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Tail risk spillovers between Shanghai oil and other markets

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ABSTRACT

This paper uses daily returns data from January 2011 to December 2022 to analyse the tail risk spillovers between Shanghai oil and a sample of stock and commodities markets. The computed CAViaR measures each market's tail risk and analyses the connectedness network using the TVP-VAR method. The tail risk spillover network estimates reveal clustering—as stocks and commodities within the same category are vigorously connected. Shanghai oil's links to the global markets remain limited, but it is a net risk receiver. As such, Shanghai oil is a lesser player in the global financial system than WTI or Brent. Nevertheless, (tail risk) connectedness between Shanghai oil and sample markets soars during crises such as the shale oil revolution, the COVID-19 pandemic, and the Russia-Ukraine war. Among the crises, COVID-19 has had the most potent effect on our markets—with connectedness indicators exceeding 70%. The spillover size and shape differ considerably by crisis events. Thus, Shanghai oil futures may be viewed as a novel financial market that permits both domestic and international investors to access the Chinese crude oil market and diversify their investment risk.

1. Introduction

China's rapid economic progress and the size of its aggregate economy culminated in being the single largest importer of crude oil in 2021 globally (Statista, 2023). On 26 March 2018, the establishment of the Shanghai International Energy Exchange (INE), for the first time, created a market of oil futures contracts market. This was undertaken due to China, hitherto exerting little or no impact on crude oil pricing (Lin and Su, 2021). The incumbent futures markets for oil—the West Texas Intermediate (WTI) and Brent crude oil—respond slowly and by a lesser extent to the demand movements in Asia. Consequently, crude oil markets in Asia are confronted with more significant risks—culminating in the "Asian premium".

The INE is often called 'Shanghai Oil Futures' or just 'Shanghai oil'. The Shanghai oil futures are yuan-denominated, and their underlying asset is specified as heavy high sulphur oil. The choice of heavy high-sulphur oil is intended to avoid direct competition with the established futures markets (that transact in US dollars) for light low-sulphur oil, such as West Texas Intermediate (WTI) and Brent crude oil futures (Joo et al., 2021). Additionally, the demand for heavy high-sulphur oil is dominated mainly by Northeast Asian countries, constituting some 44% of (crude oil) production worldwide (Yang et al., 2020). Shanghai oil remains Asia's largest crude oil futures market, exceeding that of Oman Crude Oil (Lin and Su, 2021; Wang et al., 2022). The trading hours of Shanghai oil differ from that of the WTI and Brent: with daytime trading hours of 09:00–11:30 am and 01:30–03:00 pm and night-time trading hours of 09:00 pm to 02:30 am the next day. The INE is also dominated by individual traders, many of whom are high-frequency speculative

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investors—implying unfledged maturity of the former market vis-à-vis that of the WTI and Brent. Foreign investors command a sizable fraction of Shanghai oil's transaction volumes and positions—at 15 and 22% in 2019, respectively (Yang et al., 2021a).

Shanghai oil is an alternative to Western oil futures markets—Brent and WTI. The formation of the INE was aimed at commencing futures trading in the Asia-Pacific region. The goal was to improve oil markets' ability to respond to economic conditions in Asia, especially China. In essence, China founded the Shanghai oil futures contract to improve its Global crude oil futures market position (Shao and Hua, 2022). The INE enables the formation of a 'pricing mechanism' for China and the Asia-Pacific region (Lu et al., 2020). However, as seen from the oil's high sulphur content and the market's trading hours, Shanghai Oil is intended to complement rather than substitute the major crude oil futures markets. The high transaction fees and daily price change limit of 4 % also prevent it from being a substitute for Western oil futures markets (Ji and Zhang, 2019).

Academic researchers emphasise analysing futures markets as they represent price discovery (Shao and Hua, 2022). Price discovery is the determination of an asset—crude oil, in this instance—price (often spot) via transactions in the marketplace. As Shanghai oil is a (relative) newcomer in the crude oil futures, its role in price discovery in this marketplace may involve a discount due to quality or nascence (Elder et al., 2014). Furthermore, substantial government intervention and market concentration in trading crude oil persists in China. The INE's incipience, coupled with the hitherto market failure of Chinese crude oil futures and a lack of an established exchange in the Asia-Pacific region, provides researchers with an indispensable opportunity to scrutinise the integration of China and the Asia-Pacific in the crude oil future marketplace. Stakeholders are particularly interested in understanding what role Shanghai Oil will play—i.e., that of a historical price taker or an assertive price setter—in international crude oil futures trading and the broader financial system (Zhang et al., 2021). This will allow policymakers and researchers alike to gauge the quality of the fundamentals of 'crude oil benchmarks' in the China and Asia-Pacific region. The fundamentals of Shanghai Oil may incorporate its role in global risk transmissions, 'common trends' with international markets, the profile of agents/investors, and modalities of trading, inter alia (e.g., Ji and Zhang, 2019; Shao and Hua, 2022; Wu et al., 2022; Wang et al., 2019; Yang and Zhou, 2020; Zhang et al., 2021).

This novelty of Shanghai oil futures and its potential disruptive impact on the global crude oil (futures) as well as financial markets has attracted the attention of many academic researchers since the late 2010s—e.g., Ji and Zhang (2019), Lin and Su (2021), Yang et al. (2020), Yang and Zhou (2020), Yang et al. (2021a), Yang et al. (2021b), Shao and Hua (2022), Lu et al. (2023), inter alia. The extant literature, however, remains limited to analysing the volatility spillover, the forecast ability of Shanghai oil, and the impact of macroeconomic and financial factors on the latter. In addition, most studies limit their analysis of (non-tail) risk spillover analysis of the INE vis-à-vis other crude oil futures markets. To the best of the authors' knowledge, no published study exists that performs a network connectedness analysis of tail risk between Shanghai and global stocks and commodities (see Section 2 for a detailed review and analysis of the relevant literature).

Moreover, as noted previously, Shanghai is intended to complement rather than substitute existing crude oil futures and other financial markets. Its fundamentals may be directly, and perhaps indirectly, linked with pertinent financial markets—such as competing energy sources (including clean energy), precious metals and currencies, and green stocks and carbon markets. INE's interplay with competing energy sources provides valuable insights into market decisions regarding its own demand, risk propagation, investor confidence, and portfolio risk diversification (*ex-post*). Shanghai Oil's risk dynamic risk propagation vis-à-vis precious metals and currencies would reveal information on global economic vigour and investors' and economic agents' decisions, *ex-ante* and *ex-post*. Green stocks and carbon markets are essential to Shanghai Oil futures as China aims to transition to a 'low carbon economy' and leads the globe in investing in clean energy capacity and technologies (Naeem et al., 2023a,b). As such, carbon markets and green stocks play a crucial role in influencing future demand for crude oil, especially in China—thereby impacting the risk dynamics of the INE.

Against this backdrop, this paper represents the first attempt at analysing the tail risk transmissions between Shanghai oil and a sample of stock and commodities markets. Our paper contributes to (and complements) the growing body of literature (including those cited in the previous paragraph) that analyses risk transmission and price discovery in the INE. Firstly, we avail daily returns data from January 2011 to December 2022 and implement the Conditional Autoregressive Value-at-Risk (CAViaR) as well as Time-Varying Parameter (TVP) Vector Autoregression (VAR) connectedness approaches. These methods are essential tools in analysing the dynamics of tail risk as well as its spillover networks across various financial markets (Akhtaruzzaman et al., 2022a; Akhtaruzzaman et al., 2022b). Secondly, unlike the extant literature, our paper primarily analyses risk transmissions/receipts during extreme crises—i.e., tail risk—and several stock and commodity markets (Akhtaruzzaman et al., 2022a). In particular, we implement the above-referenced methods to understand the dynamic risk spillover network between INE and other commodity and stock markets. This is also expected to reveal valuable insights into crude oil demand and investor sentiments in China and the Asia-Pacific and aid in predicting Shanghai Oil futures' volatility. Thirdly and most importantly, our paper also expects to contribute to the INE literature on price discovery (or lack thereof)—i.e., if and how it affects crude oil prices in China (and perhaps the Asia-Pacific region) and abroad (Sun et al., 2023). This is expected to assist investors/agents in determining whether Shanghai Oil can play any role in risk diversification and/or hedging benefits. Thus, our first analysis of Shanghai oil's tail risk spillover network(s) using the abovementioned estimation techniques makes unique, novel, and substantial contributions to the literature.

Our estimated results reveal some interesting findings that also contribute to the existing body of knowledge and provide specific policy implications. In particular, we find tail risk spillover network clustering—with the most robust connections occurring in the same market classification category (i.e., green, conventional energies, precious metals, Shanghai Oil, currency, and carbon). Shanghai oil is a net recipient of risk from other markets and is largely disconnected. This implies that Shanghai oil plays a relatively minimal role in the global financial system, unlike its WTI and Brent counterparts. We also observe increased (tail risk) connectedness during crisis events such as the shale oil revolution, the COVID-19 pandemic, and the Ukraine-Russia war. Among the crises, COVID-19 has had the most severe effect on the sample financial network—with connectedness measures exceeding 70%. Our findings also suggest that the size and shape of the spillovers vary considerably by crisis events. Investors and policymakers may avail our findings in comprehending the (time-varying) spillover relationships during different crises and developing appropriate and unique policy responses to counteract the adverse impacts of global events on specific markets.

