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Original Paper

Exploring the impacts of major events on the systemic risk of the international energy market

Ming-Tao Zhao [a], Su-Wan Lu [a], Lian-Biao Cui [b,*]

[a] School of Statistics and Applied Mathematics, Anhui University of Finance and Economics, Bengbu, 233030, Anhui, China
[b] Anhui Province Key Laboratory of Philosophy and Social Science of Low-Carbon Development and Carbon Finance, Anhui University of Finance and Economics, Bengbu, 233030, Anhui, China

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ABSTRACT

This study examines the systemic risk caused by major events in the international energy market (IEM) and proposes a management strategy to mitigate it. Using the tail-event driven network (TENET) method, this study constructed a tail-risk spillover network (TRSN) of IEM and simulated the dynamic spillover tail-risk process through the cascading failure mechanism. The study found that renewable energy markets contributed more to systemic risk during the Paris Agreement and the COVID-19 pandemic, while fossil energy markets played a larger role during the Russia-Ukraine conflict. This study identifies systemically important markets (SM) and critical tail-risk spillover paths as potential sources of systemic risk. The research confirms that cutting off the IEM risk spillover path can greatly reduce systemic risk and the influence of SM. This study offers insights into the management of systemic risk in IEM and provides policy recommendations to reduce the impact of shock events.

1. Introduction

The international energy market (IEM) is a complex system that plays a vital role in the global economy. However, increasing financialization and integration of IEM pose new challenges and risks to system stability, especially during shock events, such as epidemics, wars, or natural disasters. Recently, the systemic risk of IEM has largely been caused by three major shock events: the COVID-19 pandemic, the Russia-Ukraine conflict, and extreme weather (Chen et al., 2023b; Rawtani et al., 2022; Uddin et al., 2021; Wang et al., 2022c; Xiong and Chen, 2022). The collapse of IEM will seriously threaten economic activity and cause huge losses for different industries. Thus, developing an effective risk management strategy is critical.

Accurately identifying the source and transmission path of systemic risk is the key to preventing systemic risk. Tail risks due to shock events continue to accumulate and spillover in the IEM and systemic risks arise from this (Baumöhl et al., 2022; Bucci et al., 2019; Fang et al., 2018; Shahzad et al., 2022a). Especially with the integration of IEM continuing to expand, the tail-risk spillover of IEM exhibits characteristics of high correlation, high dimension, dynamic, and nonlinear. As a result, the tail-risk spillover of a single energy market is increasingly likely to result in a domino effect. The spillover path (i.e., static structure) and spillover process (i.e., dynamic process) of tail risk have become the decisive factors for the generation of systemic risk. However, few studies have fully captured these features of tail-risk spillovers. Against this background, we explore the systemic risk management strategies of IEM during shock events from a new perspective: the static structure and dynamic process of tail-risk spillovers.

This study explores systemic risk management strategies for IEM in the context of the Paris Agreement (an agreement to address extreme climate), the COVID-19 pandemic, and the Russia-Ukraine conflict. Furthermore, policy recommendations are explored to mitigate the impact of future shock events. We established the IEM by selecting 16 major energy markets classified as renewable or fossil. First, we used the tail-event driven network risk (TENET) method (Härdle et al., 2016) to construct the tail-risk spillover network (TRSN) of IEM, as well as to capture highly correlated, high-dimensional, and nonlinear tail-risk spillover paths. Then, the dynamic spillover process of tail risk in TRSN was modeled based on the cascading failure mechanism, to capture the dynamic characteristics of tail-risk spillover. Finally, whereas the shock events have an overall impact on IEM, there are differences in the impact

* Corresponding author.
E-mail address: cuilb1987@126.com (L.-B. Cui).

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on these two types of markets. Given the rapid development of renewable energy markets and their replacement targets for fossil energy markets (Boubaker and Omri, 2022; Zhou et al., 2022), we also compared and analyzed the independent and interactive relationship between the renewable energy markets and the fossil energy markets during shock events.

This study contributes significantly to the existing literature in four key aspects. Firstly, considering the growing frequency of black swan events in recent years, it is crucial to adopt more targeted approaches to risk management and control for different event types. In response to this need, we conduct a comparative study on the systemic risk characteristics of the IEM across different types of shock events. Our findings reveal divergent reactions and sensitivities between the renewable energy market and fossil energy market, as well as variations in the methods of risk spillover during different shock events. These insights enable the IEM to adopt more precise risk management strategies tailored to specific shock event types.

Second, this paper represents an attempt to simulate and quantify the dynamic process of tail-risk spillover in the IEM using the cascading failure mechanism. By employing this innovative approach, we conduct a quantitative analysis of the systemic risk contribution (SRC) of each energy market and assess the overall systemic risk level (OSR). These quantitative assessments provide valuable information for effective systemic risk management within the IEM during shock events.

Third, a distinct and noteworthy finding of this study is the identification of SM as potential risk receivers. This discovery emphasizes the need for market regulators to prioritize risk management efforts within these identified risk receiver markets, ensuring robust measures are in place to safeguard their stability and resilience.

Finally, we simulate and quantify the impact of different regulatory strengths on the OSR within the IEM. Notably, our findings indicate that strengthening the regulation of risk spillover paths holds great importance. Taking timely regulatory actions to address tail-risk spillover paths significantly reduces the risk level and risk contribution within the IEM.

This study makes significant contributions to the literature by conducting a comparative analysis of systemic risk characteristics in the IEM during different shock events, quantifying tail-risk spillover dynamics through the cascading failure mechanism, and evaluating the impact of regulatory strengths on the OSR. These contributions enhance our understanding of risk management, inform policy decisions, and provide valuable insights for stakeholders operating within the IEM. The remainder of this paper is structured as follows. Section 2 provides a literature review. Section 3 provides the methods and data sources used in this study. Section 4 presents the empirical results and analysis. Section 5 presents the conclusions and insights.

2. Literature review

Systemic risk has aroused widespread concern in the academic community. More specially, Kaufman and Scott (2003) proposed the definition of systemic risk as an entire system's risk caused by the domino effect of a single individual suffering from risk. Furthermore, Schwarcz (2008) defined systemic risk from the perspective of contagion, i.e., a series of financial institutions or systems suffering a chain of losses due to crisis events, which will lead to extreme asset price fluctuations in the financial market. With the continuous financialization and integration of the energy sector, coupled with the link between different energy types and geographical market segments, the systemic risk of the IEM is constantly increasing (Ji et al., 2020b).

Recently, black swan events have occurred frequently, and the external environment of the IEM has undergone major changes (Ji et al., 2023). Systemic risk poses a significant threat to the IEM, and developing effective systemic risk management strategies has become a top priority for researchers (Kerste et al., 2015; Zhou et al., 2022). Shock events can trigger systemic risk in the IEM, and the impact of different shock events on the IEM varies (Chen et al., 2023a; Ji et al., 2018a, b; Ouyang et al., 2021; Xia et al., 2019). Since the signing of the Paris Agreement, there has been an unprecedented adjustment in the global energy structure. The Paris Agreement has promoted the development of the renewable energy market and the growth of spillover effects (Liang et al., 2022; Pham et al., 2023). This point is confirmed by Chen et al. (2022) through the Diebold-Yilmaz spillover index. In contrast to the Paris Agreement's promotion of energy transition, the COVID-19 pandemic and the Russia-Ukraine conflict have exacerbated the risk of supply chain disruptions in the global energy market, causing intense turbulence in the IEM (Alam et al., 2023; Corbet et al., 2020; Cui et al., 2023; Hsu et al., 2023; Wu et al., 2023). The COVID-19 pandemic has significantly increased the risk spillover effect in the energy market (Hanif et al., 2023; Thompson, 2022; Wang et al., 2022b), and its impact on the energy market is greater than that of the financial crisis (Hosseini, 2020; Liu et al., 2021b). Anwer et al. (2022) modeled the systemic risk of the energy commodity market during the COVID-19 pandemic, finding that the systemic risk of the energy commodity market experienced a sudden increase to a gradual stabilization process. Moreover, the outbreak of the Russia-Ukraine conflict has led to fluctuations in the prices of the IEM, especially the prices of crude oil and natural gas (Huang et al., 2022; Zhang et al., 2023). At the same time, the conflict has promoted the substitution of renewable energy for fossil fuels and accelerated the transformation of the energy structure (Deng et al., 2022; Mohammed et al., 2022). Despite the extensive literature on the impact of a single shock event on the energy market, there is a lack of comparative analysis on the systemic risk of the IEM during these three major shock events. Additionally, there is a lack of research that combines the static structure and dynamic process of tail risk to explore systemic risk management strategies. Addressing these gaps can provide valuable insights into effective risk management in the energy market.

During the occurrence of shock events, the risk spillover within a single energy market and the inter-market spillover network structure have become important conditions for the outbreak of systemic risk (Ghosh et al., 2020; Reboredo, 2015; Shiferaw, 2019; Vacha and Barunik, 2011). Many scholars have investigated systemic risk through the inter-market spillover network structure. They mostly construct spillover networks of energy markets in terms of the mean or volatility using methods such as the Granger causality test (Billio et al., 2012; Geng et al., 2017; Sharma et al., 2022), generalized variance decomposition based on VAR models (Diebold and Yilmaz, 2014; Duppati et al., 2023; Liu et al., 2022; Papiez et al., 2022), GARCH family models (Ahmad et al., 2018; Lee et al., 2023; Liu et al., 2017b), and wavelet analysis (Boubaker and Raza, 2017; Hanif et al., 2022; Shahzad et al., 2022b). They then examine spillover effects using complex network analysis methods. For example, Furuoka et al. (2023) constructed a risk transmission network between energy and agricultural markets during the Russia-Ukraine conflict period based on an improved VAR model. Ha (2022) identified the shock process of the energy market during the COVID-19 pandemic using an improved VAR model and network analysis methods. Although these methods effectively capture the static network structure of spillover, they mostly examine the correlation between two markets in an isolated environment. More importantly, these methods cannot capture the tail-risk spillover between markets. However, systemic risk is often driven by tail risk resulting from shock events (Wang et al., 2018). During shock events, the tail risk appears in the IEM, and it dynamically spreads through spillover paths, leading to systemic risk in the IEM (Corbet et al., 2020; Shahzad et al., 2018; Wang et al., 2022d). Therefore, compared to the mean and volatility spillovers, studying the systemic risk of the IEM during shock events through tail-risk spillover is more valuable. Systemic risk arising from tail-risk spillovers between energy markets has recently attracted increasing attention; various methods have been developed to measure and analyze this type of risk. Among them, ΔCoVaR (Adrian and Brunnermeier, 2016), SRISK (Brownlees and Engle, 2016) and SES (Acharya et al., 2017) are representative methods. For instance, Liu et al. (2017a) investigated tail-risk spillovers between energy markets using CoVaR, defining this risk as the systemic risk between a pair of markets. However, these methods mainly consider local interdependence and lack the ability to capture nonlinear tail-risk spillovers, which may underestimate risk spillovers in highly correlated market systems (Hautsch et al., 2015).

To address this limitation, the Copula model and its derivative models have been widely used to study the nonlinear risk transmission mechanism (Chen et al., 2023a; Ji et al., 2019, 2020a; Liu et al., 2017a; Mensi et al., 2022). For example, Reboredo (2015) applied the Copula model to examine the systemic risk between the oil market and renewable energy markets, finding time-varying and symmetric tail dependencies between the two. Liu et al. (2021a) examined the risk relationship between oil prices and exchange rates through four tail dependencies. However, the Copula model has limitations in describing the time-varying nature of the nonlinear risk conduction relationship.

