensure utmost clarity, we explicitly define our primary research objective as the exploration of dynamic connectedness of international energy markets in the wake of significant 'black-swan' events, such as the negative pricing event in the West Texas Intermediate (WTI) crude oil markets. We aim to achieve this through a comprehensive analysis of tail risk spillovers across different energy commodity pairs, using refined extreme risk measures. The central research question we seek to answer is: 'What are the dynamics of extreme risk spillovers between crude oil futures and other energy markets in periods of significant instability, and how do these interactions evolve over time?' This focus distinguishes our work from other studies, and we believe it has potential implications for our understanding of the resilience of international energy markets and risk management strategies. Further, we supplement this question with sub-questions addressing the role of specific crude oil futures (WTI, Brent, Shanghai crude) as transmitters or receivers of extreme risk shocks and the evolution of their influence in times of market turmoil. Specifically, this research applies a combination framework of the popular tail risk model of Engle and Manganelli [2004] and the TVP-VAR connectedness approach of Antonakakis et al. [2020] to explore tail risk connectedness among several international energy markets. We explore the hypothesis that there is increased connectedness between WTI crude oil and several important energy commodities (for example, Brent crude, Shanghai crude, US gasoline, US heating oil, ICE gasoil and EUA carbon futures). Increased tail risk connectedness implies that the greater exposure to losses in one commodity market can migrate easily to the other commodity market [Chatziantoniou et al., 2022]. While several previous studies have investigated market interconnectedness in the context of WTI negative pricing events, our research seeks to fill a gap in this field by focusing on the dynamics of extreme risk spillovers across different energy commodity pairs. Prior work has largely focused on direct spillover effects without explicit attention to extreme risk, which we argue is essential for understanding the market behaviour during 'black-swan' events.

The presented tail risk connectedness analysis in this paper specifically investigates the existence and dynamic changes of systematic tail risk spillovers between major crude oil (WTI, Brent and Shanghai) and other key oil-related commodities. Corresponding connectedness results demonstrate the impact of tail risk uncertainty in the crude oil and oil-related commodity markets. Corresponding connectedness results also present evidence of significant uncertainty transmission channels

[1] Such differential dynamic effects as a result of lockdown differentials have been previously identified by Corbet et al. [2022b].

between WTI crude oil and other oil-related commodities for the effect of negative oil events in April 2020.

This paper has several interesting findings, where pairwise connectedness results are particularly interesting. WTI and Brent mainly transmit tail uncertainty shocks to other energy markets, while the remaining assets analysed mainly act as tail uncertainty receivers. During the period spanning one month before through one month after the negative WTI oil pricing event, there is evidence of increased connectedness for most WTI-based energy market pairs, indicating greater exposure to losses in the WTI market, which affects exposure to losses in the corresponding markets. Results are presented through a detailed analysis of the dynamics of extreme risk spillovers for specific pairs of commodities, where our results show that the three crude oil futures do not play the same role in the presented analysis. WTI and Brent transmit tail uncertainty shocks to other energy markets, while Shanghai crude is a shock receiver in most cases. Whereas the remaining energy-related commodities also mainly act as tail uncertainty receivers. The pairwise interaction between WTI and other energy commodities is particularly interesting, where WTI is found to be a transmitter of extreme risk for EUA, ICE gasoil, US heating oil, and Shanghai crude oil. Shanghai crude oil receives the largest tail uncertainty from WTI across other pairs. One month before and one month after the negative WTI oil pricing event, we find evidence of increased connectedness for most WTI-other energy market pairs. This implies that greater exposure to losses in WTI markets affects exposure to losses in the corresponding markets.

Including EGARCH-based robustness testing procedures presents additional evidence of the significant market connectedness shocks manifested in international energy markets due to the negative crude oil event, further validating the results. For example, on the date of the negative WTI event from gasoline and heating oil markets, Shanghai crude oil markets were discovered to be significant net receivers of shocks. Significantly elevated shock transmission is identified between EUA carbon futures and the heating oil market. In contrast, carbon futures experience significant shock transmission from gasoline markets on the same day as negative WTI events. Such results not only confirm the exceptionally dynamic nature and robust interconnectedness of the analysed markets but also bolster the pervasiveness of the negative WTI pricing event. Specifically, results relating to the substantial rebalancing of information to Shanghai crude oil and EUA carbon futures merit special attention. Their dynamic interactions reinforce evidence supporting their ongoing development to become significant, mature international markets. Such findings are of particular interest to policymakers and market participants who use such products to hedge and diversify against regional oil market fluctuations.

The remainder of this paper is structured as follows: the previous literature and theories that guide the development of our research are summarised in Section 2. Section 3 presents a thorough explanation of the wide variety of data used in this analysis while presenting a concise overview of the methodologies used in Section 4. Section 5 presents the results of the analysis, and subsequent robustness testing procedures, examining the influence of extreme risk upon pairwise spillovers and focusing specifically on exploring the effects of negative oil events. Finally, Section 6 concludes.

2. Previous Literature

The following research develops upon a TVP-VAR methodological structure, which has been used and developed for the purpose of analysing volatility connectedness across several market pairs such as broad commodity types [Degiannakis et al., 2018, Byrne et al., 2019, Liu and Gong, 2020, Chatziantoniou et al., 2021, Gong and Xu, 2022], metal markets and clean energy [Song et al., 2022], between renewables, non-renewables, and carbon emission products [Kang et al., 2019], and between several commodity markets and both international stock markets [Jebabli et al., 2014, Darehshiri et al., 2022], and Chinese stock markets [Dai et al., 2022, Dai and Zhu, 2022], and further, between sectors within Chinese stock markets [Qin et al., 2021], and both derivative and both foreign exchange products [Tian et al., 2021]. Such TVP-VAR structures develop upon VAR-based investigations [Cross and Nguyen, 2017], and upon dynamic spillover indices as proposed by Diebold and Yilmaz [2009, 2012], Diebold and Yılmaz [2014] which have been used to analyse a variety of financial market-based and regionally-based interactions [Meegan et al., 2018, Corbet et al., 2018, Mensi et al., 2021, Cioroianu et al., 2021b]. Events analysed using the TVP-VAR model to measure risk transmission include that of the COVID-19 pandemic [Bouri et al., 2021, Urom et al., 2021, Elsayed et al., 2022, Samitas et al., 2022, Chai et al., 2022], and spillovers as a result of both geopolitical risk and economic policy uncertainty [Apostolakis et al., 2021, Gu et al., 2021, Assaf et al., 2021].

TVP-VAR methodological structures have been used across several areas to isolate and examine specific market effects; however, most recently, they have been used to focus on the COVID-19 pandemic. Ha and Nham [2022] identified that health shocks appear to influence the system-wide dynamic connectedness during the outbreak of COVID-19, where crude oil and equity markets are largely found to be the recipients of spillover effects from all the other markets. Interactions between equity markets are further examined with regional and time-varying differentials by Zhang et al. [2021], Hung [2021], Umar et al. [2021], Zhang et al. [2021], much of which develops substantially upon the works of Baruník and Křehlík [2018], Diebold and Yilmaz [2009, 2012] and Diebold and Yılmaz [2014]. Tiwari et al. [2022] investigated time-varying volatility spillovers and connectedness among agricultural markets, energy markets and biofuel markets, finding that dynamics connectedness is stronger within wider quantiles than those surrounding the mean and median of the conditional distribution, where the right tail is estimated to produce higher estimates than the left tail. Such an outcome draws particular attention to the importance of systematic risk spillovers during extreme market movements. When considering energy, metals and agriculture commodities during the pandemic, Farid et al. [2022] transmission of return spillovers is stronger in the left and right tails of the conditional return distribution, and the degree of tail-dependence between the examined markets was time-varying. Adekoya and Oliyide [2021] summarised that the pandemic has been largely responsible for risk transmission across various commodity and financial markets. Further, and focusing on financial market products still in a development stage, Yousaf et al. [2023] identified interactions between Defi products and equity market sectors such as industrials, materials and information technology, each identified to be net shock transmitters, while Corbet et al. [2020] found that cryptocurrency returns are found to be significantly influenced by negative sentiment relating to COVID-19.[2]

Specifically, research based on the implementation of sanctions upon the Russian economy has focused on explaining the effects of the new banking restrictions upon the international banking system [Girardone, 2022], while Korosteleva [2022] presented evidence of the spillover of risk; as a result disruptions to Russian energy supply into Europe. Further, [Glambosky and Peterburgsky, 2022] identify significant price return differentials for companies that announced divestment from Russia after the Russia-Ukraine war compared to those that did not follow suit, while Basnet et al. [2022] linked the latter decision with poor ESG performance.

3. Data

In our analysis, we first select three major crude oil commodities, including WTI futures, Brent futures and Shanghai crude oil futures (Shanghai International Energy Exchange Crude Oil Commodity Futures). These WTI and Brent oil markets are the benchmarks for the US and wider markets in Europe, Africa and the Middle East. The newly established Shanghai crude oil market is a benchmark for Chinese domestic oil. Our analysis also includes US heating oil futures (NYMEX No2 Heating Oil), US gasoline futures (NYMEX RBOB Gasoline), and European gasoil futures (ICE Gas Oil) as they are key refined petroleum products prices (gasoline, heating oil, gas oil). We also choose European carbon price futures (Intercontinental Exchange Index European Union Allowance (EUA) in this analysis.

Insert Figure 1 about here

[2] Further research that provides specific guidance for the following methodological processes are sourced from examinations focusing on international tourism [Corbet et al., 2022c], the information technology sector Alshater et al. [2023], precious metals [Umar et al., 2021], cryptocurrency [Conlon et al., 2020, Corbet et al., 2020], and the role of an external influence such as sentiment [Huynh et al., 2021], media coverage [Umar et al., 2021], and security breaches [Goodell and Corbet, 2023].

We obtain daily data of WTI futures, Brent futures, US heating oil futures, US gasoline futures, European gasoil futures, Shanghai crude oil futures, along with European carbon price futures from the Eikon database. The sample data covers the period from 26 March 2018 to 9 September 2022 for our analysis. A time series plot of each oil-related futures price is included in Figure 1. First, all seven price series have had an upward trend after the outbreak of COVID-19. It seems that the sharp increase in energy prices correlated with the ongoing COVID-19 pandemic. Second, all energy prices fell sharply during the period surrounding the first negative oil pricing event in April 2020, with different magnitudes experienced [Corbet et al., 2021a,b]. As can be seen, WTI suffered the largest price drop even compared with other energy-related prices.