The remainder of this paper is structured as follows: Section 2 succinctly reviews the relevant literature, Section 3 outlines the methodologies used in the tail risk calculation, and spillover network and connectedness analyses, Section 4 presents the data descriptions and empirical analysis results, and Section 5 concludes the paper and provides relevant policy implications.

2. Literature review

The extant literature is replete with analyses of the risk spillovers between crude oil (non-INE) and other assets/indices. Often such studies investigate volatility spillovers, co-movements, and Value-at-Risk (VaR) between (energy) commodities and select assets as well as equities. Examples include Balli et al. (2019), Naeem et al. (2020), Tiwari et al.

(2020), Tian et al. (2022), Nguyen et al. (2021a, 2021b), Arif et al. (2021), Caporin et al. (2021), Shahzad et al. (2021a, 2021b), Naeem et al. (2021a, 2021b, 2021c, 2021d, 2021e), Farid et al. (2021), Anwer et al. (2022) inter alia. The vast repertoire of such literature is prohibitive of an exhaustive review. Consequently, our review of the literature (in sub-Section 2.1) is limited to the empirical analyses/modelling of tail risk—including its spillovers regarding oil as well as other commodities in conjunction with other assets and/or equities. In addition, we survey the burgeoning literature (in sub-Section 2.2) involving various empirical analysis of Shanghai oil futures.

2.1. Time-series analysis of tail risk in crude oil

Tail risk spillover and/or connectedness studies, despite bearing some resemblance to generic volatility spillover studies mentioned above, are relatively novel in the literature. Early tail risk analysis/modelling publications generally appeared in the mid-2010s. They can be generally classified into two broad categories: (a) Multiple regression-based cross-sections and/or panel empirical models measuring the impact(s) of tail risks, and (b) univariate and/or bivariate time-series analysis of (systemic) tail risk volatility as well as spillover (i.e., impact) networks. Our review of the literature on the tail risk analysis (of crude oil) concentrates on the latter (time-series analyses) as they resemble our empirical analysis.

An analysis of tail risk in energy portfolios of daily crude oil, natural gas, coal, and electricity futures between August 2005 and March 2012 is performed by González-Pedraz et al. (2014). The methodologies incorporate various 'generalized hyperbolic conditional distributions and time-varying conditional mean and covariance'. The authors observe that risk factors in the energy sector rely extensively on heavy tails and distributional asymmetry in the positive direction.

The diversification attributes of cryptocurrencies are analysed by Feng et al. (2018) who avail an 'extreme-value-theory' approach to measure tail risk. Their sample comprises daily price data over the period from 08 August 2015 to 01 August 2017. The tail risk correlation analyses find diversification benefits of cryptocurrencies for stock markets. However, Feng et al. (2018) fail to identify cryptocurrencies as hedging—unlike gold. Borri (2019) stumble upon a similar conclusion in their analysis of conditional tail risk between bitcoin, ether, ripple and Litecoin. The dataset covers daily closing, high, and low prices as well as daily volumes in US$ spanning the 17 January 2017 to 15 April 2018 period. Borri (2018) computes Conditional Value-at-Risk (CoVaR) and finds high levels of correlation between cryptocurrency returns. The author argues that portfolios of the above cryptocurrencies' present lucrative returns as well as hedging opportunities.

Zhang et al. (2020) utilize Tail-event driven NETwork (TENET) of Härdle et al. (2016)[1] to find Chinese stocks to exhibit greater connectedness and exposure to systemic (tail) risk. Future returns of Chinese stock markets, between 1999 and 2018, are found to be lowered, on average, by left-tail risk(s) by Zhen et al. (2020). The latter study's asset price modelling also reveals that left-tail risk impact Chinese stocks more than their US counterparts. The TENET approach is also used by Xu et al. (2021) on the daily closing prices, volumes, and market capitalisations for the top 100 cryptocurrencies ranked by the latter. An empirical analysis of the data from 18 April 2016 to 16 May 2019 reveals that a gradual increase in the total connectedness among the cryptocurrencies in question.

Tail risk contagion is found to worsen during the COVID-19 pandemic by Guo et al. (2021). Their empirical avails daily data on stock returns and corresponding drivers of risks from 19 of the largest national or regional financial markets over the period November 2019 to mid-June 2020. Guo et al. (2021) implement the Factor-Adjusted Regularized Model Selection (FARM-Selection) method to analyse the time-varying tail risk network.

The capacity of tail risk of oil to predict that of US dollar exchange rates—against the British Pound, Canadian Dollar, and Japanese Yen—is examined by Salisu et al. (2022). The authors compute the Conditional Autoregressive Value at Risk (CAViaR) using daily data from 21 May 1987 through 11 March 2021. Salisu et al. (2022) observe a positive relationship between the tail risk of oil and US dollar, and predictability of the latter by the former. The US dollar is also observed to be a safe haven in times of 'oil crises.'

Precious metals—gold, platinum, palladium, and silver—exhibit lower tail risk vis-à-vis crude oil during economic/financial crises (except during COVID-19) in a study by Ahmed et al. (2022). A univariate extreme value theory is implemented on daily data from 01 July 1987 to 31 December 2021 to compute equity tail risk. Ahmed et al. (2022) find gold to be a 'safe haven' asset while their extreme systemic risk analysis shows reduced risk in the precious metals and crude oil during times of crisis.

The impact of COVID-19 in aggravating tail risk across refined petroleum products is found to be almost analogous to that of the GFC by Chatziantoniou et al. (2022). The authors utilize data on weekly spot prices of WTI, Brent, gasoline, heating oil, kerosene, and propane from 17 January 1997 to 11 December 2020. Their methodology involves CAViaR and connectedness analysis based on time-varying VAR procedures. Chatziantoniou et al. (2022) also observe an uptick of total connectedness during other crisis events.

2.2. Studies on Shanghai oil

The nascent Shanghai oil futures market has attracted the attention of researchers since the late-2010s. The pioneering paper on this topic/market is written by Ji and Zhang (2019), who analysed realised volatility and jumps in 40 days of intraday starting from 25 May 2018. Ji and Zhang (2019) observe considerable jump risks and a return-volume relationship.

Later, a few studies investigate the forecast ability of Shanghai oil futures. These include Lu et al. (2020), who examine whether Shanghai oil can be forecasted by the CBOE crude oil volatility index (OVX). The authors use a Markov-regime mixed data sampling (MS-MIDAS) estimator on 5-min interval data from 27 March 2018 to 16 April 2020. Lu et al. (2020) find that realised volatility of Shanghai oil can indeed be predicted by OVX. A similar study by Wang et al. (2021) scrutinises the Shanghai oil's jump, jump intensity, and leverage effect forecast ability. The latter's study implements the Heterogeneous Autoregressive (HAR) method on 5-min interval data from 26 March 2018 to 17 April 2020. Wang et al. (2021) find that the future volatility of Shanghai oil is positively impacted upon by the components of the HAR estimator, monthly leverage effect, jump size, and jump intensity. The forecast ability of Shanghai oil futures by coronavirus news is investigated by Niu et al. (2021). The latter study also uses the HAR framework on 5-min interval data from 26 March 2018 to 22 October 2020. The estimated findings lead Niu et al. (2021) to surmise that Shanghai oil volatility can be 'significantly forecasted' by news of the coronavirus.

Another strand of research papers evaluates the impact of macroeconomic and financial factors on Shanghai oil. This includes Lin and Su (2021) who observe how Shanghai oil is affected by China's macro-financial factors over time. They use a Dynamic Model Averaging or DMA method on a dataset comprising six macro-financial factors as well as Shanghai oil futures on a daily basis from the latter's inception to 18 September 2020. The empirical findings of Lin and Su (2021) confirm the pivotal role Chinese macro-financial factors play in determining INE futures. In a similar vein, Yang et al. (2021a) evaluates how five global financial market uncertainty measures affect the prices of Shanghai oil on both the inter-day and intraday basis. The authors employ various Granger causality test approaches—such as linear, nonlinear, as well as quantile ones—on inter-day and intraday returns and volatility

[1] Based on the Conditional, Contagion, or Co-movement Value at Risk (CoVaR) of Adrian and Brunnermeier (2007).

measures computed using 5-min high-frequency quotes. The estimated results lead Yang et al. (2021a) to conclude that Shanghai oil comove close with the global financial market uncertainty measures. In addition, Granger causality runs from the uncertainty measures pertaining to international stock, oil, and gold markets to Shanghai oil.