The TENET method is an effective means of addressing this limitation, which combines the single-index model (SIM) and complex network methods (Härdle et al., 2016). The TENET method has been widely applied to solve the problem of variable dimension and nonlinear characterization (Fan et al., 2018; Wang et al., 2022a). In this study, we used the TENET method to obtain the level and static structure of tail-risk spillovers in the IEM.

In terms of studying the dynamic mechanism of risk spillovers, dynamic network models with random walk assumptions have been widely used to capture the dynamic process of risk spillover (Gai and Kapad, 2019; Huang et al., 2021). However, previous studies have argued that random walk assumptions cannot fully explain the economic significance of the risk spillover mechanism and may lead to inaccurate measurements of risk spillovers (Acemoglu et al., 2015; Wang et al., 2022d). To address this, some scholars have applied the cascading failure mechanism to study the risk contagion and spillover in financial markets (Watts, 2002), including banks (Pichler et al., 2021) and stock markets (Squartini et al., 2018). We simulate the dynamic process of tail risk propagation in the IEM through all possible tail-risk spillover paths based on the cascading failure mechanism, thus deriving the SRC of each energy market and the OSR of the IEM.

Our study fills a gap in the literature by providing a comprehensive analysis of the systemic risk of the IEM during shock events. We accurately assess tail-risk spillover strength and structures while simulating the dynamic spillover process. Our analysis considers the distinct features of renewable and fossil energy markets and compares the systemic risk during three different shock events. Our study makes significant contributions to the existing literature by providing a nuanced assessment of the IEM's systemic risk.

3. Methodology and data sources

3.1. TRSN construction method in IEM

In this study, the TENET method is employed to measure the level of tail-risk spillovers in the IEM, and the TRSN for the IEM is constructed. To capture the time-varying network structure of the IEM during the sample period, a sliding window approach is used, with a window length and interval of 84 and 1 trading day, respectively, resulting in a total of 2507 windows. The construction of the TRSN consisted of two steps. First, SIM is utilized to measure the conditional value at risk (CoVaR) for each energy market. Second, the level of tail-risk spillovers among the energy markets is measured to construct the TRSN for the IEM.

3.1.1. Calculation of CoVaR

First, we calculated the value at risk (VaR) for each energy market. Chao et al. (2015) found that the logarithmic return $X_{i,t}$ of market i has a linear effect on the regression of macro variables with a lag of one period:

$$X_{i,t} = \alpha_i + \gamma_i M_{t-1} + \varepsilon_{i,t} \tag{1}$$

where M_{t-1} represents the macroscopic variable lagging one period and $\varepsilon_{i,t}$ is the random error term with a zero mean. From Eq. (1), we selected the quantile level of $\tau = 0.05$, and performed sliding regression on the logarithmic returns of each energy market through linear quantile regression and the sliding window method to obtain the VaR of market i in window s, recorded as $\mathrm{VaR}_{i,s}$ (Adrian and Brunnermeier, 2016; Härdle et al., 2016).

Next, based on the VaR of each market, we use the SIM to measure the CoVaR of each energy market and identify the static structure of tail-risk spillovers in the IEM. The SIM more fully considers the influence of other energy markets in the IEM:

$$X_{i,t} = g\left(\beta_i^T R_{i,t}\right) + \varepsilon_{i,t} \tag{2}$$

where $R_{i,t} = (X_{1,t}, X_{2,t}, \cdots, X_{i-1,t}, X_{i+1,t}, X_{i+2,t}, \cdots, X_{n,t})^T$ is the logarithmic return vector of $n-1$ markets, except for market i, β_i is the corresponding single-index parameter vector, and $g(\cdot)$ is an unknown smooth function, which represents all possible nonlinear interactions of other $n-1$ markets on market i. We then performed a quantile regression of $\tau = 0.05$ on Eq. (2) to obtain the CoVaR of market i in window s, which is denoted as $\mathrm{CoVaR}_{i,s}$, as follows:

$$\mathrm{CoVaR}_{i,s} \equiv \widehat{g}\left(\widehat{\beta}_i^T \tilde{R}_{i,s}\right) \tag{3}$$

where $\tilde{R}_{i,s} = (\mathrm{VaR}_{1,s}, \mathrm{VaR}_{2,s}, \cdots, \mathrm{VaR}_{i-1,s}, \mathrm{VaR}_{i+1,s}, \mathrm{VaR}_{i+2,s}, \cdots, \mathrm{VaR}_{n,s})$.

3.1.2. Network construction

The tail-risk spillover relationship of the IEM in window s is calculated as follows:

$$\widehat{D}_{i|\tilde{R}_{i,s}} \equiv \frac{\partial \widehat{g}\left(\widehat{\beta}_i^T R_{i,s}\right)}{\partial R_{i,s}}\Big|_{R_{i,s}=\tilde{R}_{i,s}} = \widehat{g}'\left(\widehat{\beta}_i^T \tilde{R}_{i,s}\right)\widehat{\beta}_i \tag{4}$$

where $\widehat{D}_{i|\tilde{R}_{i,s}} = (\widehat{D}_{i|1}^s, \widehat{D}_{i|2}^s, \cdots, \widehat{D}_{i|i-1}^s, \widehat{D}_{i|i+1}^s, \widehat{D}_{i|i+2}^s, \cdots, \widehat{D}_{i|n}^s)$ is the marginal effect measured by gradient at $R_{i,s} = \tilde{R}_{i,s}$. We defined the DIC of market j to market i in window s as: $\mathrm{DIC}_{i|j}^s = \left|\widehat{D}_{i|j}^s\right|$, $i,j = 1, 2, \cdots, n$, $i \neq j$, where $\left|\widehat{D}_{i|j}^s\right|$ is the absolute value of $\widehat{D}_{i|j}^s$. We then constructed an $n \times n$ weighted adjacency matrix $\boldsymbol{A}_s$ with $\mathrm{DIC}_{i|j}^s$ as an element:

$$\boldsymbol{A}_s = \begin{pmatrix} 0 & |\widehat{D}^s_{2|1}| & |\widehat{D}^s_{3|1}| & \cdots & |\widehat{D}^s_{n|1}| \\ |\widehat{D}^s_{1|2}| & 0 & |\widehat{D}^s_{3|2}| & \cdots & |\widehat{D}^s_{n|2}| \\ |D^s_{1|3}| & |\widehat{D}^s_{2|3}| & 0 & \cdots & |\widehat{D}^s_{n|3}| \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ |D^s_{1|n}| & |\widehat{D}^s_{2|n}| & |\widehat{D}^s_{3|n}| & \cdots & 0 \end{pmatrix}_{n\times n} \tag{5}$$

The TRSN of the IEM is constructed by matrix $\boldsymbol{A}_s$, and the network is a directed weighted network. The network nodes are the 16 energy markets that make up the IEM, the edges of the network are the tail-risk spillover paths, and the direction of the edges is the tail-risk spillover direction.

3.2. Dynamic tail-risk spillover process in IEM

3.2.1. Cascading failure process modeling of tail-risk spillover

Whereas markets possess inherent resilience against risks, they can also accumulate risks. When cumulative risk surpasses a critical threshold, external risks can affect the market, turning it into a failure market. Such markets produce tail risks that quickly propagate, leading to failures in related markets and potentially inducing a domino effect throughout the entire IEM system, creating systemic risk. In the process of cascading failures resulting from risk spillover, if the aggregated intensity of risk spillover from a given market exceeds its own VaR, the market is classified as a failure market (Huang et al., 2012). According to the tail spillover risk network, we performed a sliding-window analysis with a fixed length of 84 days. Taking window s as an example, as long as the total DIC $\mathrm{TR}_{i,s}(N)$ received by market i at step N exceeds its VaR, market i will generate tail risk and become a failure market. The change of its risk state is as follows:

$$M_{i,s}(N+1) = M_{i,s}(N) + D_{i,s}(N) \tag{6}$$

where N represents the step of tail-risk spillover, $M_{i,s}(N)$ represents the risk status of energy market i at step N, and $D_{i,s}(N)$ represents the tail risk of market i caused by external risks. The calculation results are given by Eqs. (7) and (8):

$$D_{i,s}(N) = \begin{cases} \mathrm{VaR}_{i,s}, \mathrm{TR}_{i,s}(N) \geq \mathrm{VaR}_{i,s} \\ 0, \mathrm{TR}_{i,s}(N) < \mathrm{VaR}_{i,s} \end{cases} \text{ and} \tag{7}$$

$$\mathrm{TR}_{i,s}(N) = \sum_{q\in Q_i}^{m} W_{q,s}(N) * \left|\widehat{D}^s_{i|q}\right| \tag{8}$$

where Q_i is a set of m markets that spill risk to market i in step N, which is determined by the TRSN obtained above, and $W_{q,s}(N)$ is a binary variable used to judge whether market q is a failure market and whether it will spill risk to market i, calculated as follows:

$$W_{q,s}(N) = \begin{cases} 1, M_{q,s}(N) - M_{q,s}(N-1) = \mathrm{VaR}_{q,s} \\ 0, M_{q,s}(N) - M_{q,s}(N-1) = 0 \end{cases} \tag{9}$$

To elucidate the cascading failure process of tail-risk spillover, we present a straightforward TRSN comprising six energy markets that pertain to both the renewable and fossil energy sectors, as depicted in Fig. 1.

As demonstrated in Fig. 1(a), at each step of the dynamic process, a failure market will release its tail risk through all the spillover paths to other markets, returning to the state of Fig. 1(b) once the risk is released. The spillover path from market k to market g acts as a bridge for transmitting tail risk between the renewable and fossil energy markets.

We note that a market may be repeatedly affected by tail risks in various steps and become a failure market (simulating a complex dynamic process close to reality). For example, market e in Fig. 1(a) is a failure market in steps 4 and 5. In more complex cases, convergence can take a long time and require substantial computing resources. To simplify calculations and avoid an indefinite continuation of the process, a pragmatic termination mechanism is adopted: regulators will tighten supervision on paths with multiple spillover risks. If a path overflows risks multiple times, its risk resistance will be considerably increased. In this study, we set a path to be affected, and the overflow risk no longer due to risk resistance after r times of impact, where $r = 3$. If a risk spillover path has overflowed risks more than three times, the tail risk will no longer spill through that path.

3.2.2. Measurement of SRC and OSR based on a cascading failure mechanism

The SRC of a market is defined as the average total loss incurred by the entire system due to the dynamic risk spillover process caused by tail risks in that market (Mezei and Sarlin, 2018; Wang et al., 2022d). Taking market i as an example, we recorded the SRC of market i in window s as $\mathrm{SRC}_{i,s}$. Its calculation process is shown in Eqs. (10)–(12). Market i was set to be a failure market at the beginning, and the rest of the markets initially had no tail risk:

$$\begin{cases} M_{i,s}(N=0) = \mathrm{VaR}_{i,s} \\ M_{-i,s}(N=0) = 0 \end{cases} \tag{10}$$

In the dynamic risk spillover process, the number of failure markets in step N was recorded as $\mathrm{FM}_i(N)$, and the total tail risk increased in step N was recorded as $\mathrm{TVaR}_i(N)$. Then, the total loss of the IEM system after the dynamic process was calculated and expressed as $\mathrm{TotalVaR}_{i,s} = \sum_{N=0}^{N_{\mathrm{end}}} \mathrm{TVaR}_i(N)$, where N_{end} is the step at the end of the cascading failure. The total number of markets that have failed in the dynamic process was calculated and recorded as $\mathrm{TFM}_{i,s} = \sum_{N=0}^{N_{\mathrm{end}}} \mathrm{FM}_i(N)$. The SRC of the final market i in this window is calculated as follows:

$$\mathrm{SRC}_{i,s} = \frac{\mathrm{TotalVaR}_{i,s}}{\mathrm{TFM}_{i,s}} \tag{11}$$

The higher the $\mathrm{SRC}_{i,s}$ of market i, the more SRC this market has, and the more important it is in the system. If all markets in the IEM have high SRC values, then the IEM may suffer a financial crisis. Furthermore, we measure the OSR of the IEM over the window by aggregating the SRC values of all energy markets in the IEM:

$$\mathrm{OSR}_s = \sum\nolimits_{i=1}^{n} \mathrm{SRC}_{i,s} \tag{12}$$

where OSR_s represents the OSR of the IEM in window s and n is the total number of markets included in the IEM, and $n = 16$ in this study.