Insert Table 1 & Figure 2 about here

Individual returns series are calculated as the first differences of the natural logarithm of the price series. A time series plot of individual return series is presented in Figure 2. We particularly focus on the shaded area covering the period 1-month both before and after the April 2020 negative WTI oil pricing event in Figure 2. As can be seen, all energy return series fluctuated largely during the first negative oil pricing event in April 2020. In particular, gasoline and Brent returns are strongly affected by the negative oil pricing event. Moreover, the daily performances for all return series seem to be larger in 2022. The conflict between Russia and Ukraine may explain this in February 2022. The return series experienced a much larger increase and subsequent collapse during the time period surrounding the first negative oil pricing event compared to the periods of the Russia-Ukraine War beginning in 2022. However, the only exception is that the ICE gas oil and heating oil returns series experienced a much larger drop in March 2022, which coincides with the Russia-Ukraine War in 2022, compared with the periods in the surrounding of negative WTI oil. Table 1 presents the summary statistics for each daily return series. As can be seen, all energy series have positive returns on average.

4. Methodology

4.1. CAViaR model

The conditional autoregressive value at risk (CAViaR) models of Engle and Manganelli [2004] is a popular approach which involves autoregressive modelling of the conditional quantiles, and they make no assumptions about the shape of the conditional distribution. In this study, we apply the CAViaR approach to estimate the VaR directly, where Bao et al. [2006] shows that it is superior to other VaR models. We use the asymmetric slope CAViaR to estimate 1% VaRs. The asymmetric slope CAViaR model is formulated as follows:

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

where $f_{\alpha,t}$ is the VaR at the α level in period t. β_2 and β_3 are coefficients that measure the effects of positive and negative returns. The asymmetric slope CAViaR model, therefore, considers the leverage effect in the daily returns.

4.2. TVP-VAR approach

The following section is derived from Antonakakis et al. [2020] and provides a brief review of the TVP-VAR approach. [3] The proposed TVP-VAR-based connectedness approach has become very popular in the literature as the TVP-VAR connectedness approach does not require choosing an arbitrary rolling window size, which could lead to a loss of valuable observations and avoids sensitivity of outlier. The TVP-VAR(p) model may be written as follows:

$$y_t = A_t z_{t-1} + \epsilon_t \quad \epsilon_t \mid \Omega_{t-1} \sim N\left(\mathbf{0}, \Sigma_t\right) \tag{2}$$

$$\operatorname{vec}\left(A_t\right) = \operatorname{vec}\left(A_{t-1}\right) + \xi_t \quad \xi_t \mid \Omega_{t-1} \sim N\left(\mathbf{0}, \;{}_t\right) \tag{3}$$

where $z_{t-1} = \left[y_{t-1}, \ldots, y_{t-p}\right]'$. The time-varying coefficients and time-varying variance-covariance matrices are used to estimate the generalized connectedness procedure of Diebold and Yılmaz [2014] that is based on generalized impulse response functions (GIRF) and generalized forecast error variance decompositions (GFEVD) in accordance with Koop et al. [1996], and Pesaran and Shin [1998]. GIRF is calculated as:

$$\operatorname{GIRF}_t\left(H, \delta_{j,t}, \Omega_{t-1}\right) = E\left(y_{t+H} \mid e_j = \delta_{j,t}, \Omega_{t-1}\right) - E\left(y_{t+J} \mid \Omega_{t-1}\right) \tag{4}$$

[3] While our choice of Value at Risk (VaR) as a tail risk measure may invite comment, we consider that it appropriate for several reasons. Firstly, VaR remains a widely recognised and easily interpretable measure of risk in the financial community, lending our research a degree of familiarity and accessibility to academia and practitioners. Secondly, VaR's relative simplicity makes them less computationally intensive and more straightforward for empirical estimation, especially when dealing with multiple market data, as in our study. However, we acknowledge that other risk measures, such as Expected Shortfall (ES) and Extreme Value at Risk (EVaR), might offer more comprehensive insight into tail risk. ES, for instance, estimates the expected loss given that a VaR threshold is exceeded and thus can capture tail risk quite effectively. Similarly, EVaR, by focusing on extreme losses, offers a more robust measure of tail risk. Nevertheless, these measures come with their own limitations, including higher computational complexity and potential estimation challenges. Importantly, while our choice of VaR as a tail risk measure is guided by these considerations, we believe it does not invalidate the potential application of alternative measures like ES and EVaR. Future research could benefit from employing these measures to provide complementary insights into the dynamics of extreme risk spillovers in international energy markets.

$$\Psi_{j,t}(H) = \frac{B_{H,t}\Sigma_t e_j}{\sqrt{\Sigma_{jj,t}}} \frac{\delta_{j,t}}{\sqrt{\Sigma_{jj,t}}} \quad \delta_{j,t} = \sqrt{\Sigma_{jj,t}} \tag{5}$$

$$\Psi_{j,t}(H) = \Sigma_{jj,t}^{-\frac{1}{2}} B_{H,t}\Sigma_t e_j, \tag{6}$$

We next compute the GFEVD $\tilde{\phi}_{ij,t}(H)$, which represents the pairwise directional connectedness from j to i and illustrates the influence that the variable j has on variable i in terms of its forecast error variance share. $\tilde{\phi}_{ij,t}(H)$ is calculated as follows:

$$\tilde{\phi}_{ij,t}(H) = \frac{\sum_{t=1}^{H-1} \Psi_{ij,t}^2}{\sum_{j=1}^{m} \sum_{t=1}^{H-1} \Psi_{ij,t}^2}, \tag{7}$$

where the denominator represents the cumulative effect of all the shocks, while the numerator illustrates the cumulative effect of a shock in variable i. The total connectedness index (TCI) can be constructed by:

$$C_t(H) = \frac{\sum_{i,j=1,i\neq j}^{m} \phi\widetilde{\phi}_{ij,t}(H)}{\sum_{i,j=1}^{m} \phi\widetilde{\phi}_{ij,t}(H)} * 100 = \frac{\sum_{i,j=1,i\neq j}^{m} \tilde{\phi}_{ij,t}(H)}{m} * 100 \tag{8}$$

The total directional connectedness to others measures how variable $i$transmits its shock to all other variables j and is defined as:

$$C_{i\to j,t}(H) = \frac{\sum_{j=1,i\neq j}^{m} \tilde{\phi}_{ji,t}(H)}{\sum_{j=1}^{m} \tilde{\phi}_{ji,t}(H)} * 100. \tag{9}$$

The total directional connectedness from others measures the directional connectedness variable i receives from variables j and and can be calculated as:

$$C_{i\leftarrow j,t}(H) = \frac{\sum_{j=1,i\neq j}^{m} \tilde{\phi}_{ij,t}(H)}{\sum_{i=1}^{m} \tilde{\phi}_{ij,t}(H)} * 100. \tag{10}$$

The net total directional connectedness can be calculated by subtracting total directional connectedness to others from total directional connectedness from others. The net total directional connectedness measures the influence that variable i has upon the entire network. The net total directional connectedness is defined as:

$$C_{i,t} = C_{i\to j,t}(H) - C_{i\leftarrow j,t}(H) \tag{11}$$

If $C_{i,t} > 0$, it means that variable i influences the network more than the opposite direction. On the other hand, if $C_{i,t} < 0$, then variable i is driven by the network. The net pairwise directional connectedness can be used for examining bidirectional relationships between variable i and variable j:

$$NPDC_{ij}(H) = \left(\phi\widetilde{\phi}_{jit}(H) - \tilde{\phi}_{ijt}(H)\right) * 100 \tag{12}$$

If $NPDC_{ij}(H)$ is positive, variable i dominates variable j. If $NPDC_{ij}(H)$ is negative, variable i is dominated by the variable j. The net pairwise directional connectedness between variables i and j is the difference between the gross shocks transmitted from variable i to variable j and those transmitted from variable j to variable i.

5. Empirical results

5.1. Tail risk behaviour

As presented in Figure 3, we present the 1% tail risks for each energy futures price by applying the CAViaR model of Engle and Manganelli [2004]. The tail risks are estimated by the CAViaR model using an asymmetric slope specification.[4] The overwhelming advantage of the asymmetric slope specification is that it allows the asymmetric effects to consider the asymmetric responses to positive and negative returns.

Insert Figure 3 about here

In Figure 3, we identify a number of interesting observations. First, there exists a substantial variation of 1% VaR tail risks over the sample period from March 2018 to September 2022. Second, among these series, there is a large elevation in the estimated 1% tail risks for all seven energy-related series surrounding the first negative oil pricing event in April 2020. Between late March and May, all tail risk series exhibited evidence of a sudden, sharp shock, corresponding to the first negative WTI oil events. We also find that both WTI and US gasoline markets experience the largest spikes while other series experience moderate elevation during the same period.

5.2. Dynamic connectedness behaviour

To achieve the stationary assumption required by the TVP-VAR model, we calculate the first log difference for each tail risk estimation, which can be interpreted as the changes in expected uncertainty [Chatziantoniou et al., 2022]. All series are found stationary at the 1% significance

[4] Our selection of the asymmetric slope specification is also the same as the choice in Chatziantoniou et al. [2022]. We also utilise other model specifications of the CAViaR model and tail risk estimation results; however, the presented selected was the most suitable.

level according to various unit root tests.[5] We then use changes in expected uncertainty for the TVP-VAR connectedness approach to estimate extreme risk spillovers - the transmission of greater exposures to losses for all the above-mentioned energy markets. This section presents connectedness results.

5.2.1. Dynamic total connectedness

We present the dynamic TCI results in Figure 4, showing the evolution of tail risk connectedness over time for our selected energy markets. Generally, the value of dynamic TCI connectedness varies from 42% to 65%. In our presented analysis, connectedness measures the degree of uncertainty across a series of major oil products and the European benchmark carbon price. The dynamic TCI seems to be strongly affected by major events.

Insert Figure 4 about here

For example, connectedness appears to rise sharply after the outbreak of COVID-19. Especially the event of negative WTI oil pricing events further contributes to the uncertainty-contagion across major energy futures prices. A sharp increase in the dynamic TCI value in March 2020 indicates the presence of increased market risks. Connectedness also rises sharply in mid-2021 and after the Russia-Ukraine conflict in 2022.

5.2.2. Dynamic net connectedness

The dynamic net connectedness results are presented in Figure 5. Positive (negative) connectedness values indicate a net transmitter (receiver) of tail uncertainty shocks. On the other hand, a net receiver of tail uncertainty shocks is indicated by negative connectedness values. As shown in Figure 5, on a net term, WTI, Brent, US gasoline and US heating oil are transmitters, while EUA, ICE gasoil, and Shanghai crude oil are shock receivers.

Insert Figure 5 about here

5.2.3. Examining dynamic pairwise connectedness

The net pairwise connectedness results that measure the transmission of market uncertainty shocks for WTI, Brent, Shanghai crude oil, Gasoline, heating oil, ICE gasoil and EUA markets are presented in Figures 6 and 12, respectively. In these figures, the shaded area covers the period one

[5] For the purpose of the brevity of presentation, unit root results are omitted from the presentation and are available from the authors upon request.

month before and one month after the negative WTI oil pricing event. Net pairwise connectedness results show the transmissions of greater exposure to losses from one market to another, allowing us to understand the dynamics of extreme risk spillovers in greater depth.