A third genre of studies include investigations of co-movements (and/or long-run equilibria) between Shanghai oil and markets/factors. The pricing efficiency of Shanghai oil futures is scrutinised using time-series cointegration and Granger causality tests by Yang et al. (2020). Their empirical analysis find that Shanghai oil futures have a cointegrating (long-run equilibrium) relationship with the spot returns on the Daqing, Shengli, Oman, WTI, and Brent spot markets. The direction of causality between these markets is found, by Yang et al. (2020), to be mixed—implying Shanghai oil's efficiency in the Asia Pacific region. The co-movements of Shanghai oil and that of Brent and WTI are evaluated by Huang and Huang (2020). The authors perform wavelet transformation of daily closings prices starting from 26 March 2018 to 21 June 2019. The empirical analysis leads Huang and Huang (2020) to deduce that the co-movements between Shanghai oil and Brent as well as WTI is markedly divergent from that between Brent and WTI.

The market efficiency and potential of Shanghai oil futures to be an Asian market benchmark is explored by Joo et al. (2021). The authors determine any long-run equilibrium between Shanghai oil and 'global benchmarks' such as Brent, WTI, and Dubai crude oil. Using data from 26 March 2018 to 15 April 2019, Joo et al. (2021) computes a number of 'indices of dependence' and find that the market efficiency and long-run equilibrium remain statistically unaltered.

Yang et al. (2021b) examines the network connectedness of Shanghai oil futures and that of Brent, Oman, and WTI. The authors compute the VaR using a number of GARCH-type methods and daily data from 26 March 2018 to 16 April 2020. The empirical results lead Yang et al. (2021b) to infer that Shanghai acts a net receiver of risk within the global crude oil network. The cointegration and Granger causal relations between Shanghai oil and Brent and WTI futures prices as well as domestic (Chinese) Daqing spot prices are analysed by Wang et al. (2022). Daily data from 26 December 2018 to 28 February 2020 are analysed using various linear tests for cointegration and Granger causality. The empirical results indicate considerable differences in the relationship between oil prices in the domestic (Chinese) and international markets following establishment of the INE.

2.3. Bridging the literature gap

Our review of the literature analysing tail risk (of crude oil) and the fledgling literature relating to Shanghai oil reveals that no published study exists analysing tail risk in the former and its interplay with other markets and/or instruments. Thus, the empirical literature exhibits a gap in understanding the degree of connectedness between different markets (stocks and commodities) and identifying potential sources of risk and contagion.

3. Methodology

Our empirical methodology incorporates computation of tail risk—of Shanghai oil and other commodity stock markets—using the CAViaR measure and using it to investigate the risk spillover networks via the TVP-VAR technique.

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

The tail risk of the sample markets (see Section 4.1 for details) is computed using the CAViaR measure by Engle and Manganelli (2004). The CAViaR measure holds several advantages over its conventional counterparts in computing the VaR. The CAViaR was developed as an improvement over the widely-used Value-at-Risk (VaR) measure. Despite its simplicity and ubiquity, the VaR runs into problems when portfolio returns distributions vary over time, rendering identification of the time-varying conditional quantile model extremely difficult. The CAViaR overcomes this issue by availing appropriate autoregressive identification for the conditional quantiles over time. This allows the CAViaR to model the quantile in 'direct way' and observe its evolution over time—against the backdrop of changing 'risk environments.' Such attributes render CAViaR suitable for determining the tail risk in financial time series. The CAViaR can also account for asymmetric effects, which are achieved using an autoregressive process expressed as eq. (1).

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

here, $f_{\alpha,t}$ denotes the 5% level (α) VaR at time t, β_0 denotes the intercept term, $f_{\alpha,t-1}(\beta)$ and β_1 denote the lagged VaR and its weight, respectively, and β_2 and β_3 denote the impacts of the positive and negative returns on VaR, respectively. The latter coefficients (β_2 and β_3) permit accounting for the asymmetric effects (of positive and negative returns) in computing the CAViaR.

3.2. Time-Varying Parameter (TVP) VAR connectedness

The computed CAViaRs are used to analyse the network spillovers and connectedness across the sample markets using the TVP-VAR technique. The TVP-VAR is an estimator of dynamic risk spillover network analysis and has several methodological advantages over its counterparts, including the wavelet analyses (Akhtaruzzaman et al., 2022b). These include its ability to work with both low and high frequency data, specify the rolling window size, and robustness to outliers. These properties of the TVP-VAR render it appropriate for our empirical analyses to observe the tail risk spillover network(s) during various crisis events that are of differing durations and magnitudes of effect. The TVP-VAR method used in our empirical analyses is motivated by and following the extant literature such as Antonakakis et al. (2018, 2019), Akhtaruzzaman et al. (2022b), and Chatziantoniou et al. (2022).

The TVP-VAR approach requires implementing Koop and Korobilis's (2010) Minnesota shrinkage prior to specification. Our empirical analyses require a TVP-VAR model of order 1—i.e., TVP-VAR(1)—to be estimated based on the Schwarz Information Criterion (SIC),

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

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

here, the $k \times 1$ vectors z_t, z_{t-1}, and $\boldsymbol{u}_t$ denote all the tail risk series in t, $t-1$, and its associated disturbances. The $k \times k$ matrices $\boldsymbol{B}_t$ and $\boldsymbol{S}_t$ denote the coefficient and variance-covariance matrices from the time varying VAR. In eq. (3), $vec(\boldsymbol{B}_t)$ and $\boldsymbol{v}t$ are the $k^2 \times 1$ vectors while $\boldsymbol{R}_t$ is a matrix with the dimensions $k^2 \times k^2$.

The Wold decomposition theorem forms the basis of the Generalized Forecast Error Variance Decomposition (GFEVD) that was developed by Koop et al. (1996) and Pesaran and Shin (1998). The GFEVD requires transformation of the TVP-VAR model (2) in equation to its TVP-VMA process in eq. (4),

$$z_t = \sum_{i=1}^{p} \boldsymbol{B}_{it} z_{t-i} + \boldsymbol{u}_t = \sum_{j=0}^{\infty} \boldsymbol{A}_{jt} \boldsymbol{u}_{t-j} \tag{4}$$

The unscaled GFEVD $\Psi_{ij,t}^{g}(H)$ is normalised by the scaled GFEVD in such a way that each row of the former sums up to unity. As such, the influence on variable i by variable j through the forecast error variance is accounted for by $\widehat{\Psi}_{ij,t}^{g}(H)$. This is described as the pairwise directional connectedness from j to i and is estimated using the following:

$$\Psi^{g}_{ij,t}(H) = \frac{S^{-1}_{ii,t}\sum_{t=1}^{H-1}\left(\iota_i' A_t S_t \iota_j\right)^2}{\sum_{j=1}^{k}\sum_{t=1}^{H-1}\left(\iota_i A_t S_t A_t' \iota_i\right)},\ \widehat{\Psi}^{g}_{ij,t}(H) = \frac{\Psi^{g}_{ij,t}(H)}{\sum_{j=1}^{k}\phi^{g}_{ij,t}(H)} \tag{5}$$

where, $\sum_{j=1}^{k}\widehat{\Psi}^{g}_{ij,t}(H) = 1$, $\sum_{i,j=1}^{k}\widehat{\Psi}^{g}_{ij,t}(H) = k$, H denotes forecast horizon, and ι_i denotes a selection vector whose ith element is equal to unity in value and zero otherwise.

The shocks transmitted between two variables, i and j, can be classified as the directional connectedness TO and FROM others. The directional connectedness TO others indicates the shocks transmitted by variable i to the remaining variables j. The TO directional connectedness is computed by:

$$C^{g}_{i\to j,t}(H) = \sum_{j=1,i\neq j}^{k}\widetilde{\Psi}^{g}_{ji,t}(H) \tag{6}$$

By contrast, directional connectedness FROM others represents the shocks transmitted by the remaining variables j to variable i. Measuring the FROM directional connectedness involves eq. (7),

$$C^{g}_{i\leftarrow j,t}(H) = \sum_{j=1,i\neq j}^{k}\widetilde{\Psi}^{g}_{ij,t}(H) \tag{7}$$

The difference between the total TO directional connectedness and total FROM directional connectedness gives us the NET total directional connectedness. The NET directional connectedness denotes the influence imparted by variable i on the remainder of the network (of sample markets):

$$C^{g}_{i,t}(H) = C^{g}_{i\to j,t}(H) - C^{g}_{i\leftarrow j,t}(H) \tag{8}$$

The market interconnectedness is determined by the Total Connectedness Index (TCI), which is computed using,

$$C^{g}_{t}(H) = \frac{\sum_{i,j=1,i\neq j}^{k}\widetilde{\Psi}^{g}_{ji,t}(H)}{\sum_{i,k=1}^{k}\widetilde{\Psi}^{g}_{ij,t}(H)} = \frac{\sum_{i,j=1,i\neq j}^{k}\widetilde{\Psi}^{g}_{ij,t}(H)}{k} \tag{9}$$

One disadvantage of the TCI calculations using eq. (9) pertains to the arbitrary designation of high connectedness. Due to specification, the own-variance shares are always greater than or equal to all cross-variance shares, according to Monte Carlo simulations by Chatziantoniou and Gabauer (2021). This results in the TCI values approximating $\left[0, \frac{k-1}{k}\right]$ instead of $[0,1]$. The TCI from eq. (9), thus, requires the following (eq. 10) adjustments to aid in its interpretation.