3.3. Data sources

We identified 16 energy indices that form the IEM and can be categorized into the renewable energy and fossil energy markets

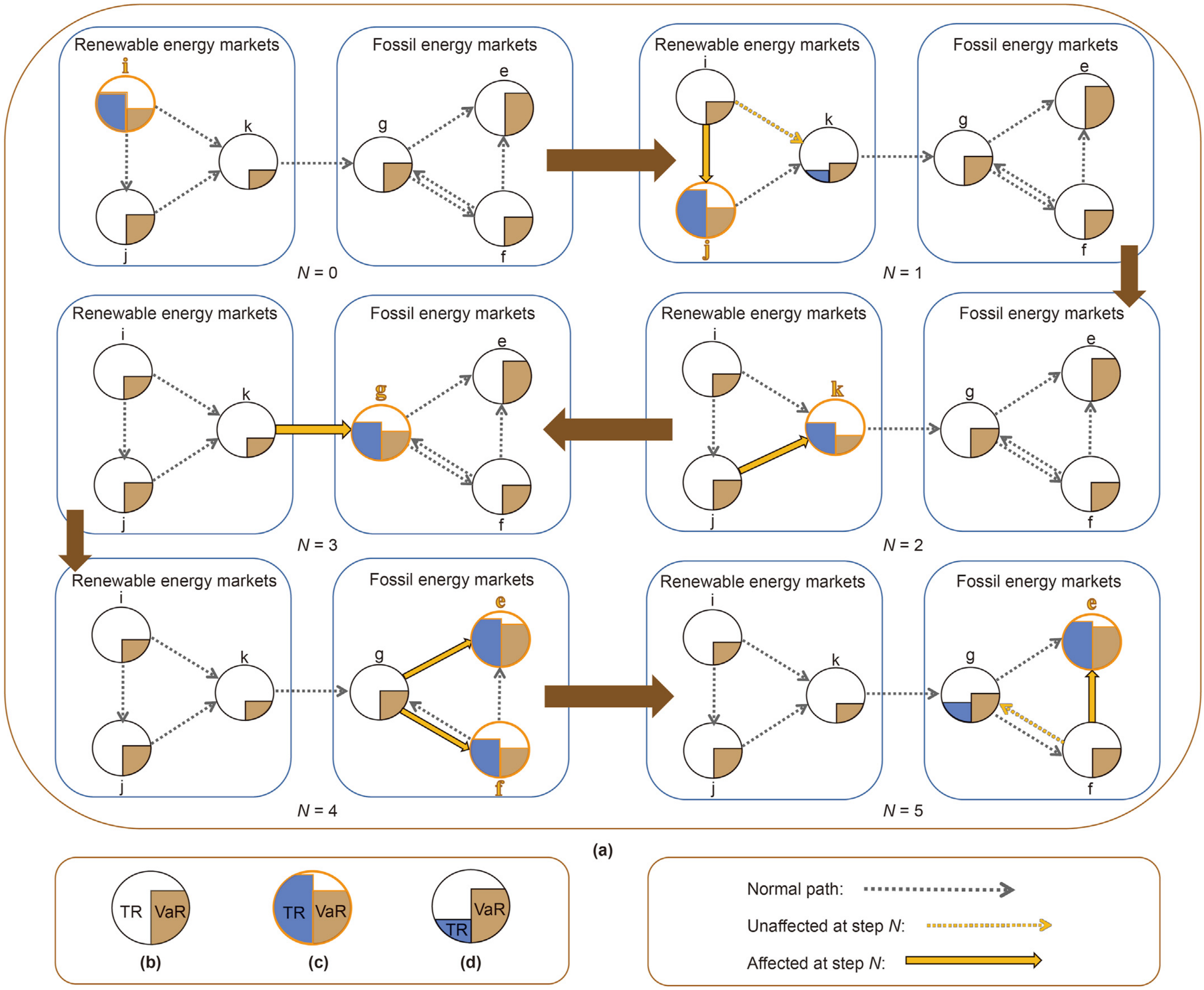

Fig. 1. Illustration of the cascading failure process of tail-risk spillover. (**a**) Illustrates the dynamic process of market *i*'s tail-risk spillover through the TRSN, with the failure markets in step *N* marked in yellow. (**b**) Shows a market not subjected to tail risk, where the market state is determined by the total received DIC (TR) and the market's VaR value (VaR). (**c**) Represents a failure market that suffers from tail-risk spillovers and has tail risk, as TR exceeds the VaR. (**d**) Presents a market that experiences tail-risk spillovers, but does not fail, as TR is lower than the VaR.

(Table 1). To investigate the renewable energy market, we selected 12 market indices from the NASDAQ OMX Clean Energy Index, representing biofuel, solar energy, wind energy, geothermal, fuel cell, developer, energy storage, smart grid, green IT, energy management, advanced materials, and water energy markets (M1–M12). For the fossil energy market, we obtained indices from the West Texas Intermediate Crude Oil Futures, Rotterdam Coal Futures, Bloomberg Natural Gas, and S&P Equity Commodity Energy Index, corresponding to the crude oil, coal, natural gas, and integrated fossil energy markets (M13–M16), respectively.

We incorporated macro variables, such as the NASDAQ Composite Index, MSCI Global Index, VIX Panic Index, and gold futures, to represent the world market. Our sample period was from November 5, 2012, to November 4, 2022, with 2591 daily observations. We calculated the daily logarithmic returns of the 16 energy market indices and used the logarithmic returns of the four macro variables lagging by one period for regression. Data was sourced from Investing.com and Yahoo Finance.

4. Empirical results and analysis

4.1. Static structure analysis of tail-risk spillover in the IEM

4.1.1. TRSN analysis in the IEM from 2012 to 2022

This study employed sliding-window technology to compute the network density of the TRSN within the IEM. Subsequently, an analysis was conducted to explore the evolving characteristics of the number of tail-risk spillover paths in the IEM throughout the sample period (Fig. 2). Network density, denoting the ratio of connections existing among the nodes within a network, serves as an indicator of the presence of tail-risk spillover paths. The results reveal that the network density of TRSN exhibited fluctuations corresponding to the temporal impact intervals of recognized shock events.

For example, the mid-2014 collapse of international oil prices, the instability observed in the Middle East during the first half of 2015, the signing of the Paris Agreement in April 2016, the United

Table 1
Descriptive statistics.

Variables	Mean	Std.Dev.	Maximum	Minimum
Biofuel (M1)	0.00018	0.01926	0.13393	−0.18196
Solar energy (M2)	0.00097	0.02088	0.12051	−0.19333
Wind energy (M3)	0.00059	0.01673	0.09154	−0.13283
Geothermal (M4)	0.00013	0.01745	0.18254	−0.13391
Fuel cell (M5)	0.00067	0.03506	0.21616	−0.20746
Developer (M6)	0.00035	0.01020	0.08701	−0.16520
Energy storage (M7)	0.00027	0.01531	0.08296	−0.09074
Smart grid (M8)	0.00022	0.01229	0.09436	−0.14951
Green IT (M9)	0.00049	0.01502	0.28891	−0.10608
Energy management (M10)	0.00031	0.01390	0.13957	−0.13891
Advanced materials (M11)	0.00026	0.01413	0.08166	−0.12100
Water energy (M12)	0.00030	0.00985	0.08759	−0.10335
Crude oil (M13)	0.00003	0.04248	0.48641	−0.50965
Coal (M14)	0.00035	0.02405	0.32622	−0.53688
Natural gas (M15)	−0.00061	0.05752	1.76738	−1.83066
Integrated fossil energy (M16)	0.11977	0.01726	0.15058	−0.22542
NASDAQ Composite Index	0.00048	0.01263	0.08935	−0.13149
MSCI Global Index	0.00021	0.00889	0.08059	−0.09997
VIX Panic Index	−0.00016	0.07859	0.29983	−0.76825
Gold futures	−0.00020	0.00971	0.05802	−0.09810

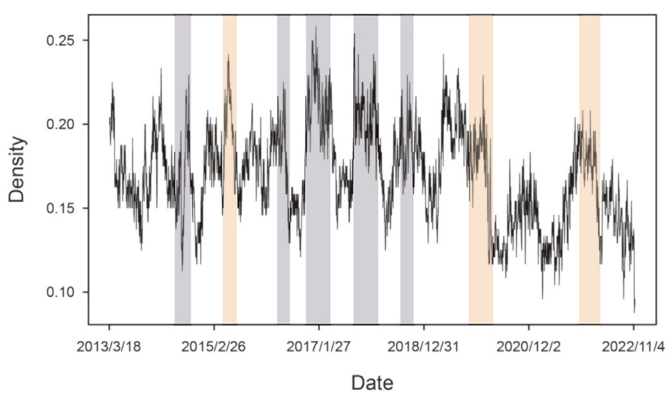

Fig. 2. Evolution of network density in the TRSN. The Paris Agreement, the COVID-19 pandemic, and the Russia-Ukraine conflict are colored yellow, whereas other shock events are shown in gray.

States' withdrawal from the Trans-Pacific Partnership in early 2017, and OPEC's implementation of production cuts in the latter half of 2018 are noteworthy instances. Furthermore, the emergence of the COVID-19 pandemic towards the end of 2019 and the Russia-Ukraine conflict in early 2022 further influenced the dynamics of the IEM. Notably, during these periods of shock events, the number of tail-risk spillover paths experienced significant increases, reaching local peaks, and subsequently declining to local troughs.

The observed increase in the number of tail-risk spillover paths during shock events can be attributed to two main reasons. First, the drastic macroeconomic changes that occur during shock events cause a rapid deepening of the actual correlation between energy markets. This deepening of the actual correlation leads to the spread of tail risk throughout the IEM, resulting in a significant increase in tail-risk spillover paths (Li et al., 2019). Second, the "herd effect" and information asymmetry in the IEM intensify during shock events. Negative impact events may cause investors to irrationally sell related market assets, increasing the transmission of risks in the IEM, thus leading to an increase in tail-risk spillover. Positive events can also disrupt the inherent supply and demand patterns in different markets. For example, whereas the Paris Agreement has made related transactions in renewable energy more active, investment in fossil fuels has shown a significant reduction trend. The combined effect leads to an increase in the number of tail-risk spillover paths.

In the aftermath of a shock event, the tail risk of the IEM temporarily subsides with the implementation of preventive measures and market self-regulation. This temporary reduction in the number of tail-risk spillover paths also aids in restoring market stability, with a two-way mechanism at play. Notably, the COVID-19 pandemic may have a lasting impact on the IEM. It has disrupted demand patterns, highlighted supply chain vulnerabilities, impacted investment decisions, and prompted policy and regulatory changes. Fig. 2 reveals that the overall level of the number of tail-risk spillover paths in the IEM since the outbreak of the COVID-19 pandemic has been lower than prior to it and continues to exhibit a downward trend.