Insert Figure 6 about here

Two of the most important crude oil futures- WTI and Brent, mainly transmit tail uncertainty shocks to other energy markets, as shown in Figure 6 and Figure 7, respectively. We focus on extreme risk spillovers from the WTI to other markets first. WTI is a transmitter for EUA, ICE gasoil, US heating oil, and Shanghai crude oil. Shanghai crude oil receives the largest tail uncertainty from WTI compared with the magnitude of connectedness across different pairs. Even more interesting is that pairwise connectedness for WTI-Shanghai oil climbs to a peak in July 2021. During the period one month before and one month after the negative WTI oil pricing event, as highlighted in grey, there is evidence of increased connectedness for most WTI pairs (with the only exception being the WTI-Brent pair). Such results indicate that greater exposure to losses in the WTI market affects exposure to losses in the corresponding markets. These results are of particular interest.

Insert Figures 7 & 8 about here

Brent is a transmitter for WTI, EUA, gasoline, heating oil, ICE gasoil and Shanghai crude oil. Figure 7 also shows pairwise connectedness between Brent and other markets that peaked during the negative WTI pricing event. Shanghai crude oil futures is another crude oil product included in our analysis. Pairwise connectedness between Shanghai crude oil and other markets is presented in Figure 8. Unlike WTI and Brent, Shanghai crude oil futures is mainly a net shock receiver for most markets. The above results suggest that different crude oil futures do not play the same role in the network.

Insert Figure 9 & 10 about here

The rest of the analysed energy markets serve, in most cases, as tail uncertainty receivers. Figure 9 shows that gasoline is a net transmitter for EUA and Shanghai crude oil. The magnitude of connectedness for gasoline-Shanghai crude oil is larger than those of the gasoline-EUA pair. As shown in Figure 10, heating oil transmits tail uncertainty for EUA, gasoil, and Shanghai crude oil, but it receives a market larger amount of uncertainty shocks from WTI, Brent and gasoline. ICE gasoil is a net recipient except for EUA and Shanghai crude oil, as depicted in Figure 11. The

European carbon market is a net receiver for all the markets in most periods, which is shown in Figure 12.

Insert Figure 11 & 12 about here

5.3. Understanding dynamic changes of market connectedness due to the 2020 negative WTI event

We next set out to establish the direct influence of the international negative oil pricing event of April 2020 upon the connectedness of our investigated markets. While considering a variety of options within the GARCH-family of models, we focus specifically on the change and volatility effects using an EGARCH(1,1) methodology, which was selected after developing upon several goodness-of-fit testing procedures[6]. We utilise the mean equation of the EGARCH(1,1) methodology as displayed in equation (13).

$$c_t = a_0 + b_1 c_{t-1} + b_2 d_t + \varepsilon_t \tag{13}$$

while we express the variance equation of our EGARCH(1,1) model as follows:

$$\ln(h_t^2) = \omega + \alpha\varepsilon_{t-1} + \gamma(|\varepsilon_{t-1}| - E(|\varepsilon_{t-1}|)) + \beta \ln(h_{t-1}^2) \tag{14}$$

In the presented EGARCH(1,1) analysis, c_t represents the estimated connectedness as estimated. We include an additional d_t term in equation (14) in our analysis to provide a coefficient relating to the observed differential respectively for each pre-determined estimation window surrounding the negative oil pricing event, including [-60,-1], [-40,-1], [-20,-1], [-10,-1], [-5,-1], [-3,-1], [0,+1] [0,+3], [0,+5], [0,+10], [0,+20], [0,+40], and [0,+60], to test for the change in connectedness both before and after[7]. Specifically, the periods [0,+20], [0,+40] and [0,+60] are used to reflect behavioural differentials, respectively, for the periods one, two, and three months after reflecting the persistence of the identified change of connectedness.[8] In equation (13), c_{t-1} represents the lagged value of the individually analysed market connectedness.

[6]EGARCH exploits information contained in realised measures of volatility while providing a flexible leverage function that accounts for return-volatility dependence. In our selection, other competitive models included EGARCH, TGARCH, Asymmetric Power ARCH (APARCH), Component GARCH (CGARCH) and the Asymmetric Component GARCH (ACGARCH). The optimal model is chosen according to three information criteria, namely the Akaike (AIC), Bayesian (BIC) and Hannan-Quinn (HQ).

[7]In total, the results incorporate the information content of 310,896 EGARCH methodologies, through which the structure of best fit was selected using each the Akaike information criterion (AIC), the Bayesian information criterion (BIC) and Hannan-Quinn information criterion (HQ) respectively. Each number refers to the specific trading days relative to each identified event.

[8]Multiple variations of this analysis were utilised, such as specifically testing the day of, through to tests inclusive

The EGARCH(1,1) analysis presents the estimated average dynamic connectedness for each specified time horizon when accounting for international effects. Positive estimates indicate that the source market is a transmitter of shocks, while negative estimates indicate that the source market is a receiver. In Tables 2 and 3, we observe the time-varying nature of market connectedness in the time surrounding the April 2020 negative WTI oil event. In particular, the changes in these estimates between the periods [-60,-1] through [-3,-1] and the period after the negative pricing event are particularly interesting. Focusing specifically on WTI, we observe that at the time [0,+1], sharp shock transmissions are evident in each market, except for Brent crude. However, the net transmission of shocks from WTI is found to be far more pertinent for each of the markets for gasoline, ICE gasoil, and EUA carbon futures throughout the 60 days examined thereafter. The net change of interaction between the Shanghai crude market and the EUA carbon markets is particularly interesting in the context of this work. Regarding Shanghai crude oil, it is important to note China's unique position in the global oil market. As one of the world's largest oil importers, China greatly influences international oil prices. The Shanghai crude market, which trades in the yuan, is additionally buffered by its relative insulation from global financial influences and direct dollar-denominated oil price swings. Furthermore, China's governmental regulations and strategic oil reserves act as additional shock absorption mechanisms, mitigating extreme risk spillovers. As for the EUA carbon futures market, it operates within a distinct economic and regulatory framework. The nature of carbon pricing inherently involves a balancing act of market forces and policy interventions, with regulatory measures often designed to stabilise price fluctuations. This, coupled with the long-term nature of carbon reduction commitments under the EU Emissions Trading System (ETS), provides inherent resistance to short-term market shocks, enabling the EUA market to function as a shock absorber. Such evidence further supports the growing positions of both products within international financial markets.

Insert Tables 2 & 3 about here

When considering the interactions between markets as measured by shocks sourced in Brent crude, no evidence of any changes are identified with Shanghai crude oil. However, significant shock transmission is identified from Brent to all other analysed markets, presenting evidence of the widespread contagion and secondary transmission effects of such a rare market event. The sharp, seven-fold elevation of shock transmission between oil markets and EUA carbon futures,

the period two weeks thereafter (ten trading days). However, results were indifferent, while theoretical justification best supported the selection of that presented [Corbet et al., 2022d, Cioroianu et al., 2021a]. Results from these additional analyses are omitted for brevity of presentation but are available from the authors upon request.

however, effects are found to dissipate in the medium term thereafter. Such results are particularly interesting as they suggest that investors were reconsidering their expectations of future carbon emissions trading behaviour in the context of significant economic shocks. Shanghai crude oil markets are found to have become significant net receptors of shocks on the exact date of the negative WTI event from gasoline and heating oil markets. Evidence of significant differentials of shock transmissions as sources from ICE Gasoil markets is not identified. While finally, significantly elevated shock transmission is identified between EUA carbon futures and the market for heating oil, whereas carbon futures are identified to experience substantial shock transmission from Gasoline markets on the same day the negative WTI events occur.

Our research builds upon and contributes to the literature on volatility spillover effects in commodity markets, particularly those focusing on oil and energy-related products. Notably, our findings diverge from, yet deepen, the understanding achieved in earlier works [Du et al., 2011, Nazlioglu et al., 2013]. For instance, significant works have suggested a more unidirectional volatility spillover from oil to other commodities [Ahmed and Huo, 2021]. Our analysis, however, highlights a more complex and multi-directional interconnectedness, where some markets transmit risk while others absorb shocks. This nuance could be attributed to our focus on extreme tail risks, a less-explored facet in previous studies. Further, our observation of Shanghai crude and EUA carbon futures predominantly functioning as shock absorbers contrast with the general perception of emerging markets as shock transmitters. This challenges previous assumptions and suggests a maturing and changing role of these markets in the global energy ecosystem. Our findings also corroborate earlier studies that noted the pivotal role of WTI in transmitting volatility to other energy markets [Liu and Gong, 2020, Corbet et al., 2021c]. However, our work extends this understanding by emphasising the magnitude of this transmission during extremely negative WTI pricing events. By considering the prevalence and intensity of extreme risk spillovers under negative oil price scenarios, our study adds granularity to the existing body of knowledge on market interconnectedness. In doing so, it underscores the intricacies and potential vulnerabilities of global energy markets, thus prompting a reevaluation of risk management strategies and regulatory policies. In conclusion, our study not only resonates with but also advances the literature on volatility spillover, presenting a more nuanced picture of the international energy market dynamics under extreme risk scenarios.

Such results verify not only the exceptionally dynamic nature and strong interconnectedness of the markets examined but reinforce the deep-rooted shock that pertained to the negative WTI pricing event. Specifically, results relating the substantial rebalancing of information to Shanghai crude oil and EUA carbon futures merit particular attention, where dynamic interactions reinforce the substantial market maturity that has continued to develop over time. The empirical results present a clear picture of the unique dynamics that dictate the behaviour of the international energy markets, particularly under conditions of extreme risk. However, to fully appreciate these dynamics, we must delve deeper into their economic underpinnings. The significant influence exerted by WTI on other energy markets during extreme risk can be explained by several factors. First, the WTI oil benchmark is deeply integrated into global financial markets, serving as one of a select number of key barometers of global economic health. Hence, severe negative shocks in the WTI market can erode confidence and trigger negative sentiment across other energy markets due to its stature and a high degree of visibility. Second, many institutional investors and financial institutions diversify their portfolios across various energy markets, creating conduits for transmitting shocks from one market to another. Thus, a negative shock in the WTI market can lead to significant contagion effects across other energy markets. Conversely, the resilience of Shanghai crude oil to negative shocks from WTI, positioning it as a significant shock absorber, can be attributed to the unique characteristics of the Chinese market. Legal and regulatory differentials, along with vast energy consumption and local alternatives to oil, partially insulate China from global shocks. The dynamic interaction between EUA carbon futures and the heating oil market can be understood from the perspective of carbon pricing. The increasing global emphasis on carbon pricing and environmental sustainability makes these markets susceptible to negative shocks, particularly during financial stress. These economic interpretations of our empirical results present the complex mechanisms underpinning extreme risk spillovers in international energy markets. By demonstrating the mechanisms of shock transmission and absorption, we further our understanding of these markets' behaviour during crises, contributing substantially to the existing body of knowledge on the financial economics of energy markets.