$$C^{g}_{t}(H) = \left(\frac{k}{k-1}\right)\frac{\sum_{i,j=1,i\neq j}^{k}\widetilde{\Psi}^{g}_{ji,t}(H)}{k}, = \frac{\sum_{i,j=1,i\neq j}^{k}\widetilde{\Psi}^{g}_{ij,t}(H)}{k-1}, 0 \le C^{g}_{t}(H) \le 1 \tag{10}$$

Lastly, the following decomposition of the TCI, in eq. (11), yields the Pairwise Connectedness Index (PCI) that quantifies two variables'—i and j—interconnectedness, as per Gabauer (2021).

$$C^{g}_{ijt}(H) = 2\left(\frac{\widetilde{\Psi}^{g}_{ij,t}(H)+\widetilde{\Psi}^{g}_{ji,t}(H)}{\widetilde{\Psi}^{g}_{ii,t}(H)+\widetilde{\Psi}^{g}_{ij,t}(H)+\widetilde{\Psi}^{g}_{ji,t}(H)+\widetilde{\Psi}^{g}_{jj,t}(H)}\right), 0 \le C^{g}_{ijt}(H) \le 1 \tag{11}$$

The PCI values are within the range of $[0,1]$ and, are thus, capable of gauging the extent of the bilateral interconnectedness between variables i and j—which the TCI is incapable of accomplishing.

4. Data and empirical analysis

4.1. Data

To assess the tail risk spillover among Shanghai oil and other markets, we collect daily price data for representative markets, which can be subdivided into six groups: SHFE-Fuel oil continuous (SHFE) that represents Shanghai oil as a future contract, is denominated in Chinese Yuan and traded on the Shanghai Futures Exchange. It is used to hedge or speculate on the price of fuel oil in China. Being the world's largest oil importer, the Shanghai oil futures market has the potential to become a significant global benchmark for oil prices. Green markets include S&P Green Bond Index (SPGB), DJSI World Index, MSCI World ESG Leaders Index (ESGW), and WilderHill Clean Energy Index (WHCL). While ESGW and DJSI track the performance of companies that meet environmental, social, and governance (ESG) criteria, WHCL tracks the performance of companies involved in energy efficiency and renewable energy. INE's interplay with stocks is vital to its position in the global risk transmission network as China aims to cut emissions and transition to a 'low carbon economy'. This will likely impact future demand for crude oil in China and the volumes and modalities of trading in Shanghai Oil.

Gold Future (GLD) and Silver Future (SLV) are considered precious metals due to their rarity and store of value. Precious metals can also hedge against economic uncertainty, inflation and oil shocks. Bitcoin (BTC) and the US Dollar (DXY) represent the currency market. BTC is a decentralized digital currency, which is highly volatile and can fluctuate in the short run, whereas the US dollar is considered a stable currency which can act as a safe haven against economic uncertainty. The INE's exchange of dynamic tail risk with precious metals and currencies will likely shed light on worldwide economic strength and *ex-ante* and *ex-post* decisions of stakeholders of these markets.

Conventional energy markets include Crude Oil WTI Futures (WTI) and Natural Gas Futures (NTGS). These futures are traded on the New York Mercantile Exchange (NYMEX) and settled physically. The carbon market is represented by EEX-EU CO2 Emissions (EUCO). Carbon markets are designed to reduce carbon emissions and combat climate change. Like green stocks, carbon markets play a crucial role in influencing future demand for crude oil, especially in China—thus affecting Shanghai Oil's global risk network position.

We collected all the data from January 2011 to December 2022 from Datastream. For the purpose of estimation, we calculate the daily log-differenced returns of sample markets from January 2011 to December 2022 from Datastream, resulting in 3600 observations.

4.2. Descriptive statistics

Table 1 represents the descriptive statistics of twelve markets. S&P Green Bond Index, SHFE, Silver Futures and Wilder Hill energy index show negative mean returns, indicating a loss on average over the study period. On the other hand, Bitcoin exhibits a higher mean return of 0.349 coupled with the highest variance of 46.546, indicating higher volatility compared to other assets, consistent with various studies (Baur and Dimpfl, 2021; Gyamerah, 2019). The EEX-EU CO2 Emissions index has the highest positive skewness of 0.962, whereas the highest negative skewness of −0.315 is WilderHill Clean Energy Index. The kurtosis values are generally higher than four, with US dollar as an exception, indicating a leptokurtic distribution for most assets. The lowest kurtosis of US dollar shows that it is less peaked, has fewer extreme values and remained stable even during Covid-19.[2] The values of the JB test of all series are significant at 1%, indicating the returns are not normally distributed. However, the significant values of ERS test show that all series are stationary at a 1% significance level which fulfills the condition of estimating TVP-VAR model.

Fig. 1 illustrates the 5% VaR tail risks, giving a first visual impression of the co-movements across the employed time series. Natural Gas Futures show the highest peaks and are exceptionally volatile in the second

[2] https://policycommons.net/artifacts/1341626/the-dominance-of-the-us/1953747/

Table 1
Summary statistics of market returns.

Market	Symbol	Mean	Variance	Skewness	Kurtosis	JB	ERS	Q(10)	Q2(10)
S&P green bond index	SPGB	−0.011	0.162	−0.269	5.598	4124.731***	−20.773***	17.557***	520.995***
DJSI world index	DJSI	0.019	0.939	−0.845	11.371	17,234.215***	−19.680***	50.836***	1384.863***
MSCI world ESG leaders index	ESGW	0.022	0.906	−0.915	14.796	28,987.654***	−17.374***	59.102***	1920.976***
WilderHill clean energy index	WHCL	−0.009	4.544	−0.315	4.826	3089.738***	−11.005***	27.871***	1224.226***
Crude oil WTI future	WTI	0.019	7.519	0.567	24.347	77,474.810***	−23.813***	19.974***	1293.051***
Natural gas future	NTGS	0.036	18.909	0.461	16.178	34,244.018***	−25.622***	59.667***	900.686***
EEX-EU CO2 emissions	EUCO	0.057	10.255	−0.962	16.117	34,358.889***	−22.118***	16.536***	91.185***
US dollar index	DXY	0.009	0.193	0.019	2.085	567.041***	−21.233***	3.36	248.411***
Bitcoin	BTC	0.349	46.546	−0.137	17.155	38,392.753***	−18.616***	121.592***	864.068***
Gold future	GLD	0.008	0.933	−0.722	7.458	7526.145***	−25.496***	1.53	82.267***
Silver future	SLV	−0.008	3.169	−0.685	5.609	4348.515***	−9.137***	5.315	329.478***
SHFE oil future	SHFE	−0.018	5.903	−0.024	16.750	36,588.441***	−24.948***	13.324**	32.084***

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: Elliott et al. (1996) unit-root test.

half of 2022, subject to various factors, including a reduction in Russian natural gas production, climate change and improved energy efficiency among others.[3] US dollar index exhibits the largest peaks of its all-time during 2013 subject to US Federal Reserve Plans to taper its quantitative easing programs, the partial shutdown of US Government in late 2013 and the US-China trade war.[4]

4.3. Correlation analysis

Fig. 2 represents the estimated 5% VaR correlation matrix for the sampled markets. The negative correlation between Shanghai oil and Bitcoin is primarily due to differences in market-specific events and supply-demand dynamics that impact their risk exposures differently (Klein et al., 2018; Bouri et al., 2017). Notably, most of the correlations are positive, indicating that their VAR estimated increase (decrease) together and are influenced by similar factors or sources of risk. The highest degree of correlation (0.97) is observed across ESGW and DJSI, followed by a 78% correlation between ESGW and WHCL. Since both ESGW and DJSI indexes include companies with high ESG rankings and WHCL tracks companies involved in clean energy, probably is high on ESG too. This common focus on sustainability perhaps is the major reason for strong correlations among them.

4.4. Empirical findings

4.4.1. Network spillovers of markets

Fig. 3 showcases the network spillovers between Shanghai oil and other markets using a CAViaR TVP-VAR model with lag 1 (SIC criteria) and a 10-step-ahead generalized forecast error variance decomposition.

The network spillover of the full sample is exhibited in Fig. 3(a), which divides our 12 markets into 6 clusters: Green, Shanghai Oil, Precious Metal, Currency, Carbon, and Conventional Energy. We observe that most of the connections are within their groups. The strongest connection we observe is between gold and silver (precious metals) and DJSI and ESGW (Green). SPGB and DXY shows the strongest return spillover connection outside the clusters. Notably, the disconnection of SHFE from other markets indicates their safe-haven properties. BTC, EUCO and NTGS are also disconnected from other markets in the full sample.

The classical within the same category connectedness of markets (precious metals and green energy) is consistent with previous studies (Lau et al., 2017; Ren and Lucey, 2022), who also reported higher intra-connectedness than inter-connectedness of energy and metals markets.