Studying the importance of energy markets in the TRSN can aid in the formulation of investment strategies and risk prevention measures. Eigenvector centrality (EC) is a common metric used to gauge the importance of a market in the spillover network. It considers both the number and quality of connections of a node. Nodes with high eigenvector centrality are considered influential and have connections to other important nodes in the network. We utilized EC to study the time-series characteristics of the importance of each energy market, as illustrated in Fig. 3. Our findings indicate that the importance of each market in the network displayed time-varying characteristics. Thus, investment strategies and risk prevention measures must be adjusted promptly to fit the time-varying attributes of the energy market. Furthermore, the EC metrics exhibited differing fluctuation patterns, indicating that various markets respond differently to distinct shock events. The solar energy market (M2), fuel cell market (M5), and crude oil market (M13) are more important in the network, with greater fluctuations in their EC values, indicating that they are more sensitive to shock events.

The solar energy market (M2) and fuel cell market (M5) are widely recognized as the most promising new energy sources. The International Renewable Energy Agency reports that the solar and fuel cell markets are rapidly developing and offer several advantages, including high efficiency, low harmful gas emissions, and long service life. These energy sources are of strategic importance in renewable energy, particularly in this era of accelerating energy transformation. In contrast, the crude oil market (M13) belongs to the fossil energy markets and has triple attributes of commodities, finance, and politics. Because of geopolitics, unique pricing system, and unbalanced supply and demand patterns, The crude oil market is highly sensitive to various risk factors, resulting in its high overall risk levels and vulnerability to shock events (Baek, 2023; Lee et al., 2023; Liu et al., 2023).

Tail risks have the potential to spread through several critical risk spillover paths, which may have far-reaching systemic consequences. It is important to identify the paths with the highest DIC and frequency of occurrence, which can guide risk management strategies. To identify the critical tail-risk spillover paths, we used a specific method to summarize the risk spillover paths with the top 3 DIC in each window, and the top 15 paths with the highest frequency of occurrence were counted (Table 2).

Table 2 indicates that most of the critical tail-risk spillover paths connect the same type of energy market, such as the path from M2 to M5. However, paths that can spill over tail risks in different types of energy markets may have more profound effects on the IEM, as exemplified by the path from the biofuel market (M1) to the integrated fossil energy market (M16). Biofuels have the potential to replace fossil energy for production, processing, heating, and power generation, which is impossible for other renewable energy sources. Consequently, the spillover path between the biofuel market and the integrated fossil energy market serves as a bridge for the

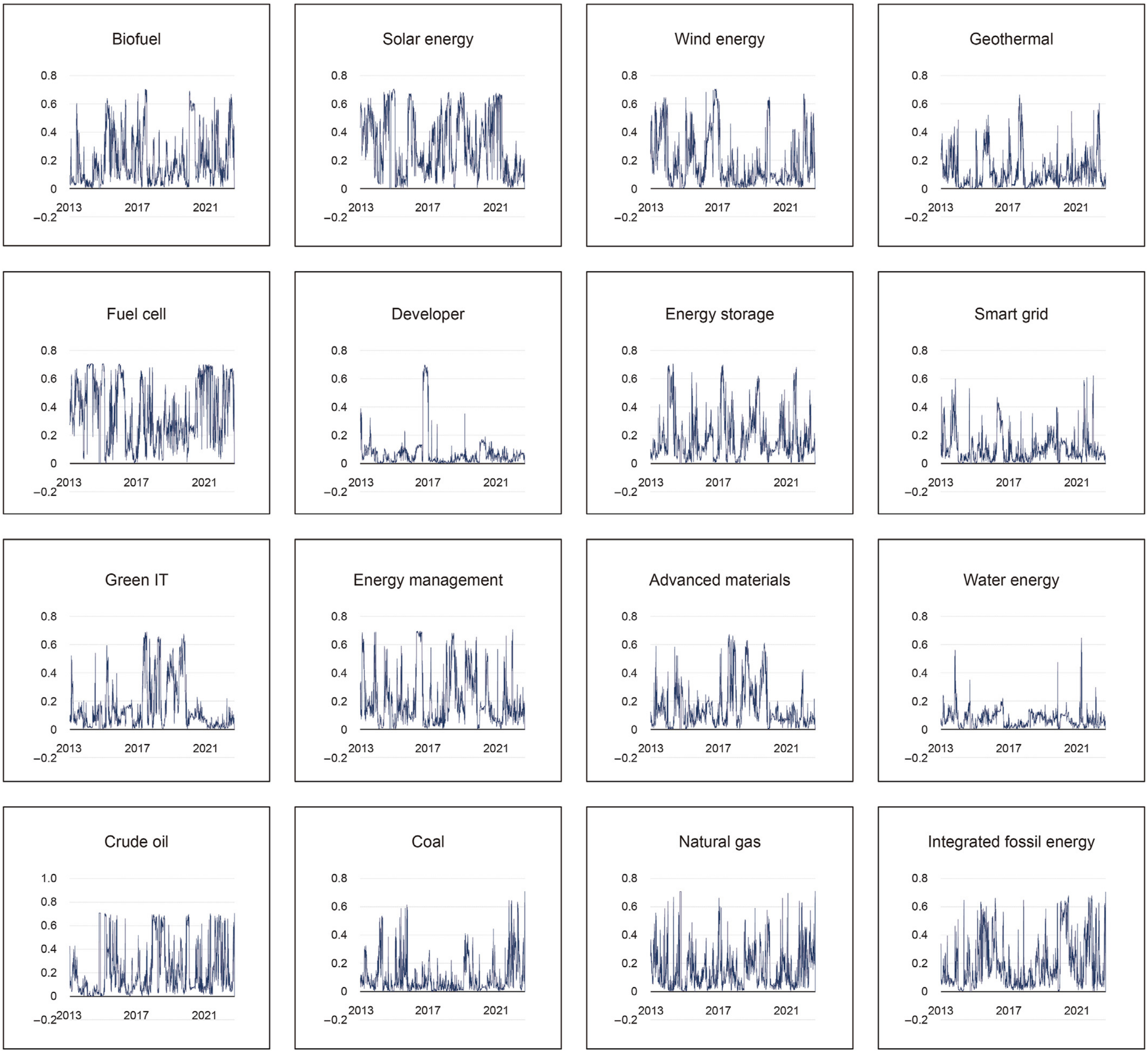

Fig. 3. Evolution of the importance of energy markets in the TRSN. The vertical axis signifies the EC of distinct energy markets.

Table 2
Critical tail-risk spillover paths.

Ranking	Energy market category	Edges	Energy market category	Number of edges
1	Renewable	M2 → M5	Renewable	713
2	Fossil	M16 → M13	Fossil	342
3	Renewable	M10 → M8	Renewable	306
4	Renewable	M1 → M5	Renewable	209
5	Renewable	M1 → M16	Fossil	203
6	Fossil	M16 → M5	Renewable	187
7	Renewable	M3 → M5	Renewable	185
8	Fossil	M16 → M1	Renewable	168
9	Renewable	M10 → M13	Fossil	143
10	Fossil	M13 → M15	Fossil	131
11	Fossil	M16 → M15	Fossil	129
12	Renewable	M9 → M1	Renewable	107
13	Renewable	M2 → M3	Renewable	105
14	Fossil	M15 → M13	Fossil	104
15	Fossil	M14 → M13	Fossil	100

transmission of tail risks between the renewable energy market and the fossil energy market.

4.1.2. TRSN analysis of IEM during shock events

In this section, we focus on the network structure of the tail-risk spillover in the IEM during the shock events. Thus, we analyzed the characteristics of the spillover paths and market nodes in the TRSN during the shock events. As listed in Table 3, we used 167 sliding windows as a group (the last group contains 169 windows), divided 2507 sliding windows into 15 periods, and summed the DIC of the 167 sliding windows in each period to yield 15 more representative TRSNs. The start and end dates of each period are the end dates of each sliding window. We denote these 15 periods by D1 to D15. Among them, D5 and D6 are the periods when the Paris Agreement was passed and officially implemented. Next, D11 and D12 are the early and late stages of the outbreak of the COVID-19 pandemic. Finally, D14 and D15 are the early and late stages of the Russia-Ukraine conflict.

Table 3 illustrates that the number of edges in the 15 periods surpassed 100, and the clustering coefficients exceeded 0.7, indicating substantial interconnectedness among the energy markets. The average DIC in the IEM was significantly elevated during the occurrence of shock events, whereas other features of the spillover paths remained relatively unchanged before and after the shock events. This implies that shock events primarily cause an increase in the DIC and do not significantly alter the structure of risk spillover.

To more clearly obtain the network structure characteristics of tail-risk spillovers during shock events, we further constructed a more streamlined TRSN. Specifically, we extracted six TRSN in the three periods of the Paris Agreement, the COVID-19 pandemic, and the Russia-Ukraine conflict. The edges smaller than the average DIC were deleted, and finally six TRSN with more research value during the three major shock events were obtained (Fig. 4). The direction of the edge in the TRSN indicates the direction of tail-risk spillover, the size of the node is the size of the tail-risk spillover effect of each market (measured by the weighted degree), and the thickness of the edge indicates the size of the DIC.

Fig. 4 shows the importance of tail spillover paths and the position of individual energy markets in the network during major shock events.

Paris Agreement (D5, D6): D5 shows that the largest risk spillover effect is the integrated fossil energy market (M16), and the strongest tail-risk spillover path is the path from the fuel cell market (M5) to the solar energy market (M2). By D6, the Paris Agreement was officially implemented, and people increased their investment in the renewable energy market. The status of the fossil energy market in the network decreased, while the renewable energy market increased.

COVID-19 pandemic (D11, D12): D11 shows that the tail-risk spillover effect of each market has a negligible difference, which indicates that the outbreak of the COVID-19 has caused a systemic impact on the IEM. By D12, in the late stage of the COVID-19 outbreak, the tail-risk spillover effects of various markets were no longer balanced, showing the characteristics of risk concentration again. The risk spillover path between the fuel cell market (M5) and solar market (M2) remained the strongest.

Russia-Ukraine conflict (D14, D15): Fossil fuel energy has always been the core of international geopolitics. The crude oil price fluctuated violently during the Russia-Ukraine conflict and the global energy supply was seriously affected (Khan et al., 2023). D14 and D15 show that the risk spillover effect in the early stage of the Russia-Ukraine conflict mainly appeared in the fossil energy market and fuel cell market. It shows that the tail risk of the energy market during the Russia-Ukraine conflict was first transmitted in the fossil energy market and fuel cell market, gradually spreading to the entire IEM.

4.2. Dynamic process analysis of tail-risk spillover in IEM

4.2.1. Evolution of SRC in IEM from 2012 to 2022

We obtained the SRC of 16 energy markets in the dynamic process of tail-risk spillover and studied its evolution from 2012 to 2022 using the sliding-window method. In Fig. 5, most of the energy markets have an SRC ranging from 0.5 to 1. Furthermore, when a market has a high SRC, it maintains a relatively high level for several months, indicating the momentum effects of the market with a high SRC. In the renewable energy market (M1–M12), the SRC of the fuel cell market (M5) is 1.5. Although its SRC has not experienced extreme values, it has always been at a relatively high level. In contrast, the developer market (M6) and water energy market (M12) have a lower SRC close to 0. Furthermore, the SRC of the fossil energy market (M13–M16) is higher than the renewable energy market. The development and use of the renewable energy market are still in its early stages, and there is a considerable gap in production and use compared to the well-established fossil energy market. Moreover, the fossil energy market is more financially integrated and more responsive to macroeconomic conditions than the renewable energy market.