6. Concluding comments

International energy markets have, as a result of significant black-swan events, experienced various rare events in recent years, including a significant negative pricing event in WTI crude oil markets, the implementation of price caps, international sanction packages, and the broad restriction of oil trading across many geographical regions. Using a TVP-VAR analytical framework, this study explores the change and persistence of the dynamic connectedness of international energy markets, as well as the market for EUA carbon credits. Specifically, this research completes such a task by applying the popular tail risk model of Engle and Manganelli [2004] and the TVP-VAR connectedness approach of Antonakakis et al. [2020]. Of particular interest is that we study the dynamics of extreme risk spillovers for specific pairs by looking at the interactions for each pairwise connectedness, and for additional methodological robustness, by exploring the effects of negative oil events and subsequent changes on major oil markets using GARCH analysis. While considering the interactions between crude oil markets and other energy variants such as gasoline and gasoil, the broad destabilisation effects that have been sourced within recent political and epidemiological events have the potential to be quite disruptive to the continued growth and development of several regional oil markets.

The results are presented via a comprehensive analysis of the dynamics of extreme risk spillovers for particular commodity pairs. Crude oil futures do not present evidence of significant influence in the analysis, as demonstrated by our pairwise results. WTI and Brent transmit tail uncertainty shocks to other energy markets, whereas Shanghai crude typically acts as a shock absorber. The remaining energy-related commodities also primarily function as tail uncertainty receivers. The interaction between WTI and other energy commodities is particularly interesting within this context. WTI is a transmitter of extreme risk for EUA, ICE gasoil, US heating oil, and Shanghai crude oil. Shanghai crude oil, in particular, receives the greatest tail risk from WTI compared to other pairs. One month before and one month after the negative WTI oil pricing event, results indicate increased connectedness for most WTI-other energy market pairs, indicating that greater exposure to losses in the WTI market directly manifested in exposure to losses across the respective examined markets.

Incorporating EGARCH-based robustness testing procedures that test for significant market connectedness shocks that manifested within international energy markets adds further validity to the results. On the date of the negative WTI event, among several changes of dynamic interaction, Shanghai crude oil markets were found to be significant net receivers of shocks. Further, significantly elevated shock transmission is observed between EUA carbon futures and the heating oil market. In contrast, carbon futures experience significant shock transmission on the same day as negative WTI events from gasoline markets. Such results not only substantiate the exceptionally dynamic and robust interconnectedness of the analysed markets but also bolster the pervasiveness of the negative WTI pricing event. Specifically, results relating to the substantial rebalancing of information to Shanghai crude oil futures and EUA carbon futures merit special consideration. Their dynamic interactions strengthen evidence supporting their continued maturation into significant international markets. These findings are particularly interesting to policymakers and market participants who use such products to hedge against and diversify regional oil market fluctuations. With the analysis and findings presented in this paper, we believe we have addressed our central research question and its related sub-questions satisfactorily. We have unveiled the intricate dynamics of extreme risk spillovers across international energy markets in periods of upheaval, focusing on the interconnectedness of WTI, Brent, and Shanghai crude oil futures with other energy markets. These findings not only enrich our understanding of the complex market mechanisms in play but also provide actionable insights for market participants seeking to hedge against or diversify oil market fluctuations.

Our study's contributions to the existing literature on international energy markets' interconnectedness during the WTI negative pricing events can be summarised in three main points. First, our examination of tail risk spillovers provides a more nuanced perspective of market interconnectedness than previous studies. Second, our findings about the differing roles of WTI, Brent, and Shanghai crude as either transmitters or receivers of extreme risk shocks in different market situations provide new insights into the role of market structure and market dynamics in extreme risk transmission. Finally, our methodological approach, which includes the EGARCH-based robustness testing procedures, introduces a novel way of investigating market connectedness during periods of instability. These contributions deepen our understanding of market dynamics in times of crisis and provide useful insights for policymakers and market participants alike.

Overall, our analysis reveals that extreme risk spillovers in international energy markets exhibit a complex, dynamic behaviour, with different commodities playing transmitter or receiver roles under different conditions. This finding has immediate implications for market participants and policymakers who seek to understand the resilience and vulnerability of these markets in the face of significant disturbances, such as the WTI negative pricing event. For market participants, understanding the dynamics of extreme risk spillovers is critical for effective risk management. Our findings suggest that diversification strategies should consider not only the correlations between different energy markets but also their potential to transmit or absorb extreme risk during periods of turbulence. The fact that WTI transmits significant tail risk to other energy commodities, including EUA, ICE gasoil, US heating oil, and Shanghai crude oil, implies that portfolio managers and traders dealing with these commodities may need to review their risk mitigation strategies to manage potential losses during severe market shocks better. For policymakers, evidence suggests that market disturbances can disrupt the equilibrium of energy markets, causing potential spillover effects on other sectors of the economy. Particularly, the demonstrated susceptibility of the Shanghai crude oil market to extreme risk shocks from the WTI market could be of strategic interest to Chinese regulators. The insights provided in this research also underline the importance of close international cooperation in managing the global energy markets' stability, particularly during periods of crisis. The strong interconnectedness between different markets suggests that any significant shock in one market will likely have repercussions in others, underscoring the need for joint policy responses. Overall, this research contributes a more nuanced understanding of extreme risk dynamics in the international energy markets.

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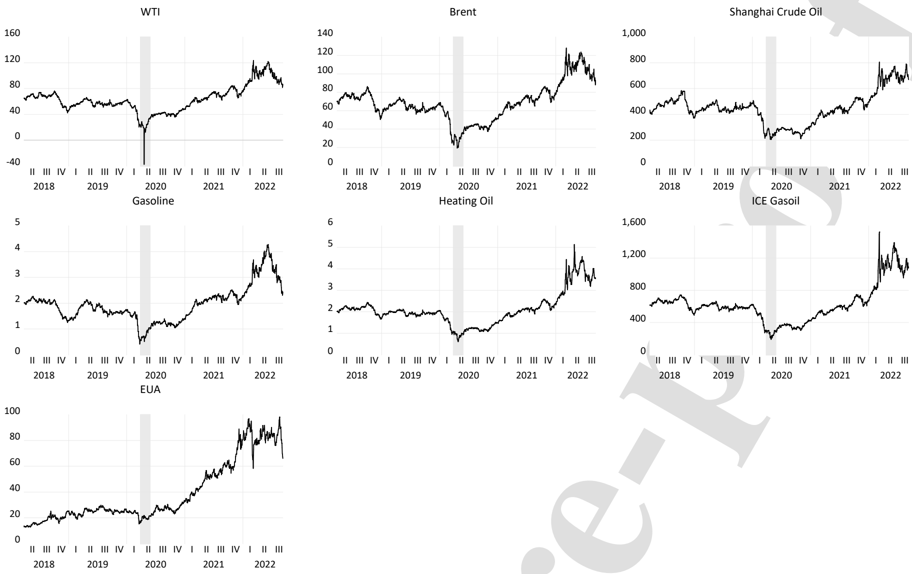
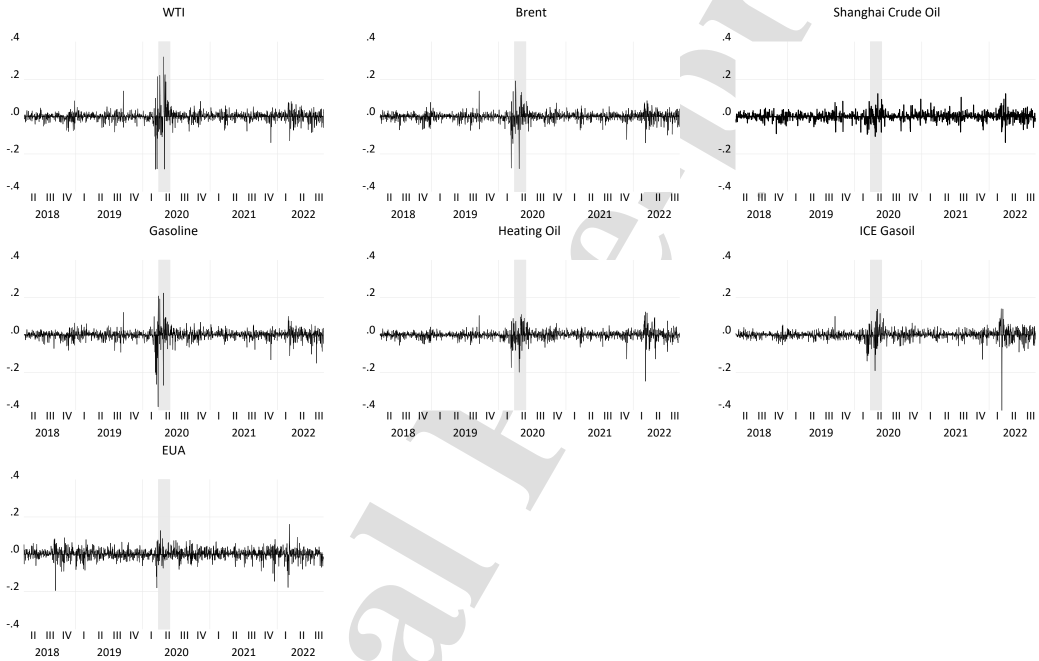
Figure 1: Price performance of analysed assets, USD$