Moreover, the strong disconnection of Shanghai oil from the rest of the markets indicates that shanghai oil does not spillover other markets and is still a minor player on the world stage as compared to WTI (Palao et al., 2020). This disconnection has other economic implications as well. For instance, it suggests that investors can use SHFE to hedge against risks in other markets and reduce the volatility of investment portfolios.

We further analyse the spillover network of sample market connectedness during three crises, including Shale Oil Revolution, Covid-19 pandemic and Russia-Ukraine war. Fig. 3(b) presents the spillover network connectedness of sample markets during shale oil revolution. We do not see a difference in the connectedness of sample markets during Shale Oil Revolution and during the entire period, indicating the irrelevance of Shale oil revolution to Shanghai oil and other markets.

Fig. 3(c) presents the spillover connectedness of Shanghai oil and other markets during the Covid-19 pandemic. Highest spillovers are found during Covid-19 crisis; even SHFE which remains disconnected under the whole sample and other two crises gets risk transmission from WTI. Risk transmission from WTI to SHFE implies strong connectivity between them (Wei et al., 2022) and pronounced Covid-19 impacts. The interconnectedness between Bitcoin and SPGB is formed during the pandemic. Bitcoin also receives risk spillovers from WHCL and ESGW and transmits risk to DXY. NTGS is the only market that remains disconnected during Covid-19, highlighting its potential to serve as a diversifier because of its low risk-bearing features (Mensi et al., 2022).

Fig. 3(d) reflects the connectedness network of Shanghai oil and other markets during Russia-Ukraine war. Shanghai oil which receives spillover from WTI during Covid-19 remains disconnected afterward. Our findings are consistent with the previous studies, for example Yang et al. (2021a) find that Shanghai oil commove close with the global financial market uncertainty measures. BTC, EUCO, NTGS and WTI receive moderate risk spillovers from the green market. WTI receives moderate spillover from EUCO, indicating the increased awareness of using clean energy and the subsequent reduction in carbon emissions during the Russia-Ukraine war. Notably, Natural Gas Futures remains disconnected from each market during all crises, consistent with various studies, offering short-term diversification benefits (Qin et al., 2020; Lovcha and Perez-Laborda, 2020).

4.4.2. Average pairwise spillover

First, we look into averaged pairwise spillover among markets for the whole sample and then we present the pairwise averaged results for three crisis periods, namely the Shale oil revolution, Covid-19 pandemic and Ukraine-Russia war. Table 2(a) reports pairwise results based on the Pairwise Connectedness Index (PCI) for the whole sample, which reports the averaged pairwise co-movement between any two markets for the whole sample period. The pairwise averaged connectivity ranges from 0 to 100%, while all diagonal elements are equal to 100%. The major

[3] https://blogs.worldbank.org/opendata/bubble-trouble-whats-behind-highs-and-lows-natural-gas-markets#:~:text=Natural%20gas%20prices%20saw%20large,the%20end%20of%202021%20Q3.

[4] https://www.reuters.com/article/us-global-forex-idUSKBN148037

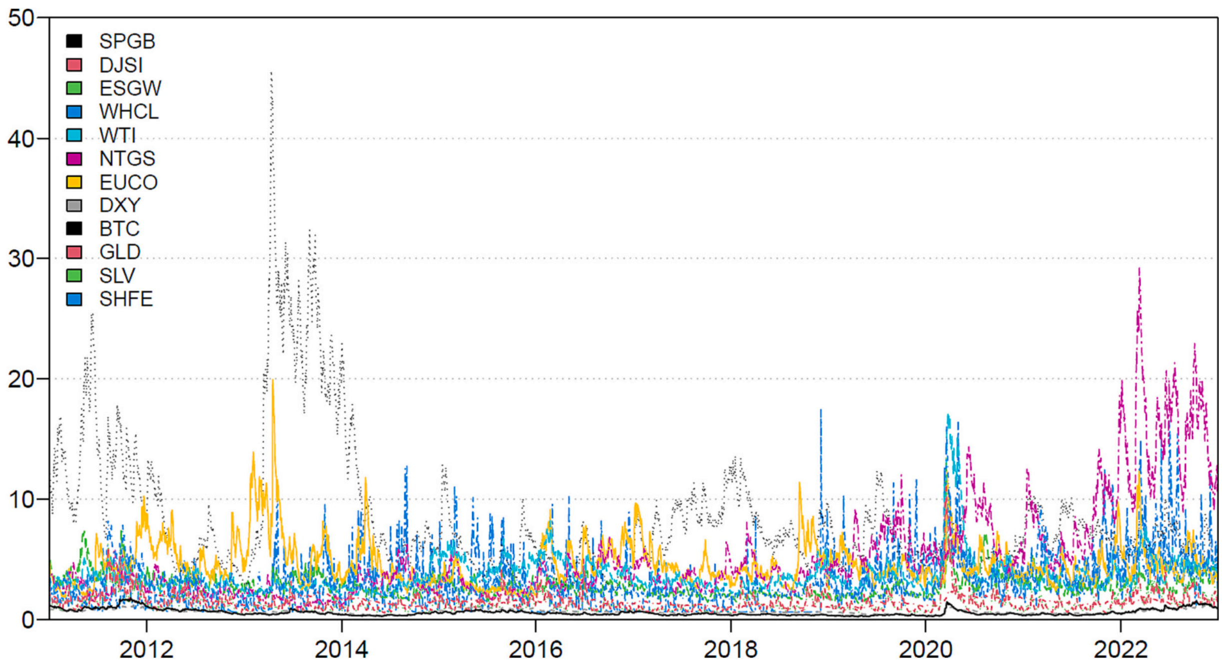

Fig. 1. Tail risk of markets.
Notes: This figure represent the 5% VaR using the asymmetric slope (AS) CAViaR model.

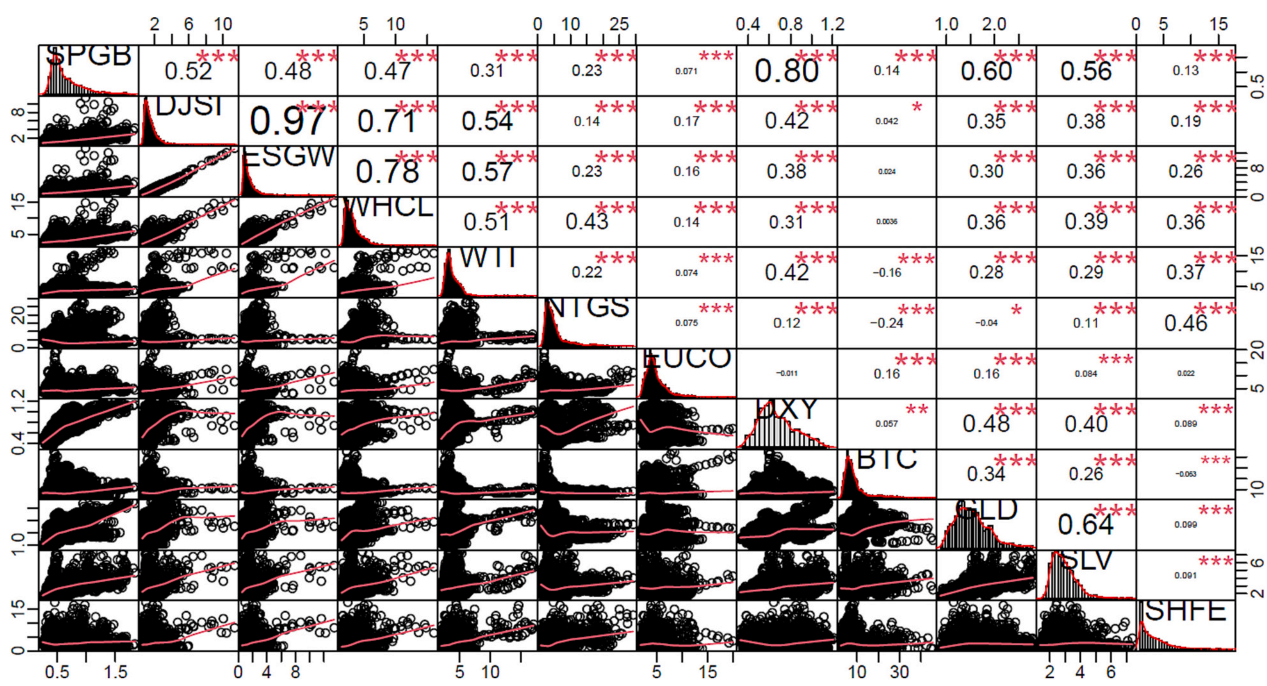

Fig. 2. Correlation matrix.
Notes: This figure represent the correlation matrix of the estimated 5% VaR for the sampled markets.

benefit of the PCI Table is its simplicity in identifying co-movements between all pairs of markets under investigation. We observe the strongest connectedness between DJSI and ESGW with a value of 95.37% and, GLD and SLV with a value of 53.96%. The lowest pairwise connectedness (3.4%) is observed between SHFE and BTC followed by the pairwise connectedness of 3.45 between SHFE and DXY. Our results are consistent with the previous analysis, such as Huang and Huang (2020) suggest that the co-movements between Shanghai oil and Brent as well as WTI is markedly divergent from that between Brent and WTI. Overall, findings suggest strong co-movements of markets within their clusters, such as green markets or precious metals. However, across the two groups, a strong connectedness of 52.12% is found between DXY and SPGB.