To gain further insights, we investigated the top 15 values of SRC and their occurrence periods, which are listed in Table 4. Our results reveal that the extreme values over 2.5 were all generated by the biofuel market (M1) and integrated fossil energy market (M16) during the COVID-19 pandemic (Table 4). Considering that SRC can

Table 3
Characteristics of spillover paths in the TRSN over 15 periods.

	Period	Number of edges	Average DIC	Clustering coefficient	Average path length
D1	03/08/2013–11/01/2013	133	9.946	0.811	2.414
D2	11/04/2013–07/03/2014	145	12.189	0.845	1.419
D3	07/07/2014–02/25/2015	144	9.734	0.862	0.562
D4	02/26/2015–10/16/2015	153	12.951	0.869	2.664
D5	10/19/2015–06/07/2016	140	10.580	0.833	1.377
D6	06/08/2016–01/26/2017	154	12.585	0.868	0.892
D7	01/27/2017–09/18/2017	174	10.058	0.908	0.888
D8	09/19/2017–05/09/2018	163	13.501	0.907	1.256
D9	05/10/2018–12/28/2018	173	11.307	0.922	0.535
D10	12/31/2018–08/20/2019	170	10.767	0.892	0.678
D11	08/212019–04/09/2020	165	12.881	0.914	1.653
D12	04/10/2020–12/01/2020	124	11.555	0.816	2.365
D13	12/02/2020–07/22/2021	121	9.094	0.789	6.466
D14	07/23/2021–03/14/2022	151	8.905	0.857	0.752
D15	03/15/2022–11/04/2022	115	14.756	0.746	2.336

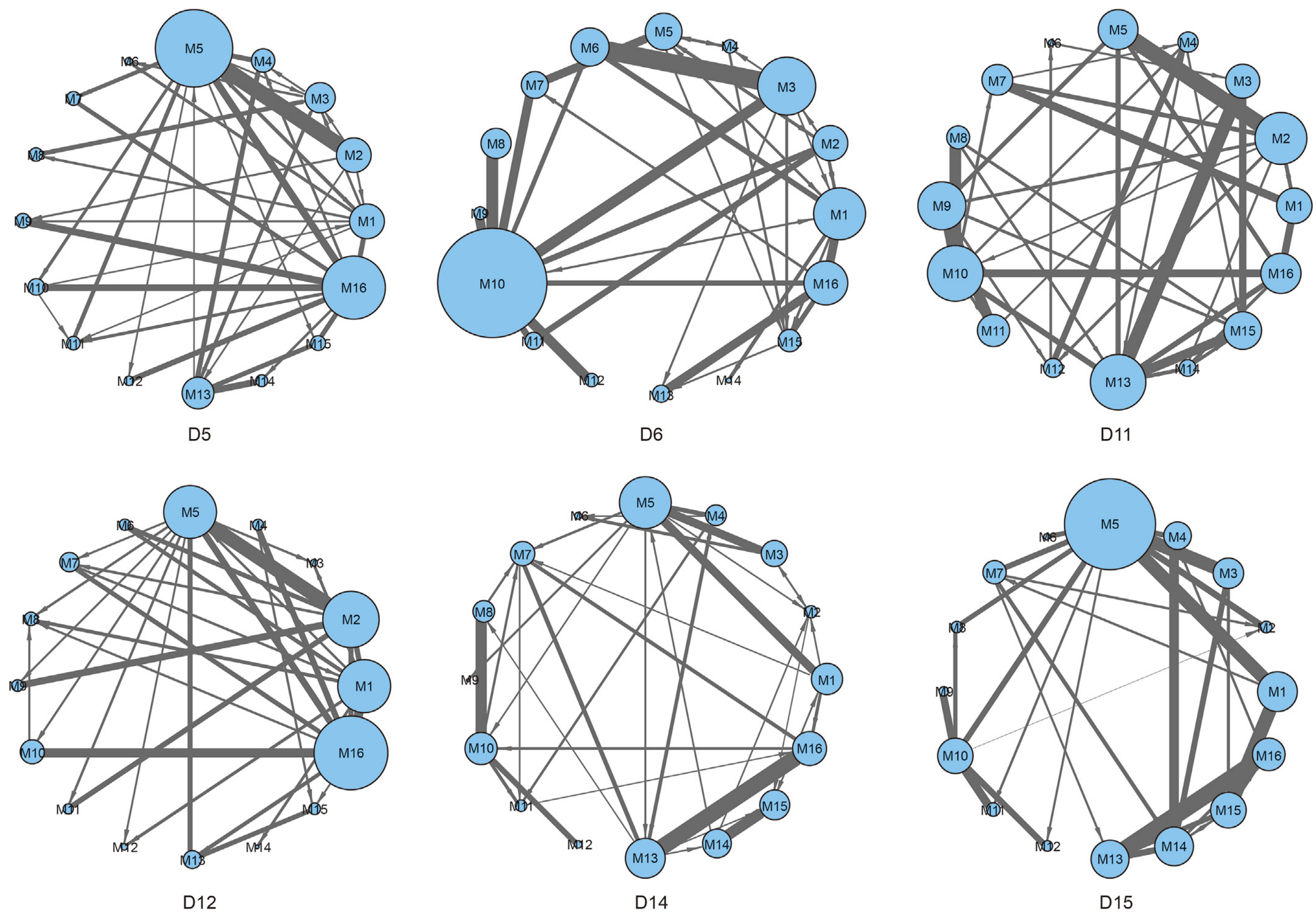

Fig. 4. TRSN of the IEM during major shock events.

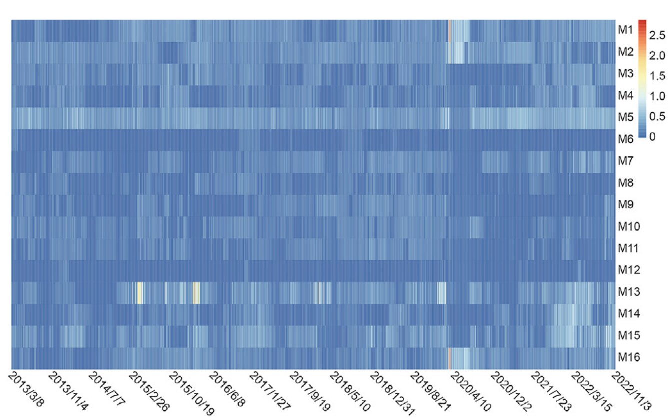

Fig. 5. Heatmap of the SRC of the energy markets. Red indicates a high SRC, and blue indicates a low SRC.

reflect the risks that a market has during this period and the systemic risk growth of the energy market, the COVID-19 pandemic has seriously deteriorated the external business environment and internal economic fundamentals of the IEM (Szczygielski et al., 2021). The extreme values were secondarily distributed during the signing of the Paris Agreement, mainly generated by the crude oil market (M13). As the first global agreement on climate change, the Paris Agreement has promoted the development of the renewable energy market, but also yielded turmoil in the fossil energy market.

4.2.2. OSR and systemically important markets in IEM during shock events

First, we studied the OSR and its evolution in the IEM by aggregating the SRC of 16 energy markets, thus obtaining a macroscopic analysis of the systemic risk of the IEM. Fig. 6 shows that the OSR is mainly between 1 and 4: a date with an OSR greater than 4 is a high systemic risk day. The fluctuation in the OSR corresponds to the impact range of the shock events, which is similar to the evolution characteristics of the TRSN in Fig. 2 There may be two reasons for this volatility feature: (1) the risk environment may degrade the fundamentals of the energy market development, making the energy market vulnerable to unstable factors, especially shock events. (2) Shock events cause the DIC of the IEM to rise, increasing the OSR (Abuzayed et al., 2021; Carlomagno and Albagli, 2022; Gai and Kapad, 2019).

Then, we analyzed the OSR of the IEM during the three shock events of the Paris Agreement, COVID-19 pandemic, and Russia-Ukraine conflict. These three periods are marked in light blue in Fig. 6. During the period of the Paris Agreement, there were fewer days with high systemic risk, which exceeded 4 only at the two nodes of the adoption and formal implementation of the Paris Agreement. During the COVID-19 pandemic, the OSR of the IEM soared to a peak of 9.3 in the sample period. Subsequently, with market recovery and the reduction of risks, the OSR dropped to

Table 4
Extreme value and occurrence period of SRC.

Ranking	Window period	Market	SRC	Ranking	Window period	Market	SRC
1	11/09/2019–03/13/2020	M1	2.905	9	10/22/2015–02/16/2016	M13	1.867
2	11/09/2019–03/13/2020	M16	2.897	10	10/20/2017–02/14/2018	M13	1.862
3	11/28/2019–03/24/2020	M1	2.838	11	11/06/2015–03/02/2016	M13	1.860
4	11/28/2019–03/24/2020	M16	2.735	12	10/16/2017–02/08/2018	M13	1.855
5	11/04/2015–02/29/2016	M13	2.221	13	11/25/2019–03/19/2020	M2	1.799
6	10/29/2015–02/23/2016	M13	1.965	14	10/26/2015–02/18/2016	M13	1.786
7	12/27/2014–04/13/2015	M13	1.955	15	11/23/2015–03/17/2016	M13	1.775
8	11/25/2019–03/19/2020	M16	1.923				

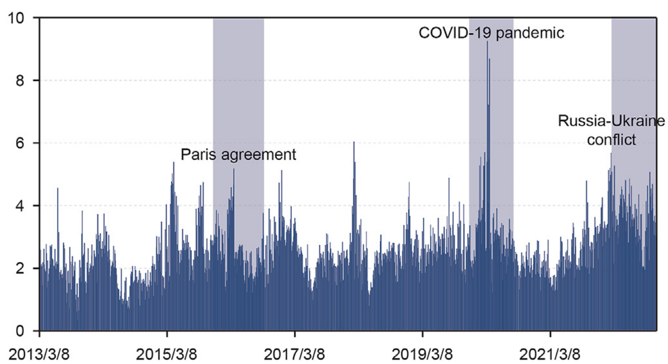

Fig. 6. Evolution of the OSR in the IEM. The vertical axis signifies the OSR value.

below 4. During the Russia-Ukraine conflict, half of the OSR values of the IEM exceeded 4, and the proportion of high systemic risk days was the highest among the three shock events analyzed.

The evidence shows that the impact of the COVID-19 pandemic on the IEM was rapid and extreme, and worldwide production and economies came to a standstill during the COVID-19 outbreak. Furthermore, the shock of the Russia-Ukraine conflict is lasting. The Russia-Ukraine conflict is essentially the result of the interaction between energy trade patterns and geopolitics, the negative impact of intense geopolitical conflicts triggered by energy is profound and long-lasting (Qin et al., 2023). Additionally, energy is an industry that is highly sensitive to geopolitical factors. The Russia-Ukraine conflict and various subsequent sanctions and counter-sanctions will cause continuous turmoil in the IEM (Thompson, 2022). The impact of the Paris Agreement on the IEM has been more gradual. This may be because the Paris Agreement is not a crisis event, it is more of an increase in the demand for the renewable energy market. Furthermore, the energy transition is gradual and slow, thus not yielding extreme and lasting shocks to the IEM.