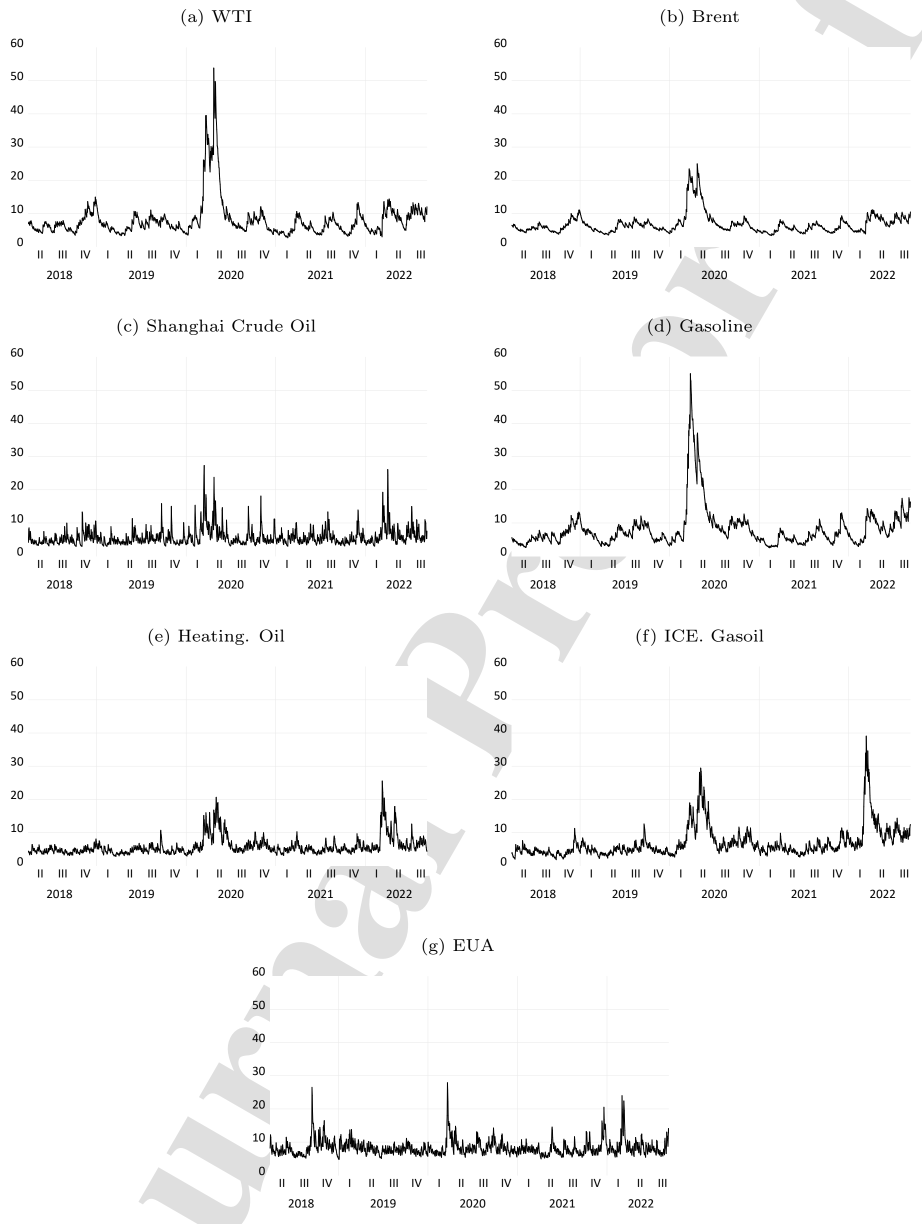
Note: This figure depicts the daily price of six oil-related futures with European carbon price futures between 26 March 2018 to 9 September 2022. The shaded area covers one month before and after the April 2020 negative WTI oil pricing event. We obtain daily data on WTI futures, Brent futures, US heating oil futures, US gasoline futures, European gasoil futures, Shanghai crude oil futures, and European carbon price futures from the Eikon database.

Figure 2: Time series plot of each daily return series



Note: This figure depicts the daily return of six oil-related futures with European carbon price futures from 26 March 2018 to 9 September 2022. The shaded area covers the period of one month both before and after the April 2020 negative WTI oil pricing event. We obtain daily data on WTI futures, Brent futures, US heating oil futures, US gasoline futures, European gasoil futures, Shanghai crude oil futures, and European carbon price futures from the Eikon database.

Figure 3: 1% tail risks.

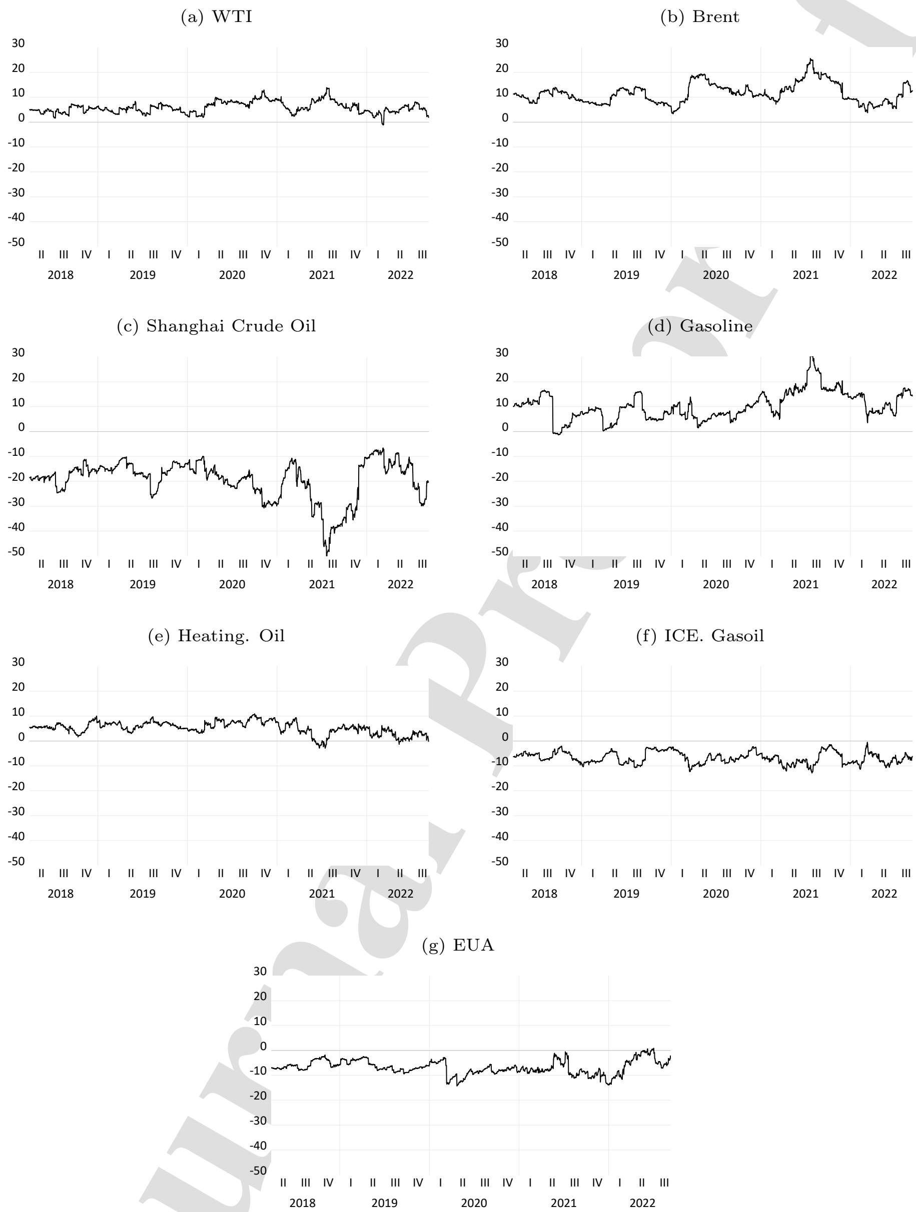


Note: 1% tail risk is calculated using asymmetric slope CAViaR model, which is formulated as $f_{\alpha,t} = \beta_0 + \beta_1 f_{\alpha,t-1}(\beta) + \beta_2 x^+_{t-1} + \beta_3 x^-_{t-1}$ where $f_{\alpha,t}$ is the VaR at the α level in period t. β_2 and β_3 are coefficients that measure the effects of positive and negative returns. The asymmetric slope CAViaR model, therefore, considers the leverage effect in the daily returns.

Figure 4: Total connectedness based on 1% VaR tail risk changes

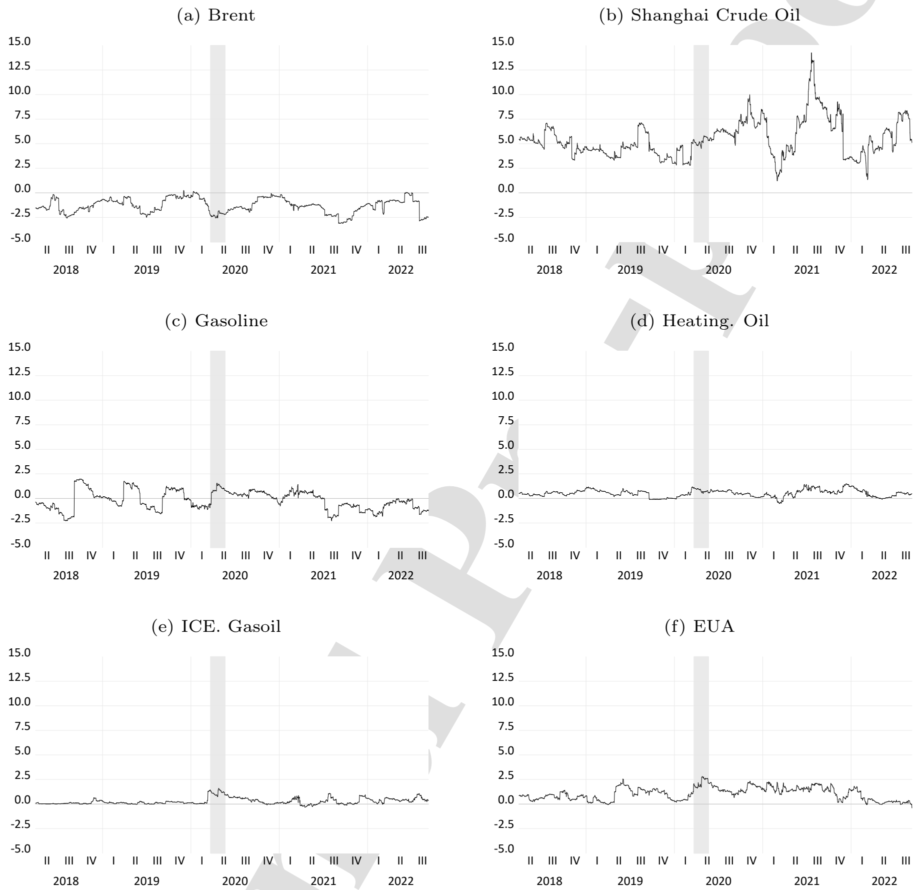
Note: Results are obtained from a TVP-VAR model with a lag length of order one, and a 20-step ahead forecast error variance, which is formulated as: $f_{\alpha,t} = \beta_0 + \beta_1 f_{\alpha,t-1}(\beta) + \beta_2 x^+_{t-1} + \beta_3 x^-_{t-1}$ where $f_{\alpha,t}$ is the VaR at the α level in period t. β_2 and β_3 are coefficients that measure the effects of positive and negative returns. The asymmetric slope CAViaR model, therefore, considers the leverage effect in the daily returns. The shaded area covers the period of one month both before and after the April 2020 negative WTI oil pricing event.