Table 2(b, c & d) represents the average pairwise spillover among shale oil futures and other markets for three crises, including Shale oil revolution, Covid-19 crisis and Post Ukraine-Russia conflict. We observe similar connectivity within and across markets during Shale oil revolution and Ukraine- Russia conflict. The highest pairwise spillover remains the same during these two crises, whereas the lowest pairwise connectivity reduces to 1.34 (between DXY and BTC) and 1.12 (between

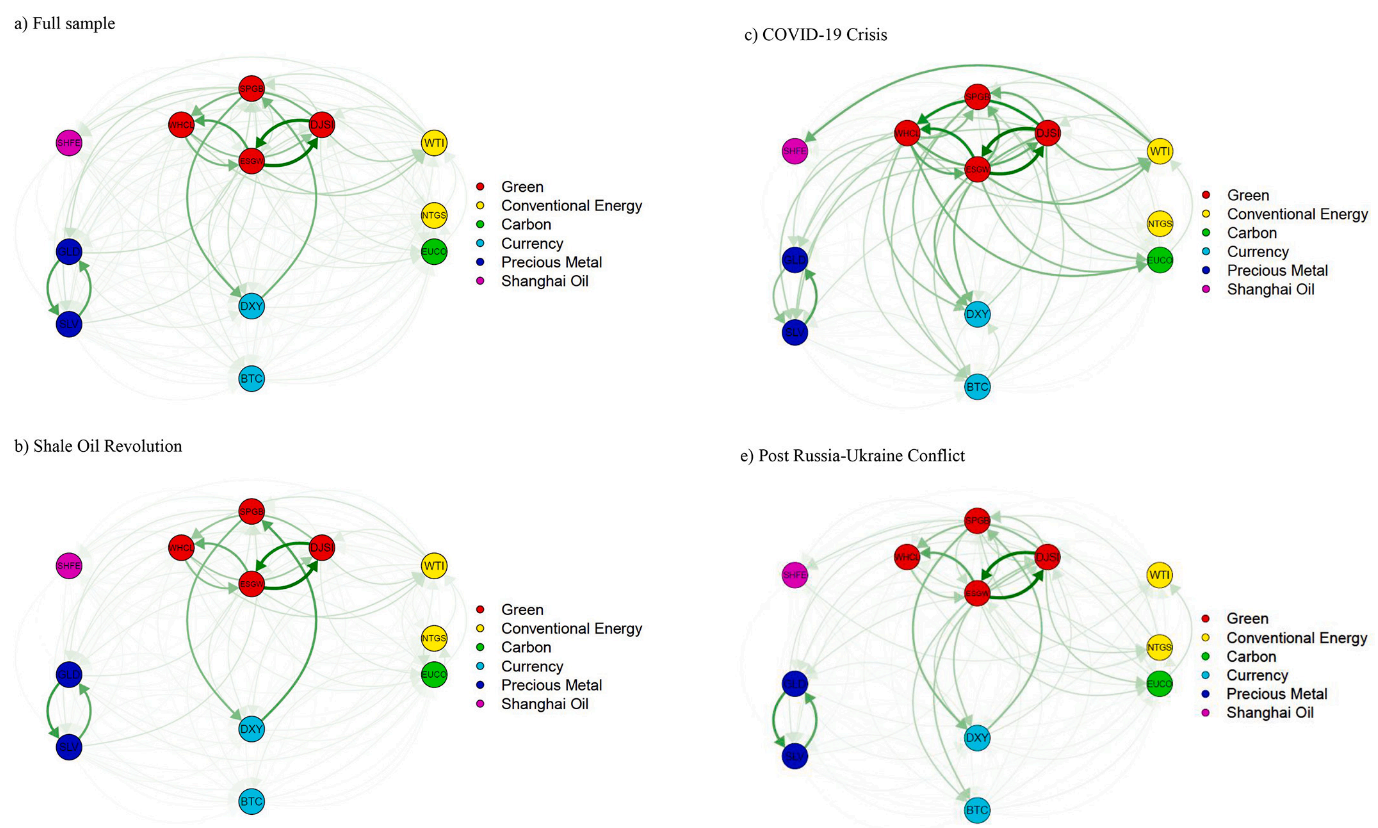

Fig. 3. Network spillovers of markets.
Note: This figure showcases the network spillovers between Shanghai oil and other markets using a TVP-VAR model with lag 1 (SIC criteria) and a 10-step-ahead generalized forecast error variance decomposition.

GLD & WHCL). On the contrary, the average pairwise connectedness within and across markets is highest between DJSI and ESGW (99.12) and lowest between WHCL and NTGS with a value of 0.69 during Covid-19, which is consistent with the view that the risk connectedness between clean and dirty energy is generally low in the short run (Farid et al., 2022).

4.4.3. Time-varying total spillover of markets

To examine the time-varying connectedness of our markets, we estimate the 5% CAViaR spillover dynamics and plot information spillover both at the 2.5% and 10% CAViaR propagation mechanism against the original 5% connectedness plot in Fig. 4 as it ensures the robustness of our empirical results. We observe similar patterns (peaks and troughs) across all connectedness plots, indicating that CAViaR dynamics are alike quantitatively and qualitatively. Since the information transmission mechanism follows a similar connectedness in terms of patterns and magnitude, it suggests no disparities in net transmitting/receiving behavior among different CAViaR series.

Dynamic total spillovers of markets in Fig. 4 suggest that connectedness varies over time and is likely influenced by significant global events at particular moments in time. We observe that over time total connectivity takes on values that fall between a range of around 35% to 75% level. Given that dynamic connectivity, which reflects the degree of uncertainty-contagion across shanghai oil futures and other markets, seems to be increasing due to particular occurrences. For instance, connectedness increases with the start of the Shale oil revolution, reaches new, previously unheard-of peak levels in 2020 that can be linked to the COVID-19 outbreak, and then again gradually increases towards the end of our sample period in 2022, which can be linked to the Ukraine-Russian war.

The connectedness of sample markets reaches 57% during the Shale oil revolution. The augmented connectivity during crisis is due to the increased investor caution brought on by economic uncertainty and global market reconfiguration (Zhu et al., 2021; Naeem et al., 2020). The pronounced connectivity reaches its highest during the Covid-19 pandemic, which surpasses that of the Global Financial Crisis of 2007–08 (Zhang et al., 2021). In particular, the pandemic had a huge negative impact on the energy market (Jie et al., 2021), which reflects in strong co-movement among clean and traditional energy markets. The total spillovers of markets touch another height of almost 50% during the Ukraine-Russia war, subject to reduced energy supply to Europe. We identify that the lowest information connectivity of sample markets during the Ukraine-Russia war is mainly due to its exposure at the regional level (Europe) instead of global impacts. However, we draw the conclusion that the dynamic total connectedness can capture the scope of the market uncertainty propagation across the network under investigation. The increased connectivity of Shanghai oil with sample markets during crises has numerous economic implications for China. On the one hand, it might make the Chinese economy more susceptible to shocks in foreign markets. For instance, a big drop in oil prices could cause the Chinese economy to halt down. On the other side, the Chinese economy may benefit from the greater interconnectivity of Shanghai oil with other markets, such as it might be possible for Chinese businesses to gain access to financial resources and export their goods.

4.4.4. Time-varying NET spillovers of commodity markets

Next, we examine the time-varying net spillovers of markets and present intriguing results on dynamic patterns illustrating the net position of each market with respect to risk transmission or reception in Fig. 5. Our findings are based on a TVP-VAR model with lag 1 (SIC) and a 10-step-ahead generalized forecast error variance decomposition. A variable's spillover color, reddish orange (greenish blue), denotes the

Table 2
Average pairwise spillover table.