The OSR of the IEM has shown a downward trend since October 2022. Combined with the downward trend of the network density during the same period in Fig. 2, it shows that reducing the number of tail-risk spillover paths will help maintain market stability.

Additionally, to more effectively control and prevent systemic risk to the IEM during shock events, it is highly important to focus on the market with high SRC during shock events. Such markets are one of the main reasons for systemic risk in the IEM during shock events (Xiong and Chen, 2022), referred to as systemically important markets (SM).

To more clearly obtain the OSR and SM of the IEM in each period, the total sample time was divided into 15 segments using the method described in section 4.1.2; the total OSR of the IEM in each period and the ranking of the SRC of each energy market was calculated. The corresponding numbers indicating the total OSR of the IEM for each period are presented in brackets in Table 5. The last column of Table 5, titled "AVG," presents the ranking of the average SRC of each energy market during the three major shock events.

Table 5 and Fig. 5 indicate that the highest peak of the OSR in the IEM occurred during the COVID-19 pandemic and the total OSR during the Russia-Ukraine conflict period was the highest level in the sample period. This can be attributed to the higher proportion of high systemic risk days observed during the Russia-Ukraine conflict compared to the other shock events analyzed. Thus, we identified SM during the shock events as.

- **Paris Agreement:** biofuel market (M1), fuel cell market (M5), and crude oil market (M13).
- **COVID-19 Pandemic**: biofuel market (M1), solar energy market (M2), fuel cell market (M5), and crude oil market (M13).
- **Russia-Ukraine Conflict**: fuel cell market (M5), crude oil market (M13), coal market (M14), and natural gas market (M15).

The renewable energy market was more affected by the Paris Agreement and COVID-19 pandemic, whereas the fossil energy market was more affected by the Russia-Ukraine conflict. The fuel cell and crude oil markets ranked highest in terms of the average SRC values during the three major shock events, indicating that they were all SM during the three shock events.

In this study, unlike previous research conclusions that the SM is the main risk spillover, the SM may also be the main risk receiver. Specifically, both the fuel cell and the crude oil markets were mainly risk receivers in the critical risk spillover paths (Table 2). Furthermore, as the tail-risk spillover path was relatively stable across different periods, we recommend that market regulators continue to focus on the SM and their main tail risk source markets. Combining Table 2 and Fig. 4, the solar energy market (M2), biofuel market (M1), integrated fossil energy market (M16), and wind energy market (M3) were the main sources of tail risk in the fuel cell market. Furthermore, the integrated fossil energy market was the main source of tail risk in the crude oil market.

4.2.3. Robustness check

Previously, we simulated the dynamic process of tail-risk spillover through the TRSN and cascading failure mechanism, selecting the termination mechanism of $r = 3$. To test the robustness of the conclusion, we changed the value of r and analyzed the situation of the IEM systemic risk under different termination mechanisms. We set r to 1, 2, 3, 5, and 7, which indicates that if a risk spillover path has repeated overflow times greater than r, the path will be supervised by market regulators and will no longer spill tail risks. Fig. 7 shows the evolution of the OSR in the IEM when r has different values.

Fig. 7 shows that the fluctuation trend of the OSR under different r was basically the same. With the increase in r, the OSR of the IEM also increased. The more extreme the OSR value, the more dramatic the increase. For example, the maximum value of the OSR during the COVID-19 pandemic was approximately 16. When the r values were 1 and 2, the OSR of the IEM falls within 4, indicating that if a

Table 5
OSR of the IEM and SRC ranking of each energy market in the 15 periods.

	D1 (295)	D2 (339)	D3 (256)	D4 (437)	D5 (423)	D6 (391)	D7 (360)	D8 (366)	D9 (376)	D10 (409)	D11 (475)	D12 (373)	D13 (329)	D14 (473)	D15 (536)	AVG
M1	10	15	3	3	4	3	4	11	4	9	3	3	4	6	5	3
M2	2	3	2	8	5	4	5	3	2	2	2	2	2	9	10	5
M3	4	4	6	4	6	6	12	8	13	10	12	12	10	7	6	7
M4	7	6	12	7	8	12	11	9	11	14	11	9	9	5	9	8
M5	1	1	1	2	2	1	1	2	1	1	4	4	1	1	1	**1**
M6	15	16	15	15	16	14	15	16	15	15	16	14	16	14	16	15
M7	14	5	10	12	13	10	6	4	9	4	7	8	5	10	8	10
M8	9	10	11	14	11	8	14	14	12	13	13	13	11	13	15	13
M9	8	12	13	10	14	15	7	6	6	5	8	10	15	15	12	14
M10	5	8	7	9	12	5	9	12	7	8	9	6	13	11	11	9
M11	11	7	8	13	10	13	13	7	5	7	10	11	12	12	13	12
M12	16	13	16	16	15	16	16	15	16	16	15	15	14	16	14	16
M13	6	11	9	1	1	7	3	1	3	6	1	5	8	4	3	**2**
M14	13	9	14	11	9	11	8	13	14	12	14	16	7	3	4	11
M15	3	2	4	6	7	2	2	5	8	3	6	7	6	2	2	4
M16	12	14	5	5	3	9	10	10	10	11	5	1	3	8	7	6

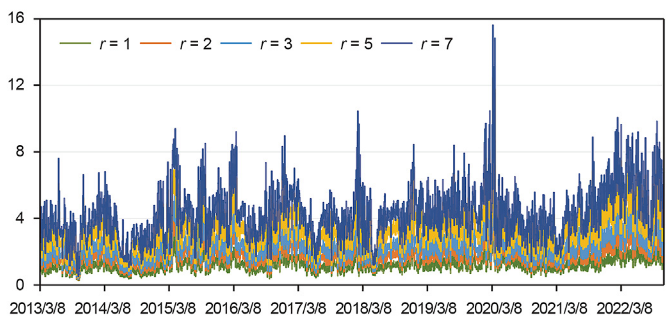

Fig. 7. Evolution of the OSR in the IEM at different *r* values. The vertical axis signifies the *r* value.

risk spillover path is promptly controlled by regulators after being attained, the OSR of IEM will be significantly reduced.

Further, we divided the total sample period into 15 periods to study the impact of different *r* values on the OSR during shock events (Table 6). Similar to the characteristics in Table 5, the OSR during the Russia-Ukraine conflict and COVID-19 pandemic was the highest among all periods.

The maximum value of the OSR at $r = 1$ was 283, which is the middle value at $r = 2$ and half of the minimum value at $r = 7$. If market regulators can manage and control risk spillover paths in a timely and effective manner, the risks caused by shock events will be significantly reduced. Finally, we list the SRC changes and the rankings of changes in energy markets under different *r* values (Table 7).

Table 7 indicates that the solar energy market (M2), fuel cell market (M5), and crude oil market (M13) had the largest change in the SRC when the risk spillover path was regulated in time. The fuel cell market (M5) and crude oil market (M13) were the SM; the solar energy market (M2) was the main source of risk in the fuel cell market. Strengthening the supervision of risk spillover paths can significantly reduce the SRC of the SM; thus, we should manage both market nodes in the TRSN and the risk spillover paths.

Table 7
Change and change ranking of the SRC in energy markets under different *r* values.

	2 → 1	Ranking	3 → 2	Ranking	5 → 2	Ranking	7 → 5	Ranking
M1	128.1	4	109.7	4	210.2	4	209.1	4
M2	147.9	3	129.6	2	248.7	2	248.0	2
M3	93.5	7	82.2	7	157.1	7	156.2	7
M4	72.7	10	63.1	11	119.0	11	118.1	11
M5	212.0	1	179.2	1	347.1	1	346.1	1
M6	10.6	15	9.3	15	18.0	15	17.9	15
M7	86.4	8	73.4	8	138.2	8	137.2	8
M8	45.3	14	38.9	14	72.6	14	72.0	14
M9	55.2	13	48.7	13	95.0	13	94.9	13
M10	76.2	9	65.0	9	121.4	9	120.6	9
M11	62.3	12	53.9	12	102.0	12	101.3	12
M12	6.8	16	5.8	16	10.8	16	10.7	16
M13	150.6	2	124.6	3	233.2	3	231.8	3
M14	71.9	11	63.8	10	120.7	10	119.9	10
M15	124.8	5	107.9	5	204.1	5	203.0	5
M16	116.9	6	102.7	6	195.0	6	194.1	6

Notes: 2 → 1 refers to the reduction value of SRC in each energy market when $r = 2 \rightarrow r = 1$.

5. Conclusions and policy implications

This study investigates the systemic risk of the IEM from the perspective of static structure and the dynamic process of tail-risk spillover. We compare and analyze the characteristics of the IEM systemic risk during different types of shock events and examined the development and interconnections between the renewable energy market and the fossil energy market during these events. This study enriches the research on the systemic risk of the IEM during shock events and aids market regulators in effectively

Table 6
OSR of the IEM at different *r* values in 15 periods.

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	D12	D13	D14	D15
$r = 1$	160	180	136	236	223	206	186	201	195	215	258	218	181	240	283
$r = 2$	233	267	198	344	332	306	281	290	294	319	375	303	257	361	418
$r = 3$	295	339	256	437	423	391	360	366	376	409	475	373	329	473	536
$r = 5$	410	476	370	611	594	549	509	512	529	581	666	509	469	679	766
$r = 7$	526	612	484	783	765	706	656	657	684	753	856	644	608	884	995

managing the IEM and promoting the development of the energy sector. The main findings of this study and their corresponding policy implications are as follows.

First, the impact of various shock events differs in terms of magnitude and duration. The COVID-19 pandemic, for example, had a rapid and extreme impact on the IEM, while the Russia-Ukraine conflict had a more enduring effect. In contrast, the Paris Agreement had a relatively mild influence. Therefore, we suggest that policymakers adopt tailored plans and strategies to mitigate the specific risks associated with different types of shock events. By recognizing the varying impact patterns, policymakers can allocate resources and design policies that effectively respond to each event's unique characteristics.

Second, the tail-risk spillover path of the IEM is relatively fixed. This study highlights the importance of managing tail-risk spillover paths in the IEM. The tail risk will spread through several key tail-risk spillover paths during shock events. It indicates that policymakers closely monitor these spillover paths during different shock events, as timely monitoring can significantly reduce the OSR and the importance of the SM within the IEM. By focusing on risk spillover paths, policymakers can identify potential vulnerabilities and take proactive measures to mitigate systemic risks. The management of risk spillover paths is more important than market node management.

Third, this study reveals that most critical tail-risk spillover paths connect the same type of energy markets, indicating that the diversification of energy sources can reduce the risk of tail-risk spillovers between markets. Governments can encourage the development of multiple types of energy markets to avoid over-reliance on a single market, thereby mitigating the impact of market fluctuations on the overall IEM. Policymakers should support the adoption of diversified investment portfolios by market participants, as this can help mitigate risks associated with specific energy markets and enhance overall portfolio resilience.

Fourth, our study emphasizes the different reactions and sensitivities of the renewable energy and fossil energy markets to different types of shock events. Policymakers should consider these differences and accordingly adjust their management strategies. For example, during geopolitical conflicts, such as the Russia-Ukraine conflict, policymakers should pay particular attention to managing volatility in the fossil energy market. By adopting targeted management strategies that align with the characteristics of different market types, policymakers can mitigate risks and promote market stability.

Lastly, we highlight the importance of monitoring SM and its corresponding tail risk markets. Market regulators should continue to monitor these markets closely and identify potential sources of tail-risk spillovers. In doing so, they can implement proactive measures to prevent and mitigate systemic risks.