Figure 5: Net connectedness based on 1% VaR tail risk changes



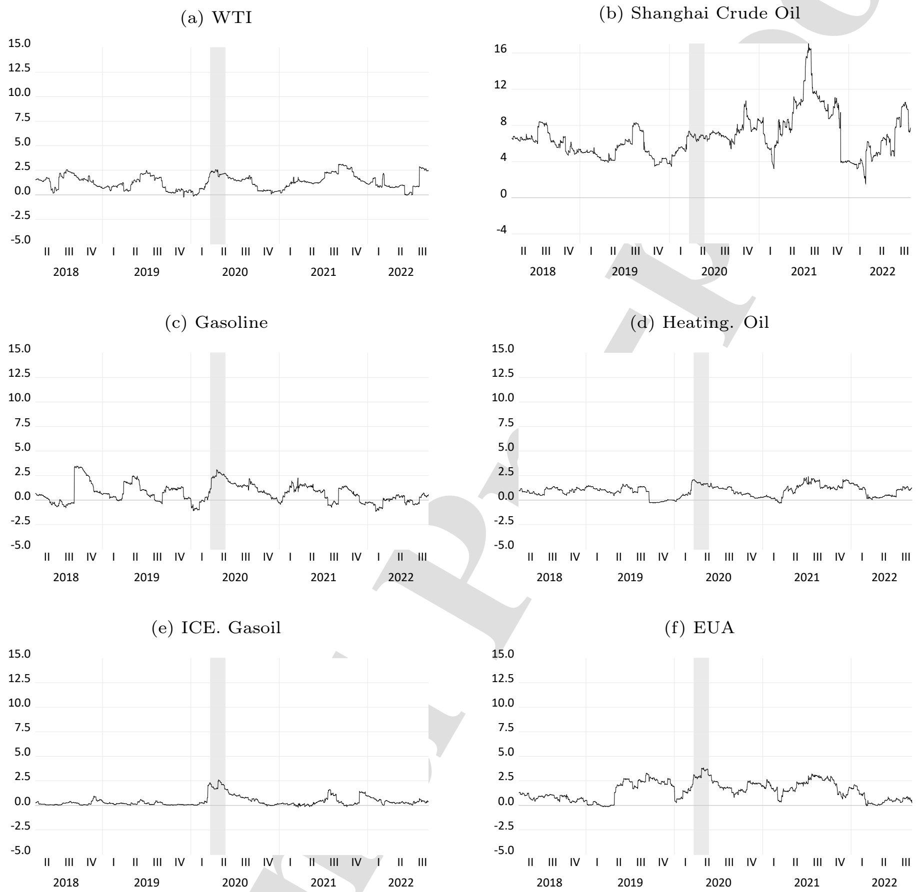
Note: The 1% tail risk is calculated using asymmetric slope CAViaR model, which is formulated as $f_{\alpha,t} = \beta_0 + \beta_1 f_{\alpha,t-1}(\beta) + \beta_2 x^+_{t-1} + \beta_3 x^-_{t-1}$ where $f_{\alpha,t}$ is the VaR at the α level in period t. β_2 and β_3 are coefficients that measure the effects of positive and negative returns. The asymmetric slope CAViaR model, therefore, considers the leverage effect in the daily returns.

Figure 6: Pairwise connectedness between WTI and other markets



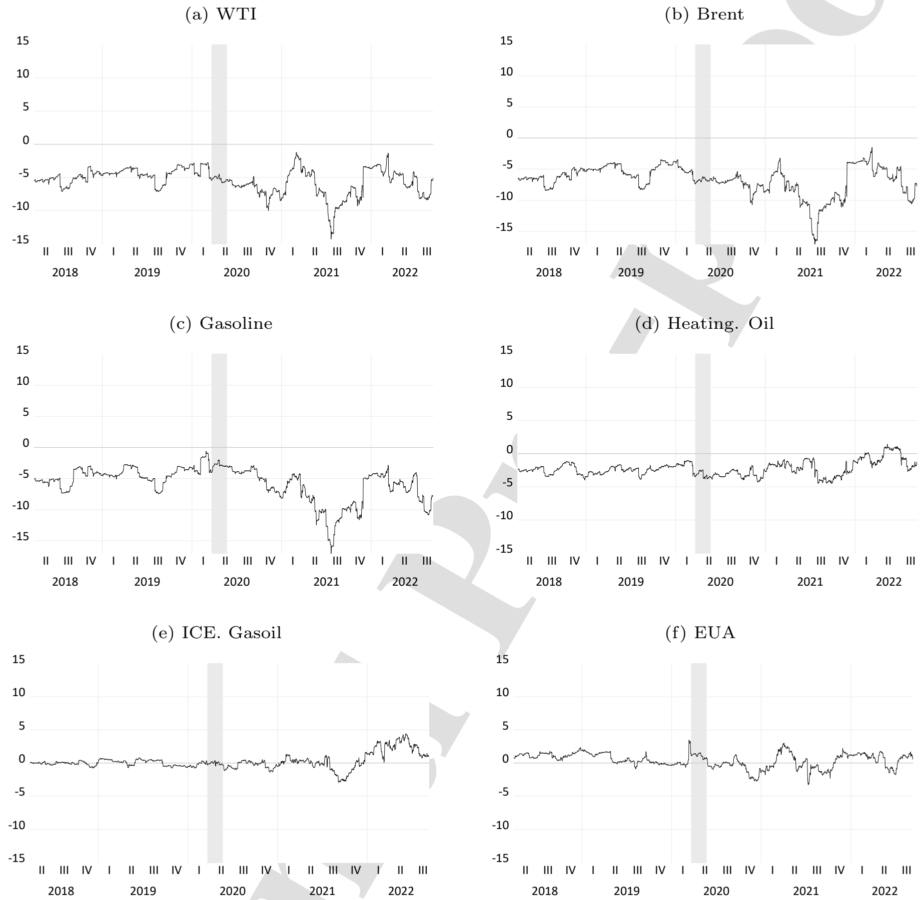
Note: Results are obtained from a TVP-VAR model with a lag length of order one, and a 20-step ahead forecast error variance. The 1% tail risk is calculated using the asymmetric slope CAViaR model, which is formulated as $f_{\alpha,t} = \beta_0 + \beta_1 f_{\alpha,t-1}(\beta) + \beta_2 x^+_{t-1} + \beta_3 x^-_{t-1}$ where $f_{\alpha,t}$ is the VaR at the α level in period t. β_2 and β_3 are coefficients that measure the effects of positive and negative returns. The asymmetric slope CAViaR model, therefore, considers the leverage effect in the daily returns. The shaded area covers one month before and after the April 2020 negative WTI oil pricing event.

Figure 7: Pairwise connectedness between Brent and other markets



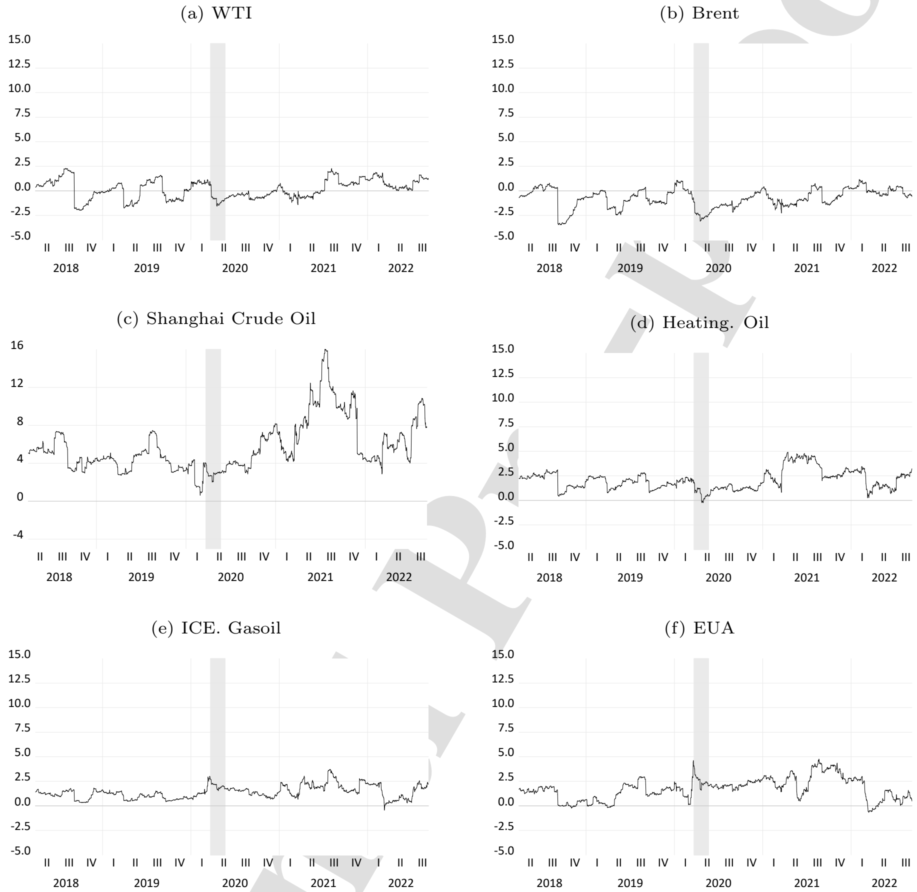
Note: Results are obtained from a TVP-VAR model with a lag length of order one, and a 20-step ahead forecast error variance. The 1% tail risk is calculated using the asymmetric slope CAViaR model, which is formulated as $f_{\alpha,t} = \beta_0 + \beta_1 f_{\alpha,t-1}(\beta) + \beta_2 x^+_{t-1} + \beta_3 x^-_{t-1}$ where $f_{\alpha,t}$ is the VaR at the α level in period t. β_2 and β_3 are coefficients that measure the effects of positive and negative returns. The asymmetric slope CAViaR model, therefore, considers the leverage effect in the daily returns. The shaded area covers the period of one month both before and after the April 2020 negative WTI oil pricing event.