a) Full sample

	SPGB	DJSI	ESGW	WHCL	WTI	NTGS	EUCO	DXY	BTC	GLD	SLV	SHFE
SPGB	100	23.73	20.63	14.72	9.77	6.73	6.75	52.12	6.46	23.34	19.18	4.79
DJSI	23.73	100	95.37	53.44	25.2	4.62	11.29	20.04	7.62	11.08	9.37	4.86
ESGW	20.63	95.37	100	63.11	26.26	4.97	10.58	18	7.34	9.82	9.08	5.7
WHCL	14.72	53.44	63.11	100	24.02	6.31	8.97	11.03	5.88	9.3	9.49	6.98
WTI	9.77	25.2	26.26	24.02	100	7.86	7.4	11.29	4.39	8.34	7.67	9.5
NTGS	6.73	4.62	4.97	6.31	7.86	100	8.42	5.11	6.6	4.11	6.66	9.64
EUCO	6.75	11.29	10.58	8.97	7.4	8.42	100	6.53	4.74	5.51	5.19	4.16
DXY	52.12	20.04	18	11.03	11.29	5.11	6.53	100	4.93	12.94	7.1	3.45
BTC	6.46	7.62	7.34	5.88	4.39	6.6	4.74	4.93	100	4.25	5.02	3.4
GLD	23.34	11.08	9.82	9.3	8.34	4.11	5.51	12.94	4.25	100	53.96	4.24
SLV	19.18	9.37	9.08	9.49	7.67	6.66	5.19	7.1	5.02	53.96	100	6.04
SHFE	4.79	4.86	5.7	6.98	9.5	9.64	4.16	3.45	3.4	4.24	6.04	100

b) Shale oil revolution

	SPGB	DJSI	ESGW	WHCL	WTI	NTGS	EUCO	DXY	BTC	GLD	SLV	SHFE
SPGB	100	8.67	8.05	5.44	6.06	3.26	3.16	49.69	1.95	13.25	14.49	2.52
DJSI	8.67	100	94.15	44.06	18.13	3.69	11.22	10.2	4.24	9.84	4.39	5.48
ESGW	8.05	94.15	100	55.13	17.77	3.81	9.46	10.58	4.01	8.47	5.32	5.17
WHCL	5.44	44.06	55.13	100	19.04	3.31	7.06	5.17	3.86	2.56	5.75	3.96
WTI	6.06	18.13	17.77	19.04	100	6.45	7.98	8.48	3.24	5.23	5.59	2.67
NTGS	3.26	3.69	3.81	3.31	6.45	100	12.63	3.5	2.86	3.34	2.61	3.08
EUCO	3.16	11.22	9.46	7.06	7.98	12.63	100	4.63	5.16	8.95	3.89	1.89
DXY	49.69	10.2	10.58	5.17	8.48	3.5	4.63	100	1.34	5.16	5.03	1.79
BTC	1.95	4.24	4.01	3.86	3.24	2.86	5.16	1.34	100	1.52	1.71	3.46
GLD	13.25	9.84	8.47	2.56	5.23	3.34	8.95	5.16	1.52	100	54.39	2.08
SLV	14.49	4.39	5.32	5.75	5.59	2.61	3.89	5.03	1.71	54.39	100	3.54
SHFE	2.52	5.48	5.17	3.96	2.67	3.08	1.89	1.79	3.46	2.08	3.54	100

c) COVID-19 crisis

	SPGB	DJSI	ESGW	WHCL	WTI	NTGS	EUCO	DXY	BTC	GLD	SLV	SHFE
SPGB	100	49.06	47.38	46.71	11.77	4.95	21.94	57.95	35.63	4.09	7.18	4.21
DJSI	49.06	100	99.12	83.4	39.52	0.94	33.86	41.77	22.95	18.93	23.72	5.51
ESGW	47.38	99.12	100	84.59	41.29	0.79	35.22	41.89	20.15	19.69	23.3	4.72
WHCL	46.71	83.4	84.59	100	32.68	0.65	41.97	37.15	21.33	17.06	25.12	1.51
WTI	11.77	39.52	41.29	32.68	100	1.67	16.06	12.45	1.32	8.71	2.47	28.18
NTGS	4.95	0.94	0.79	0.65	1.67	100	3.75	5.12	3.52	3.84	5.98	2.29
EUCO	21.94	33.86	35.22	41.97	16.06	3.75	100	8.78	3.63	5.68	13.6	2.65
DXY	57.95	41.77	41.89	37.15	12.45	5.12	8.78	100	20.05	7.18	5.4	6.13
BTC	35.63	22.95	20.15	21.33	1.32	3.52	3.63	20.05	100	3.64	10.37	2.44
GLD	4.09	18.93	19.69	17.06	8.71	3.84	5.68	7.18	3.64	100	54.55	2.13
SLV	7.18	23.72	23.3	25.12	2.47	5.98	13.6	5.4	10.37	54.55	100	2.89
SHFE	4.21	5.51	4.72	1.51	28.18	2.29	2.65	6.13	2.44	2.13	2.89	100

d) Post Russia-Ukraine conflict

	SPGB	DJSI	ESGW	WHCL	WTI	NTGS	EUCO	DXY	BTC	GLD	SLV	SHFE
SPGB	100	34.77	30.13	7.64	4.64	18.21	5.87	43.11	4.84	9.83	14.39	4.66
DJSI	34.77	100	96.09	38.81	8.21	10.48	20.15	30.97	24.15	10.24	9.34	2.66
ESGW	30.13	96.09	100	52.07	6.32	9.66	15.8	24.4	21.62	5.46	7.73	1.83
WHCL	7.64	38.81	52.07	100	1.83	7.61	1.93	4.32	7.15	1.12	3.68	1.5
WTI	4.64	8.21	6.32	1.83	100	3.16	10.14	3.62	7.01	5.16	4.88	7.54
NTGS	18.21	10.48	9.66	7.61	3.16	100	6.75	5.45	1.77	2.32	1.88	9.29
EUCO	5.87	20.15	15.8	1.93	10.14	6.75	100	7.85	3.14	9.83	3.47	7.86
DXY	43.11	30.97	24.4	4.32	3.62	5.45	7.85	100	5.56	10.62	5.31	1.75
BTC	4.84	24.15	21.62	7.15	7.01	1.77	3.14	5.56	100	3.48	4.93	2.08
GLD	9.83	10.24	5.46	1.12	5.16	2.32	9.83	10.62	3.48	100	57.58	2.21
SLV	14.39	9.34	7.73	3.68	4.88	1.88	3.47	5.31	4.93	57.58	100	3.77
SHFE	4.66	2.66	1.83	1.5	7.54	9.29	7.86	1.75	2.08	2.21	3.77	100

Notes: Results are based on a TVP-VAR model with lag length of 1 (SIC) and a 10-step-ahead generalized forecast error variance decomposition.

spillover's net transmission (reception) among other markets.

Looking at Fig. 5, it becomes obvious that with reference to SHFE, the picture is rather straightforward, SHFE remains a net risk receiver throughout the study period, except in 2019 when it became the net risk transmitter, consistent with Yang et al. (2021b). The Chinese oil market matured before the Covid-19 outbreak when SHFE became a net risk transmitter. However, with the pandemic outburst, such informational influence deteriorated significantly with the decreased oil demand in China[5] (Corbet et al., 2022; Wang et al., 2022). Moreover, SHFE is a good investment option for those who want to reduce their overall risk through diversification of portfolios as Shanghai oil is largely disconnected with other markets. However, investors need to be aware that SHFE is a net- risk receiver, so it is still vulnerable to negative shocks in other markets.

[5] https://www.bloomberg.com/news/articles/2020-02-02/china-oil-demand-is-said-to-have-plunged-20-on-virus-lockdown?leadSource=uverify%20wall

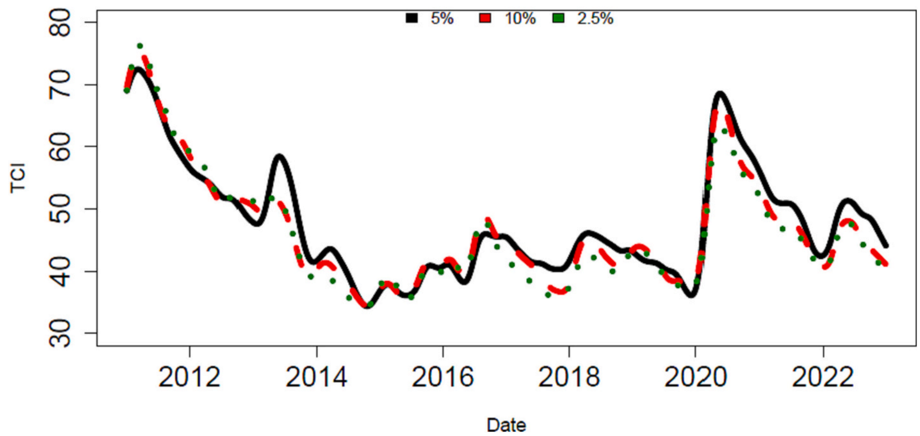

Fig. 4. Time-varying TOTAL spillovers of markets.
Notes: Results are based on a TVP-VAR model with lag 1 (SIC) and a 10-step-ahead generalized forecast error variance decomposition. Black line represents the 5% VaR, while the red (dashed) and the green (dotted) lines represent the results of the 10% and 2.5% VaR, respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