This paper enriches previous research on systemic risk in the IEM during shock events, which will help market regulators effectively manage the IEM and promote the development of the energy sector. Admittedly, this study still has some limitations. For example, more impact events could be included in the research scope, which may be further explored.

CRediT authorship contribution statement

Ming-Tao Zhao: Conceptualization, Data curation, Formal analysis, Methodology, Investigation, Resources, Software, Writing – original draft, Writing – review & editing. **Su-Wan Lu:** Methodology, Resources, Software, Validation, Visualization, Writing – original draft. **Lian-Biao Cui:** Funding acquisition, Investigation, Methodology, Project administration, Supervision, Validation, Writing – review & editing.

Declaration of competing interest

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

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References

Abuzayed, B., Bouri, E., Al-Fayoumi, N., et al., 2021. Systemic risk spillover across global and country stock markets during the COVID-19 pandemic. Econ. Anal. Pol. 71, 180–197. https://doi.org/10.1016/j.eap.2021.04.010.

Acemoglu, D., Ozdaglar, A., Tahbaz-Salehi, A., 2015. Systemic risk and stability in financial networks. Am. Econ. Rev. 105, 564–608. https://doi.org/10.1257/aer.20130456.

Acharya, V.V., Pedersen, L.H., Philippon, T., et al., 2017. Measuring systemic risk. Rev. Financ. Stud. 30 (1), 2–47. https://doi.org/10.1093/rfs/hhw088.

Adrian, T., Brunnermeier, M.K., 2016. CoVaR. American Economics Review 106 (7), 1705–1741. https://doi.org/10.1257/aer.20120555.

Ahmad, W., Sadorsky, P., Sharma, A., 2018. Optimal hedge ratios for clean energy equities. Econ. Modell. 72, 278–295. https://doi.org/10.1016/j.econmod.2018.02.008.

Alam, M.S., Murshed, M., Manigandan, P., et al., 2023. Forecasting oil, coal, and natural gas prices in the pre- and post-COVID scenarios: contextual evidence from India using time series forecasting tools. Resour. Pol. 81, 103342. https://doi.org/10.1016/j.resourpol.2023.103342.

Anwer, Z., Khan, A., Naeem, M.A., et al., 2022. Modelling systemic risk of energy and non-energy commodity markets during the COVID-19 pandemic. Ann. Oper. Res. 1–35. https://doi.org/10.1007/s10479-022-04879-x.

Baek, J., 2023. Supply and demand shocks in the global oil market: how much do they matter for exchange rates in OPEC members? Resour. Pol. 81, 103306. https://doi.org/10.1016/j.resourpol.2023.103306.

Baumöhl, E., Bouri, E., Hoang, T.H.V., et al., 2022. Measuring systemic risk in the global banking sector: a cross-quantilogram network approach. Econ. Modell. 109, 105775. https://doi.org/10.1016/j.econmod.2022.105775.

Billio, M., Getmansky, M., Lo, A.W., et al., 2012. Econometric measures of connectedness and systemic risk in the finance and insurance sectors. J. Financ. Econ. 104 (3), 535–559. https://doi.org/10.1016/j.jfineco.2011.12.010.

Boubaker, H., Raza, S.A., 2017. A wavelet analysis of mean and volatility spillovers between oil and BRICS stock markets. Energy Econ. 64, 105–117. https://doi.org/10.1016/j.eneco.2017.01.026.

Boubaker, S., Omri, A., 2022. How does renewable energy contribute to the growth versus environment debate? Resour. Pol. 79, 103045. https://doi.org/10.1016/j.resourpol.2022.103045.

Brownlees, C., Engle, R.F., 2016. SRISK: a conditional capital shortfall measure of systemic risk. Rev. Financ. Stud. 30 (1), 48–79. https://doi.org/10.1093/rfs/hhw060.

Bucci, A., Torre, D.L., Liuzzi, D., et al., 2019. Financial contagion and economic development: an epidemiological approach. J. Econ. Behav. Organ. 162, 211–228. https://doi.org/10.1016/j.jebo.2018.12.018.

Carlomagno, G., Albagli, E., 2022. Trade wars and asset prices. J. Int. Money Finance 124, 102631. https://doi.org/10.1016/j.jimonfin.2022.102631.

Chao, S.K., Härdle, W.K., Wang, W., 2015. Quantile Regression in Risk Calibration. Handbook of Financial Econometric and Statistics. Springer, New York, NY. https://doi.org/10.1007/978-1-4614-7750-1_54.

Chen, Y., Xu, J., Miao, J., 2023a. Dynamic volatility contagion across the Baltic dry index, iron ore price and crude oil price under the COVID-19: a Copula-VAR-BEKK-GARCH-X approach. Resour. Pol. 81, 103296. https://doi.org/10.1016/j.resourpol.2023.103296.

Chen, Y., Wei, Y., Bai, L., et al., 2023b. Can green economy stocks hedge natural gas market risk? Evidence during Russia-Ukraine conflict and other crisis periods. Finance Res. Lett. 53, 103632. https://doi.org/10.1016/j.frl.2023.103632.

Chen, Y., Zhu, X., Chen, J., 2022. Spillovers and hedging effectiveness of non-ferrous metals and sub-sectoral clean energy stocks in time and frequency domain. Energy Econ. 111, 105954. https://doi.org/10.1016/j.eneco.2022.106070.