Figure 8: Pairwise connectedness between Shanghai crude oil and other markets



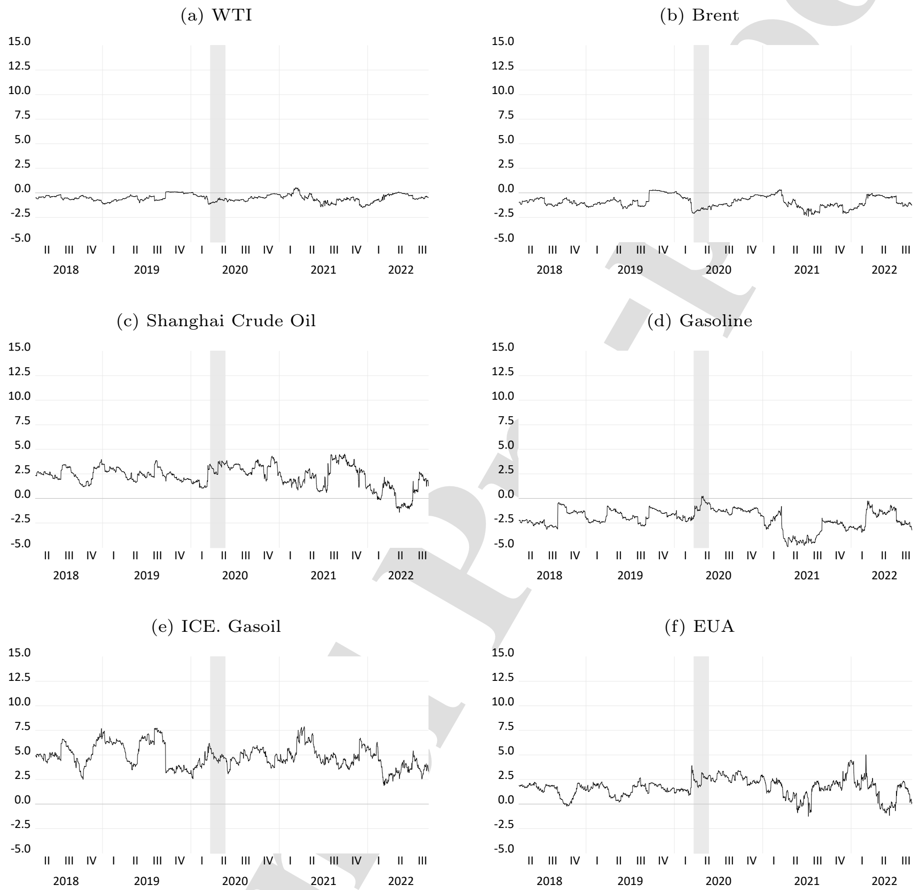
Note: Results are obtained from a TVP-VAR model with a lag length of order one, and a 20-step ahead forecast error variance. The 1% tail risk is calculated using the asymmetric slope CAViaR model, which is formulated as $f_{\alpha,t} = \beta_0 + \beta_1 f_{\alpha,t-1}(\beta) + \beta_2 x^{+}_{t-1} + \beta_3 x^{-}_{t-1}$ where $f_{\alpha,t}$ is the VaR at the α level in period t. β_2 and β_3 are coefficients that measure the effects of positive and negative returns. The asymmetric slope CAViaR model, therefore, considers the leverage effect in the daily returns. The shaded area covers the period of one month both before and after the April 2020 negative WTI oil pricing event.

Figure 9: Pairwise connectedness between gasoline and other markets



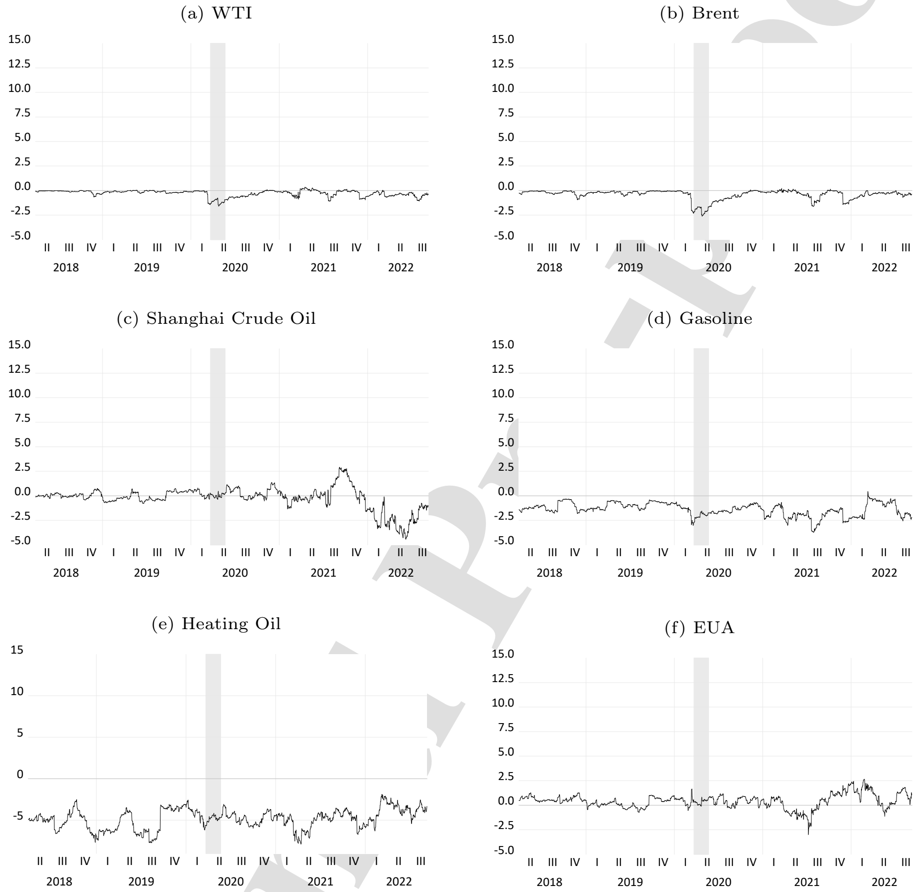
Note: Results are obtained from a TVP-VAR model with a lag length of order one, and a 20-step ahead forecast error variance. The 1% tail risk is calculated using the asymmetric slope CAViaR model, which is formulated as $f_{\alpha,t} = \beta_0 + \beta_1 f_{\alpha,t-1}(\beta) + \beta_2 x^+_{t-1} + \beta_3 x^-_{t-1}$ where $f_{\alpha,t}$ is the VaR at the α level in period t. β_2 and β_3 are coefficients that measure the effects of positive and negative returns. The asymmetric slope CAViaR model, therefore, considers the leverage effect in the daily returns. The shaded area covers the period of one month both before and after the April 2020 negative WTI oil pricing event.

Figure 10: Pairwise connectedness between heating oil and other markets



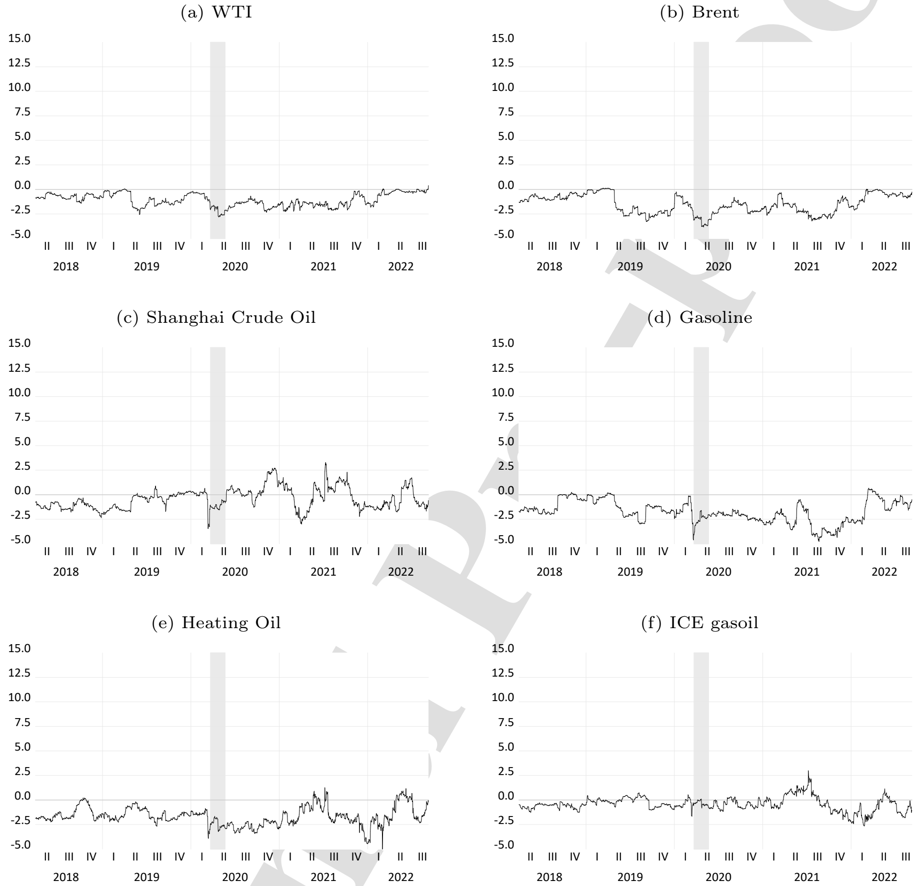
Note: Results are obtained from a TVP-VAR model with a lag length of order one, and a 20-step ahead forecast error variance. The 1% tail risk is calculated using the asymmetric slope CAViaR model, which is formulated as $f_{\alpha,t} = \beta_0 + \beta_1 f_{\alpha,t-1}(\beta) + \beta_2 x^+_{t-1} + \beta_3 x^-_{t-1}$ where $f_{\alpha,t}$ is the VaR at the α level in period t. β_2 and β_3 are coefficients that measure the effects of positive and negative returns. The asymmetric slope CAViaR model, therefore, considers the leverage effect in the daily returns. The shaded area covers one month before and after the April 2020 negative WTI oil pricing event.

Figure 11: Pairwise connectedness between ICE. gasoil and other markets



Note: Results are obtained from a TVP-VAR model with a lag length of order one, and a 20-step ahead forecast error variance. The 1% tail risk is calculated using the asymmetric slope CAViaR model, which is formulated as $f_{\alpha,t} = \beta_0 + \beta_1 f_{\alpha,t-1}(\beta) + \beta_2 x^{+}_{t-1} + \beta_3 x^{-}_{t-1}$ where $f_{\alpha,t}$ is the VaR at the α level in period t. β_2 and β_3 are coefficients that measure the effects of positive and negative returns. The asymmetric slope CAViaR model, therefore, considers the leverage effect in the daily returns. The shaded area covers one month before and after the April 2020 negative WTI oil pricing event.

Figure 12: Pairwise connectedness between EUA and other markets



Note: Results are obtained from a TVP-VAR model with a lag length of order one, and a 20-step ahead forecast error variance. The 1% tail risk is calculated using the asymmetric slope CAViaR model, which is formulated as $f_{\alpha,t} = \beta_0 + \beta_1 f_{\alpha,t-1}(\beta) + \beta_2 x^+_{t-1} + \beta_3 x^-_{t-1}$ where $f_{\alpha,t}$ is the VaR at the α level in period t. β_2 and β_3 are coefficients that measure the effects of positive and negative returns. The asymmetric slope CAViaR model, therefore, considers the leverage effect in the daily returns. The shaded area covers the period one month before and after the April 2020 negative WTI oil pricing event.

Table 1: Summary statistics for each daily return series

	WTI	Brent	Shanghai	Gasoline	Heating oil	ICE. Gasoil	EUA
Mean	0.000543	0.000172	0.0003	0.0001	0.0004	0.0004	0.0009
Median	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Max	0.3196	0.1908	0.1216	0.2239	0.1236	0.1399	0.1614
Min	-0.2822	-0.2797	-0.1387	-0.3853	-0.2475	-0.4085	-0.1942
Std Dev.	0.02916	0.0245	0.0201	0.0280	0.0224	0.0246	0.0256
Skewness	0.0869	-1.7163	-0.2922	-2.6842	-1.5265	-3.0482	-0.8016
Kurtosis	37.2837	30.4722	10.6803	45.2931	23.443	56.8643	11.2011

Note: This table reports the descriptive statistics of the return series of six major oil-related futures with European carbon price futures from 26 March 2018 to 9 September 2022. Returns are calculated as the first differences of natural logarithms of price series.