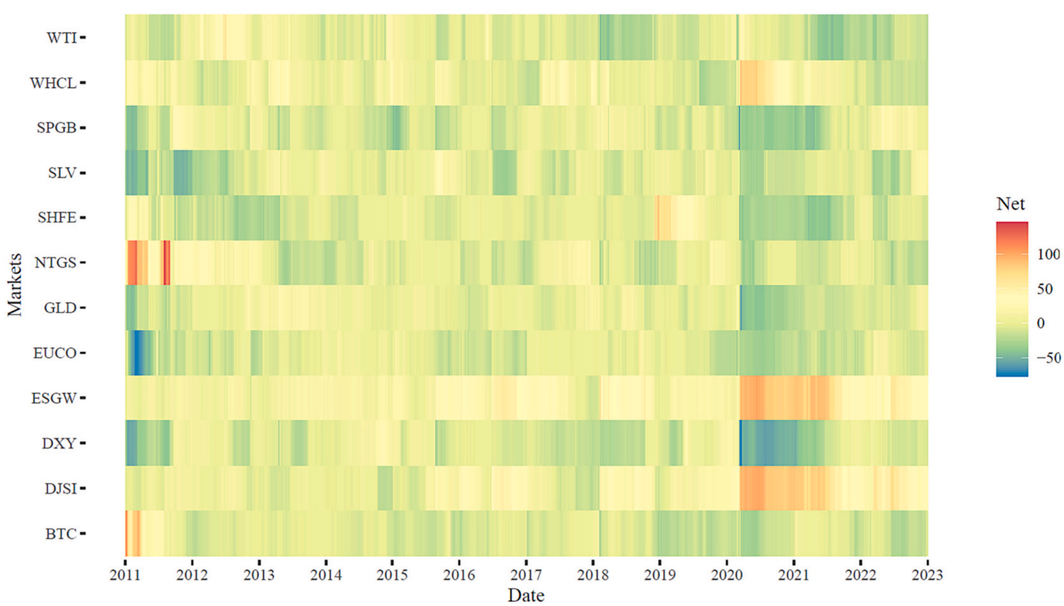

Fig. 5. Time-varying NET spillovers of commodity markets.
Notes: Results are based on a TVP-VAR model with lag 1 (SIC) and a 10-step-ahead generalized forecast error variance decomposition.

We only find one persistent transmitter i.e., ESGW and persistent receivers (GLD, SLV, DXY, SPGB & EUCO) of market uncertainty. In other words, these markets do not appear to take on a different role within the network (at least not for a noticeable period). Gold and silver are often considered safe-haven assets during periods of economic uncertainty or market turbulence, as they are assumed to keep their value better than other assets during the crisis (Mensi et al., 2022). However, GLD and SLV can experience increased demand during market stress, making them risk receivers. Similarly, DXY, which tracks the value of the US dollar against a basket of other currencies, can also be considered a risk receiver during economic uncertainty or geopolitical tensions. This is because the US dollar is often seen as a safe-haven currency due to the stability of the US economy and the currency's widespread use in global trade and finance. Carbon is a net receiver of spillovers from oil and clean energy markets, consistent with previous literature (Umar et al., 2022; Ding et al., 2022).

ESGW remains a smart choice for investors wishing to make huge returns on their investment as ESGW has the potential to outperform other markets in times of economic expansion. However, investors should know that ESGW is susceptible to losses during volatile market times. Investing in previous metals, such as gold and silver is a better choice to remain protected from market volatility due to the less chances of losses in these markets during crises.

By contrast, WHCL, DJSI, NTGS, SHFE, and BTC are asymmetric in terms of negative or positive spillovers. As these markets are sensitive to interest rates, their position of net receivers or net receivers keep changing. WHCL, ESGW and DJSI markets switch their roles during the sample period, acting as strong net receivers until early 2021 and then as net transmitters of market uncertainty in the period that follows, covering Covid-19 pandemic and the Ukraine-Russia war. Similarly, NTGS and BTC act as net transmitters till 2012, but they switch their role as risk receivers till the end of the sample period. Finally, our results support the previous findings that the green energy sector becomes the net risk receiver after Covid-19 due to significant oil shocks (Zhang et al., 2022; Zhang, 2017). Investors that are confident in the long-term expansion of the renewable energy industry can consider investing in the carbon market though, carbon market is more volatile as compared to other markers as it is still developing. On the other side, investors in the markets for WHCL, DJSI, NTGS, SHFE, and BTC need to be aware of the potential risks and challenges as these markets can either be net transmitters or net receivers, depending on the market conditions.

5. Conclusion

We investigate the tail risk spillover among Shanghai oil and other markets using the daily returns from January 2011 to December 2022. We employ the CAViaR and dynamic connectedness approach as they have become a powerful tool for understanding the dynamics of financial markets and identifying potential sources of risk and contagion. The network analysis aids in understanding the degree of connectedness between different markets and identifying potential sources of risk and contagion.

Our study provides insights into the tail-risk spillovers among Shanghai oil and other markets. We observe that most connections are within their clusters, and the strongest connections are within the same category, for that matter (green, conventional energies, precious metals, Shanghai oil, currency, and carbon). Shanghai oil remains disconnected and risk receiver from other markets, indicating its minor role on the world stage compared to WTI. Time-varying analysis observes various ups and downs where significant crisis events are the shale oil revolution, the COVID-19 pandemic, and the Ukraine-Russia war. The augmented connectivity during crises is due to increased investor caution brought on by economic uncertainty and global market reconfiguration. Sub-sample analysis entails that the tail risk spillover among Shanghai oil and other markets depends on the nature of crisis events (Farid et al., 2022; Naeem and Arfaoui, 2023). COVID-19 has the most pronounced impact on the financial markets, evident in >70% connectedness during the pandemic, followed by 55% and 45% connectedness during the Shale oil revolution and the Russia-Ukraine war, respectively.

This study presents intriguing results on the dynamic risk transmission and reception patterns in SHFE and other markets. Our findings suggest that a few markets remain persistent in their role as either net risk transmitters (ESGW) or receivers (GLD, SLV, DXY, SPGB & EUCO), while others switch their roles during the sample period (WHCL, DJSI, and SHFE). The Chinese oil market, of which SHFE is a part, becomes mature before the Covid-19 outbreak, and this is when SHFE became a net risk transmitter. As pandemic has caused a decline in oil demand in China, it significantly deteriorates SHFE's informational spillover to global energy markets. Although SHFE does not currently affect global markets, including WTI, it appears to be developing into a significant product in information transmission in the future (Wei et al., 2022; Palao et al., 2020). GLD, SLV and DXY are identified as safe-haven assets and risk receivers during market stress and economic uncertainty. The green energy sector is found to be a net risk receiver after the Covid-19 outbreak due to significant oil shocks.

5.1. Implication for academia

Though SHFE is a minor player as compared to WTI, it has started playing a significant role in information transmission in recent years and may become a vital source of risk and contagion in future. It suggests academics to pay close attention SHFE's its role in the global financial system, exploring various aspects, such as information transmission mechanism with other oil markets and the vulnerability of the financial system to SHFE-related shocks.

In addition, we used the dynamic connectedness approach to identify the time-varying nature of the tail-risk spillovers among Shanghai oil and other markets, which does not explicitly account for the role of safe-haven assets. Therefore, academics should develop new dynamic connectedness measures that can account for the role of safe-haven assets for the emerging market of Shanghai oil.

5.2. Implications for policymakers

Our findings indicate that different crisis affect markets differently in terms of spillovers' size and shape. This information is insightful for investors and policymakers in configuring the relationship of spillovers under specific crisis events. Further, our study underscores the need for a holistic approach to understanding the dynamics of shanghai oil futures and its connectivity with global markets to comprehend the underlying factors driving market volatility and develop more effective strategies to manage risks and promote stability. Shanghai oil futures can be seen as a new financial tool that offers both domestic and international investors the chance to access the Chinese oil market and diversify their investment risk. In addition, a comprehensive understanding of the said market is also necessary for investors to make informed investment decisions and develop active risk management strategies.

5.3. Limitations and future research

Since the focus of our study remains on Shanghai oils and its interplay with other markets within the given time frame of 2011–2022, the generalizability of our findings is limited. The dynamics of tail risk spillovers can vary significantly across different assets classes, markets, and regions. Therefore, one should take caution in extrapolating our findings to other markets or different time periods, and conclusions may not apply unanimously to all financial markets or during different crises. Moreover, it is vital to understand that Shanghai oil is just one component of global oil market, acknowledging that its dynamics may be influenced by unique factors, events, market conditions and financial regulations specific to China. Chinese financial and energy policies, local market dynamics and government interventions that are not fully explored in our study can significantly affects SHFE's risk transmission to other markets, limiting the scope of wider applicability of our findings. The future research should incorporate role of Chinese energy policies and government interventions while studying the tail-risk spillovers between Shanghai oil and other markets. Future research should also explore the role of safe-haven assets, such as gold and silver, in mitigating the tail-risk spillovers between Shanghai oil and other markets. Future studies may examine the time varying tail-risk spillovers between SHFE and other markets during different economic conditions, such as boom and bust periods, to identify the underlying factors that drive changes in the spillover effects.

CRediT authorship contribution statement

Muhammad Abubakr Naeem: Conceptualization, Methodology, Software, Visualization, Writing – review & editing, Project administration, Funding acquisition. **Raazia Gul:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Muhammad Shafiullah:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Sitara Karim:** Writing – review & editing. **Brian M. Lucey:** Conceptualization, Writing – review & editing, Supervision.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2023.107182.

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