Corbet, S., Goodell, J.W., Günay, S., 2020. Co-movements and spillovers of oil and renewable firms under extreme conditions: new evidence from negative WTI prices during COVID-19. Energy Econ. 92, 104978. https://doi.org/10.1016/j.eneco.2020.104978.
Cui, L., Yue, S., Nghiem, X.H., et al., 2023. Exploring the risk and economic vulnerability of global energy supply chain interruption in the context of Russo-Ukrainian war. Resour. Pol. 81, 103373. https://doi.org/10.1016/j.resourpol.2023.103373.
Deng, M., Leippold, M., Wagner, A.F., et al., 2022. Stock prices and the Russia-Ukraine war: sanctions, energy, and ESG. CEPR discussion paper No. DP17207. Available at SSRN: https://ssrn.com/abstract=4121382.
Diebold, F.X., Yilmaz, K., 2014. On the network topology of variance decompositions: measuring the connectedness of financial firms. J. Econom. 182 (1), 119–134. https://doi.org/10.1016/j.jeconom.2014.04.012.
Duppati, G., Younes, B.Z., Tiwari, A.K., et al., 2023. Time-varying effects of fuel prices on stock market returns during COVID-19 outbreak. Resour. Pol. 81, 103317. https://doi.org/10.1016/j.resourpol.2023.103317.
Fan, Y., Härdle, W.K., Wang, W., et al., 2018. Single-index-based CoVaR with very high-dimensional covariates. J. Bus. Econ. Stat. 36 (2), 212–226. https://doi.org/10.1080/07350015.2016.1180990.
Fang, L., Chen, B., Yu, H., et al., 2018. Identifying systemic important markets from a global perspective: using the ADCC ΔCoVaR approach with skewed-t distribution. Finance Res. Lett. 24, 137–144. https://doi.org/10.1016/j.frl.2017.08.002.
Furuoka, F., Yaya, O.S., Ling, P.K., et al., 2023. Transmission of risks between energy and agricultural commodities: frequency time-varying VAR, asymmetry and portfolio management. Resour. Pol. 81, 103339. https://doi.org/10.1016/j.resourpol.2023.103339.
Gai, P., Kapad, S., 2019. Networks and systemic risk in the financial system. Oxf. Rev. Econ. Pol. 35 (4), 586–613. https://doi.org/10.1093/oxrep/grz023.
Geng, J.B., Ji, Q., Fan, Y., 2017. The relationship between regional natural gas markets and crude oil markets from a multi-scale nonlinear Granger causality perspective. Energy Econ. 67, 98–110. https://doi.org/10.1016/j.eneco.2017.08.006.
Ghosh, I., Sanyal, M.K., Jana, R.K., et al., 2020. Co-movement and dynamic correlation of financial and energy markets: an integrated framework of nonlinear dynamics, wavelet analysis and DCC-GARCH. Comput. Econ. 57, 1–25. https://doi.org/10.1007/s10614-019-09965-0.
Ha, L.T., 2022. Storm after the Gloomy days: influences of COVID-19 pandemic on volatility of the energy market. Resour. Pol. 79, 102921. https://doi.org/10.1016/j.resourpol.2022.102921.
Hanif, W., Mensi, W., Alomari, M., et al., 2023. Downside and upside risk spillovers between precious metals and currency markets: evidence from before and during the COVID-19 crisis. Resour. Pol. 81, 103350. https://doi.org/10.1016/j.resourpol.2023.103350.
Hanif, W., Mensi, W., Gubareva, M., et al., 2022. Impacts of COVID-19 on dynamic return and volatility spillovers between rare earth metals and renewable energy stock markets. Resour. Pol. 80, 103196. https://doi.org/10.1016/j.resourpol.2022.103196.
Härdle, W.K., Wang, W., Yu, L., 2016. TENET: tail-Event driven NETwork risk. J. Econom. 192 (2), 499–513. https://doi.org/10.1016/j.jeconom.2016.02.013.
Hautsch, N., Schaumburg, J., Schienle, M., 2015. Financial network systemic risk contributions. Rev. Finance 19 (2), 685–738. https://doi.org/10.1093/rof/rfu010.
Hosseini, S.E., 2020. An outlook on the global development of renewable and sustainable energy at the time of COVID-19. Energy Res. Social Sci. 68, 101633. https://doi.org/10.1016/j.erss.2020.101633.
Hsu, C.C., Chau, K.Y., Chien, F.S., 2023. Natural resource volatility and financial development during Covid-19: implications for economic recovery. Resour. Pol. 81, 103343. https://doi.org/10.1016/j.resourpol.2023.103343.
Huang, C., Wen, S., Li, M., et al., 2021. An empirical evaluation of the influential nodes for stock market network: Chinese A-shares case. Finance Res. Lett. 38, 101517. https://doi.org/10.1016/j.frl.2020.101517.
Huang, M., Shao, W., Wang, J., 2022. Correlations between the crude oil market and capital markets under the Russia-Ukraine conflict: a perspective of crude oil importing and exporting countries. Resour. Pol. 80, 103233. https://doi.org/10.1016/j.resourpol.2022.103233.
Huang, W., Liu, Q., Rhee, S.G., et al., 2012. Extreme downside risk and expected stock returns. J. Bank. Finance 36 (5), 1492–1502. https://doi.org/10.1016/j.jbankfin.2011.12.014.
Ji, Q., Bouri, E., Roubaud, D., et al., 2018a. Risk spillover between energy and agricultural commodity markets: a dependence-switching CoVaR-Copula model. Energy Econ. 75, 14–27. https://doi.org/10.1016/j.eneco.2018.08.015.
Ji, Q., Liu, B.Y., Nehler, H., et al., 2018b. Uncertainties and extreme risk spillover in the energy markets: a time-varying Copula-based CoVaR approach. Energy Econ. 76, 115–126. https://doi.org/10.1016/j.eneco.2018.10.010.
Ji, Q., Liu, B.Y., Fan, Y., 2019. Risk dependence of CoVaR and structural change between oil prices and exchange rates: a time-varying copula model. Energy Econ. 77, 80–92. https://doi.org/10.1016/j.eneco.2018.07.012.
Ji, Q., Liu, B.Y., Zhao, W.L., et al., 2020a. Modelling dynamic dependence and risk spillover between all oil price shocks and stock market returns in the BRICS. Int. Rev. Financ. Anal. 68, 101238. https://doi.org/10.1016/j.irfa.2018.08.002.
Ji, Q., Zhang, D., Kutan, A.M., 2020b. Energy financialization, risk and challenges. Int. Rev. Financ. Anal. 68 (1), 101485. https://doi.org/10.1016/j.irfa.2020.101485.
Ji, Q., Zhang, D., Zhang, Z.X., 2023. Energy market financialization, integration and systemic risks. Energy Econ. 117, 106448. https://doi.org/10.1016/j.eneco.2022.106448.
Kaufman, G.G., Scott, K.E., 2003. What is systemic risk, and do bank regulators retard or contribute to it? Indepen. Rev. 7 (3), 371–391.
Kerste, M., Gerritsen, M., Weda, J., et al., 2015. Systemic risk in the energy sector—is there need for financial regulation? Energy Pol. 78, 22–30. https://doi.org/10.1016/j.enpol.2014.12.018.
Khan, N., Saleem, A., Ozkan, O., 2023. Do geopolitical oil price risk influence stock market returns and volatility of Pakistan: evidence from novel non-parametric quantile causality approach. Resour. Pol. 81, 103355. https://doi.org/10.1016/j.resourpol.2023.103355.
Lee, C.C., Zhou, H., Xu, C., et al., 2023. Dynamic spillover effects among international crude oil markets from the time-frequency perspective. Resour. Pol. 80, 103218. https://doi.org/10.1016/j.resourpol.2022.103218.
Li, Z., Liu, Q., Liang, Q., 2019. A study on forestalling China's systemic risk based on financial industry and real economy interacted network. Statistical Research 36 (2), 23–37. https://doi.org/10.19343/j.cnki.11-1302/c.2019.02.003 (in Chinese).
Liang, C., Umar, M., Ma, F., et al., 2022. Climate policy uncertainty and world renewable energy index volatility forecasting. Technol. Forecast. Soc. Change 182, 121810. https://doi.org/10.1016/j.techfore.2022.121810.
Liu, B.Y., Fan, Y., Ji, Q., et al., 2022. High-dimensional CoVaR network connectedness for measuring conditional financial contagion and risk spillovers from oil markets to the G20. Energy Econ. 105, 105749. https://doi.org/10.1016/j.eneco.2021.105749.
Liu, B.Y., Ji, Q., Fan, Y., et al., 2017a. Dynamic return-volatility dependence and risk measure of CoVaR in the oil market: a time-varying mixed copula model. Energy Econ. 68, 53–65. https://doi.org/10.1016/j.eneco.2017.09.011.
Liu, B.Y., Ji, Q., Nguyen, D.K., et al., 2021a. Dynamic dependence and extreme risk comovement: the case of oil pieces and exchange rates. Int. J. Finance Econ. 26 (2), 2612–2636. https://doi.org/10.1002/ijfe.1924.
Liu, F., Umair, M., Gao, J., 2023. Assessing oil price volatility co-movement with stock market volatility through quantile regression approach. Resour. Pol. 81, 103375. https://doi.org/10.1016/j.resourpol.2023.103375.
Liu, X., An, H., Huang, S., et al., 2017b. The evolution of spillover effects between oil and stock markets across multi-scales using a wavelet-based GARCH-BEKK model. Phys. Stat. Mech. Appl. 465, 374–383. https://doi.org/10.1016/j.physa.2016.08.043.
Liu, T., Nakajima, T., Hamori, S., 2021b. The impact of economic uncertainty caused by COVID-19 on renewable energy stocks. Empir. Econ. 62, 1495–1515. https://doi.org/10.1007/s00181-021-02087-3.
Mensi, W., Rehman, M.U., Vo, X.V., 2022. Spillovers and diversification benefits between oil futures and ASEAN stock markets. Resour. Pol. 79, 103005. https://doi.org/10.1016/j.resourpol.2022.103005.
Mezei, J., Sarlin, P., 2018. RiskRank: measuring interconnected risk. Econ. Modell. 68, 41–50. https://doi.org/10.1016/j.econmod.2017.04.016.
Mohammed, K.S., Usman, M., Ahmad, P., et al., 2022. Do all renewable energy stocks react to the war in Ukraine? Russo-Ukrainian conflict perspective. Environ. Sci. Pollut. Control Ser. 30, 36782–36793. https://doi.org/10.1007/s11356-022-24833-5.
Ouyang, Z.Y., Qin, Z., Cao, H., et al., 2021. A spillover network analysis of the global crude oil market: evidence from the post-financial crisis era. Petrol. Sci. 18 (4), 1256–1269. https://doi.org/10.1016/j.petsci.2021.05.003.
Papiez, M., Rubaszek, M., Szafranek, K., et al., 2022. Are European natural gas markets connected? A time-varying spillovers analysis. Resour. Pol. 79, 103029. https://doi.org/10.1016/j.resourpol.2022.103029.
Pham, L., Hao, W., Truong, H., et al., 2023. The impact of climate policy on U.S. environmentally friendly firms: a firm-level examination of stock return, volatility, volume, and connectedness. Energy Econ. 119, 106564. https://doi.org/10.1016/j.eneco.2023.106564.
Pichler, A., Poledna, S., Thurner, S., 2021. Systemic risk-efficient asset allocations: minimization of systemic risk as a network optimization problem. J. Financ. Stabil. 52, 100809. https://doi.org/10.1016/j.jfs.2020.100809.
Qin, M., Su, C.W., Pirtea, M.G., et al., 2023. The essential role of Russian geopolitics: a fresh perception into the gold market. Resour. Pol. 81, 103310. https://doi.org/10.1016/j.resourpol.2023.103310.
Rawtani, D., Gupta, G., Khatri, N., et al., 2022. Environmental damages due to war in Ukraine: a perspective. Sci. Total Environ. 850, 157932. https://doi.org/10.1016/j.scitotenv.2022.157932.
Reboredo, J.C., 2015. Is there dependence and systemic risk between oil and renewable energy stock prices? Energy Econ. 48, 32–45. https://doi.org/10.1016/j.eneco.2014.12.009.
Schwarcz, S.L., 2008. Systemic risk. Duke law school legal studies paper No. 163. Georgetown Law J. 97 (1), Available at SSRN: https://ssrn.com/abstract=1008326.
Shahzad, S.J.H., Hoang, T.H.V., Bouri, E., 2022a. From pandemic to systemic risk: contagion in the U.S. tourism sector. Curr. Issues Tourism 25 (1), 34–40. https://doi.org/10.1080/13683500.2021.1881050.
Shahzad, S.J.H., Hernandez, J.A., Al-Yahyaee, K.H., et al., 2018. Asymmetric risk spillovers between oil and agricultural commodities. Energy Pol. 118, 182–198. https://doi.org/10.1016/j.enpol.2018.03.074.
Shahzad, U., Mohammed, K.S., Tiwari, S., et al., 2022b. Connectedness between geopolitical risk, financial instability indices and precious metals markets: novel findings from Russia Ukraine conflict perspective. Resour. Pol. 80, 103190. https://doi.org/10.1016/j.resourpol.2022.103190.
Sharma, G.D., Shahbaz, M., Singh, S., et al., 2022. Investigating the nexus between green economy, sustainability, bitcoin and oil prices: contextual evidence from the United States. Resour. Pol. 80, 103168. https://doi.org/10.1016/

j.resourpol.2022.103168.
Shiferaw, Y.A., 2019. Time-varying correlation between agricultural commodity and energy price dynamics with Bayesian multivariate DCC-GARCH models. Phys. Stat. Mech. Appl. 526, 120807. https://doi.org/10.1016/j.physa.2019.04.043.
Squartini, T., Caldarelli, G., Cimini, G., et al., 2018. Reconstruction methods for networks: the case of economic and financial systems. Phys. Rep. 757, 1–47. https://doi.org/10.1016/j.physrep.2018.06.008.
Szczygielski, J.J., Bwanya, P.R., Charteris, A., et al., 2021. The only certainty is uncertainty: an analysis of the impact of COVID-19 uncertainty on regional stock markets. Finance Res. Lett. 43, 101945. https://doi.org/10.1016/j.frl.2021.101945.
Thompson, H., 2022. The geopolitics of fossil fuels and renewables reshape the world. Nature 603 (7901), 364. https://doi.org/10.1038/d41586-022-00713-3.
Uddin, M., Chowdhury, A., Anderson, K., et al., 2021. The effect of COVID-19 pandemic on global stock market volatility: can economic strength help to manage the uncertainty? J. Bus. Res. 128, 31–44. https://doi.org/10.1016/j.jbusres.2021.01.061.
Vacha, L., Barunik, J., 2011. Co-movement of energy commodities revisited: evidence from wavelet coherence analysis. Energy Econ. 34 (1), 241–247. https://doi.org/10.1016/j.eneco.2011.10.007.
Wang, G.J., Jiang, Z.Q., Lin, M., et al., 2018. Interconnectedness and systemic risk of China's financial institutions. Emerg. Mark. Rev. 35, 1–18. https://doi.org/10.1016/j.ememar.2017.12.001.
Wang, G.J., Xu, Z.S., Xie, C., 2022a. Connectedness and systemic risk contribution of Chinese financial institutions: a perspective from tail-risk spillover network. Journal of Management Sciences in China 25 (5), 109–126 (in Chinese).
Wang, Q., Yang, X., Li, R., 2022b. The impact of the COVID-19 pandemic on the energy market - a comparative relationship between oil and coal. Energy Strategy Rev. 39, 100761. https://doi.org/10.1016/j.esr.2021.100761.
Wang, Y., Bouri, E., Fareed, Z., et al., 2022c. Geopolitical risk and the systemic risk in the commodity markets under the war in Ukraine. Finance Res. Lett. 49, 103066. https://doi.org/10.1016/j.frl.2022.103066.
Wang, Z., Gao, X., Huang, S., et al., 2022d. Measuring systemic risk contribution of global stock markets: a dynamic tail-risk network approach. Int. Rev. Financ. Anal. 84, 102361. https://doi.org/10.1016/j.irfa.2022.102361.
Watts, D.J., 2002. A simple model of global cascades on random networks. Proc. Natl. Acad. Sci. U.S.A. 99 (9), 5766–5771. https://doi.org/10.1073/pnas.082090499.
Wu, J., Levi, N., Araujo, R., et al., 2023. An evaluation of the impact of COVID-19 lockdowns on electricity demand. Elec. Power Syst. Res. 216, 109015. https://doi.org/10.1016/j.epsr.2022.109015.
Xia, T., Ji, Q., Zhang, D., et al., 2019. Asymmetric and extreme influence of energy price changes on renewable energy stock performance. J. Clean. Prod. 241, 118338. https://doi.org/10.1016/j.jclepro.2019.118338.
Xiong, S., Chen, W., 2022. A robust hybrid method using dynamic network analysis and Weighted Mahalanobis distance for modeling systemic risk in the international energy market. Energy Econ. 109, 105954. https://doi.org/10.1016/j.eneco.2022.105954.
Zhang, Z., Wang, Y., Xiao, J., et al., 2023. Not all geopolitical shocks are alike: identifying price dynamics in the crude oil market under tensions. Resour. Pol. 80, 103238. https://doi.org/10.1016/j.resourpol.2022.103238.
Zhou, W., Chen, Y., Chen, J., 2022. Risk spread in multiple energy markets: extreme volatility spillover network analysis before and during the COVID-19 pandemic. Energy 256, 124580. https://doi.org/10.1016/j.energy.2022.124580.