Table 2: EGARCH-estimated connectedness change as a result of 2020 negative oil event, sourced from WTI and Brent Crude

Connectedness To	[-60,-1]	[-40,-1]	[-20,-1]	[-10,-1]	[-5,-1]	[-3,-1]	[0,+1]	[0,+3]	[0,+5]	[0,+10]	[0,+20]	[0,+40]	[0,+60]
Testing connectedness change from: West Texas Intermediate Oil													
Brent	-0.071	-0.542***	-1.098***	-1.121***	-1.174***	-1.125**	-1.460	-0.969	-0.651	-0.686**	-0.759***	-0.711***	-0.571***
	(0.71)	(4.56)	(6.70)	(4.79)	(3.55)	(2.67)	(0.86)	(1.16)	(1.54)	(2.71)	(4.48)	(6.00)	(5.87)
Shanghai	-1.353***	-1.024***	-0.435	-0.455	-0.355	-0.407	4.285*	0.640	-0.025	-0.046	0.092	0.053	0.320
	(5.44)	(3.36)	(1.02)	(0.75)	(0.42)	(0.38)	(2.04)	(0.30)	(0.02)	(0.07)	(0.21)	(0.17)	(1.27)
Gasoline	-0.186	0.094	0.889***	1.138***	1.262**	1.456**	4.287***	3.053**	1.885***	1.587***	1.393***	1.155***	1.011***
	(1.44)	(0.59)	(4.09)	(3.69)	(2.90)	(2.64)	(4.92)	(2.80)	(3.41)	(4.80)	(6.31)	(7.49)	(8.01)
ICE Gasoil	0.318***	0.587***	0.794***	0.680***	0.636***	0.639***	2.441***	1.570***	1.215***	1.132***	1.028***	0.813***	0.694***
	(7.60)	(11.94)	(11.59)	(6.76)	(4.45)	(3.50)	(3.31)	(4.38)	(6.76)	(10.77)	(15.18)	(17.55)	(18.42)
Heating Oil	0.164***	0.331***	0.453***	0.432***	0.398*	0.416*	1.047	0.186	0.128	0.106	0.152	0.170**	0.201***
	(3.47)	(5.80)	(5.71)	(3.82)	(2.50)	(2.05)	(1.27)	(0.46)	(0.63)	(0.87)	(1.85)	(2.95)	(4.25)
EUA Carbon	0.012	0.356***	0.798***	0.885***	0.906**	0.999**	7.016***	3.678***	2.061***	1.699***	1.571***	1.275***	1.049***
	(0.14)	(3.37)	(5.46)	(4.26)	(3.10)	(2.68)	(4.69)	(5.04)	(5.58)	(7.74)	(10.90)	(12.80)	(12.82)
Testing connectedness change from: Brent Crude Oil													
Shanghai	-0.630*	-0.255	0.195	0.109	0.117	-0.023	2.774	0.032	-0.190	-0.197	-0.006	-0.038	0.142
	(2.03)	(0.67)	(0.37)	(0.15)	(0.11)	(0.02)	(0.52)	(0.01)	(0.14)	(0.25)	(0.01)	(0.10)	(0.46)
Gasoline	0.018	0.618***	1.628***	1.849***	1.996***	2.153***	5.379*	3.714***	2.383***	2.144***	2.012***	1.737***	1.497***
	(0.14)	(3.97)	(7.65)	(6.08)	(4.64)	(3.93)	(2.42)	(3.43)	(4.35)	(6.58)	(9.34)	(11.69)	(12.35)
ICE Gasoil	0.672***	1.099***	1.454***	1.333***	1.339***	1.366***	5.287***	3.143***	2.215***	2.044***	1.876***	1.493***	1.238***
	(10.85)	(15.25)	(14.37)	(8.86)	(6.23)	(4.97)	(4.75)	(5.82)	(8.19)	(13.09)	(19.14)	(22.68)	(23.02)
Heating Oil	0.263***	0.617***	0.943***	0.877***	0.876***	0.881**	2.817*	1.048	0.713*	0.668***	0.699***	0.591***	0.522***
	(3.45)	(6.75)	(7.45)	(4.83)	(3.42)	(2.70)	(2.13)	(1.62)	(2.18)	(3.41)	(5.33)	(6.45)	(6.95)
EUA Carbon	0.515***	0.933***	1.469***	1.506***	1.564***	1.643**	9.129***	4.904***	2.754***	2.313***	2.179***	1.768***	1.437***
	(4.09)	(6.15)	(7.00)	(5.01)	(3.69)	(3.04)	(4.20)	(4.63)	(5.13)	(7.25)	(10.38)	(12.16)	(12.02)

Note: To estimate the change of dynamic connectedness, we utilise the mean equation of the EGARCH(1,1) methodology as displayed in equation (13), expressed as $c_t = a_0 + b_1 c_{t-1} + b_2 d_t + \varepsilon_t$, where c_t represents the estimated connectedness as estimated. We specifically examine the time periods: [-60,-1], [-40,-1], [-20,-1], [-10,-1], [-5,-1], [-3,-1], [0,+1] [0,+3], [0,+5], [0,+10], [0,+20], [0,+40], and [0,+60], to test for the change in connectedness both before and after. In equation (13), c_{t-1} represents the lagged value of the individually analysed market connectedness. Further methodological specifications and associated pre- and post-estimation testing results are available from the authors upon request. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 3: EGARCH-estimated connectedness change as a result of 2020 negative oil event, sourced from Shanghai crude, gasoline, ICE gasoil and heating oil

Connectedness To	[-60,-1]	[-40,-1]	[-20,-1]	[-10,-1]	[-5,-1]	[-3,-1]	[0,+1]	[0,+3]	[0,+5]	[0,+10]	[0,+20]	[0,+40]	[0,+60]
Testing connectedness change from: Shanghai Crude Oil													
Gasoline	3.339***	3.267***	2.950***	3.184***	3.250**	3.356*	2.195	3.578	2.902	2.837**	2.798***	2.768***	2.502***
	(9.63)	(7.65)	(4.89)	(3.71)	(2.69)	(2.18)	(0.35)	(1.18)	(1.89)	(3.07)	(4.53)	(6.42)	(7.09)
ICE Gasoil	-0.345*	-0.215	-0.237	-0.141	-0.222	-0.162	-1.006	-0.680	-0.458	-0.276	-0.310	-0.640***	-0.757***
	(2.21)	(1.13)	(0.90)	(0.37)	(0.42)	(0.24)	(0.37)	(0.51)	(0.68)	(0.68)	(1.14)	(3.37)	(4.88)
Heating Oil	0.174	-0.205	-0.612*	-0.350	-0.395	-0.359	-5.705*	-2.364	-1.532*	-1.310***	-1.280***	-1.201***	-1.188***
	(1.17)	(1.13)	(2.43)	(0.98)	(0.79)	(0.56)	(2.22)	(1.88)	(2.41)	(3.43)	(5.01)	(6.75)	(8.20)
EUA Carbon	0.277	0.684***	0.841***	0.765*	0.619	0.655	-1.369	0.151	0.808	0.834*	0.579*	0.003	-0.321*
	(1.91)	(3.91)	(3.46)	(2.21)	(1.27)	(1.06)	(0.55)	(0.12)	(1.31)	(2.24)	(2.31)	(0.01)	(2.22)
Testing connectedness change from: Gasoline													
ICE Gasoil	0.471***	0.762***	0.831***	0.733***	0.658*	0.565	1.980	0.571	0.351	0.366	0.476**	0.400***	0.378***
	(5.36)	(7.20)	(5.59)	(3.46)	(2.20)	(1.49)	(1.29)	(0.76)	(0.92)	(1.60)	(3.10)	(3.71)	(4.28)
Heating Oil	-0.325*	-0.500**	-0.995***	-0.967**	-1.042*	-1.132*	-3.743	-3.344**	-2.360***	-2.141***	-1.887***	-1.600***	-1.373***
	(2.45)	(3.10)	(4.46)	(3.05)	(2.33)	(1.99)	(1.63)	(2.99)	(4.17)	(6.35)	(8.43)	(10.31)	(10.82)
EUA Carbon	0.119	0.451*	1.123***	0.828*	0.651	0.418	4.455*	1.983	0.814	0.548	0.566*	0.433*	0.358*
	(0.80)	(2.49)	(4.48)	(2.32)	(1.30)	(0.65)	(2.06)	(1.57)	(1.27)	(1.42)	(2.19)	(2.39)	(2.40)
Testing connectedness change from: ICE Gasoil													
Heating Oil	0.133	-0.199	-0.131	0.182	0.293	0.372	-0.245	1.353	0.694	0.483	0.216	0.584**	0.517**
	(0.84)	(1.02)	(0.48)	(0.48)	(0.55)	(0.55)	(0.09)	(1.00)	(1.02)	(1.18)	(0.78)	(3.02)	(3.25)
EUA Carbon	-0.127	-0.191	-0.251	-0.378	-0.363	-0.379	0.511	0.425	0.223	0.096	0.076	0.199	0.182
	(1.33)	(1.64)	(1.55)	(1.65)	(1.13)	(0.93)	(0.31)	(0.53)	(0.54)	(0.39)	(0.46)	(1.71)	(1.90)
Testing connectedness change from: Heating Oil													
EUA Carbon	0.218	0.444**	0.443*	0.197	0.256	0.247	5.736**	3.199**	1.775**	1.378***	1.147***	1.069***	1.144***
	(1.73)	(2.90)	(2.08)	(0.65)	(0.60)	(0.46)	(2.63)	(3.01)	(3.30)	(4.27)	(5.30)	(7.09)	(9.39)

Note: To estimate the change of dynamic connectedness, we utilise the mean equation of the EGARCH(1,1) methodology as displayed in equation (13), expressed as $c_t = a_0 + b_1 c_{t-1} + b_2 d_t + \varepsilon_t$, where c_t represents the estimated connectedness as estimated. We specifically examine the time periods: [-60,-1], [-40,-1], [-20,-1], [-10,-1], [-5,-1], [-3,-1], [0,+1] [0,+3], [0,+5], [0,+10], [0,+20], [0,+40], and [0,+60], to test for the change in connectedness both before and after. In equation (13), c_{t-1} represents the lagged value of the individually analysed market connectedness. Further methodological specifications and associated pre- and post-estimation testing results are available from the authors upon request. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Highlights

We reveal interconnectedness in global energy markets

We explore the impact of extreme 'black swan' events

WTI is identified as a significant role in shock transmission

Shanghai crude and EUA markets are shown to be shock absorbers

We contributed a novel method to investigate market connectedness

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