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Original Paper

Multi-layer risk spillover network of Chinese Energy companies under the background of carbon neutralization

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ABSTRACT

As global climate change and environmental challenges intensify, governments across the globe are increasingly concerned about the sustainable development of the energy industry, with the identification of risk spillover directions and characteristics among energy companies playing a pivotal role in effective risk management within the sector, particularly in the context of carbon neutrality. This study uses the TVP-VAR-DY (Time-Varying Parameter–Vector Auto Regression–Dynamic) model to comprehensively investigate the intricate transmission mechanisms of risk spillover effects among energy companies from both static and dynamic perspectives. The results indicate that: 1) A small number of coal energy companies are net risk spillover exporters, playing a crucial role in the risk spillover among similar energy companies. 2) There exist differences in the network topological structure characteristics of energy companies during different events, and different types of energy companies play different roles in the network. 3) In the context of carbon neutrality, cooperation between traditional energy companies and new energy companies has increasingly become a trend.

1. Introduction

With the occurrence of extreme weather events, reducing greenhouse gas emissions has become an international consensus to address climate change. The United Nations Framework Convention on Climate Change, established in 1992, laid the foundation for global cooperation in addressing climate change (Kumar, 2018). Subsequently, the signing of global agreements such as the Kyoto Protocol and the Paris Agreement has further promoted the process of carbon neutrality. Energy companies, being the main source of carbon emissions, have become the primary focus of low-carbon transformation efforts (Matthews et al., 2008). To meet the demands of low-carbon production, traditional energy companies need to make structural and technological adjustments in production, which in turn increases their operational and innovation risks. With the implementation of various policies such as green subsidies and tax credits to promote green demand (Halkos, 2019), consumers are increasingly fond of low-carbon products. This shift in consumer preferences will inevitably impact the investment decisions of traditional energy companies (Morrison, 2011).

Due to the dependence and connection between energy companies, risk spillovers between companies have a certain degree of conductivity. As global policymakers pay increasing attention to the clean energy market (Bouri et al., 2022), the relationship between traditional and new energy companies has become more complex. In the context of carbon neutrality, the relationship between energy companies is complex (Restrepo et al., 2018), and the information and risks of individual companies will be disseminated to other companies along with capital flows, strengthening cross-company risk interconnections (Wu et al., 2021). Hence, as carbon neutrality goals progress, the level of uncertainty surrounding the development of energy companies has reached unprecedented heights, amplifying the manifestation of internal transmission of systemic risks within the energy industry.

Understanding the risk spillovers and interconnectedness structures among different types of energy companies in China in the context of carbon neutrality policies and events is instrumental for policymakers to identify potential systemic risks within the

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energy sector. Scholars have conducted numerous studies on this issue. Some scholars believed the energy companies also face corresponding innovation risks in building a green development system that aligns with carbon neutrality goals. The risks in the energy industry can further trigger systemic risks, posing a threat to the achievement of national carbon reduction targets (Tang et al., 2023). Therefore, the risk issues faced by energy companies in the context of carbon neutrality are of utmost importance. Wang et al. (2024) analyzed the risk spillover effect between the green economy and energy metals, finding that the uncertainty of climate policies amplifies the transmission of extreme risks between them. Many scholars have further researched and found that carbon neutrality will affect the risk spillover among different energy companies. Guo and Zhao (2024) examined the volatility spillover between China's crude oil and coal markets, discovering that oil risk exposure can be effectively hedged in coal portfolios. Therefore, identifying early signals of risk contagion among energy companies and understanding the inherent structural vulnerabilities of the system are crucial for energy security.

In previous studies, many researchers have used methods such as CoVaR (Liu et al., 2022), GARCH (Tian et al., 2022), VAR, and copulas (Liu et al., 2017) to investigate risk spillover effects. With the introduction and development of network models, some studies have also adopted single-layer complex network methods (Wen et al., 2023). In recent years, the application of multi-layer network models has become more widespread. Compared to single-layer networks, multi-layer complex networks not only reveal the connectivity and centrality patterns of energy companies within the network but also enable the identification of cross-layer differences (Wu et al., 2021). Dai et al. (2023) constructed a multi-layer information network based on returns, volatility, and extreme risk information to investigate the systemic risks in the oil market and G20 stock markets. Elsayed et al. (2023) examined the linkages and risk transmission between oil shocks and the banking sector of the Gulf Cooperation Council (GCC) countries using a multi-layer information spillover network. However, most of the literature primarily focuses on constructing multi-layer networks for different types of financial institutions, with fewer scholars utilizing multi-layer complex networks to study the risk spillover effects between energy companies.

In summary, previous studies have mostly focused on a series of impacts generated by specific events or policies, primarily examining the changes in stock prices and risk effects of a particular type of energy company in the carbon neutrality process. Few scholars have utilized multi-layer complex networks to investigate the risk spillover effects between different types of energy companies. To reveal the transmission patterns of time-varying risks among energy companies, this paper will employ the TVP-VAR-DY method to examine the transmission paths and evolutionary characteristics of risk among energy companies from the perspective of multi-layer risk spillover networks, under the background of carbon neutrality events. The contributions of this paper are as follows: 1) From the perspective of "Dual-Carbon" events, this study explores the impact of different "Dual-Carbon" events on the risk spillover of energy companies through an analysis of ten significant "Dual-Carbon" events. 2) A comparative analysis is conducted to examine the risk spillover effects among energy companies from both dynamic and static perspectives. 3) By constructing a three-tier risk spillover network for energy companies, this study comprehensively examines the risk transmission mechanisms between different types of energy companies, providing a novel perspective for the research on risk spillover effects at the micro-enterprise level.

2. Methods and data

2.1. TVP-VAR-DY

The TVP-VAR-DY model has found widespread application in the field of economics (Antonakakis et al., 2019; Wang et al., 2023). In contrast to the traditional rolling-window VAR method, this model obviates the need for selecting a rolling window size, thereby mitigating issues associated with sample data loss (Wang et al., 2023). The model enhances regression accuracy by considering the heteroscedasticity process, which is generally deemed more reliable than the homoscedasticity process, leading to regression outcomes that are more aligned with economic realities. Furthermore, the incorporation of the Kalman filter estimation with a forgetting factor in the model mitigates the sensitivity to outliers (Luo et al., 2024).

The representation of the TVP-VAR model is illustrated in Eqs. (1) and (2), where y_t denotes an m-dimensional column vector, Ω_{t-1} signifies all available information up to period $t-1$, $\boldsymbol{A}_t$ represents an $m \times mp$ dimensional matrix, $\boldsymbol{z}_{t-1}$ represents an $m \times p$ dimensional column vector.

$$y_t = \boldsymbol{A}_t \boldsymbol{z}_{t-1} + \epsilon_t,\ \ \epsilon_t|_{\Omega t-1} \sim N(0, \boldsymbol{\Sigma}_t) \tag{1}$$

ϵ_t and ξ_t represent m-dimensional and m^2p dimensional column vectors, respectively. The time-varying covariance matrix $\boldsymbol{\Sigma}_t$ and $\boldsymbol{\Xi}_t$ are $m \times m$ and $m^2p \times m^2p$ dimensional matrices, respectively. $vec\,(\boldsymbol{A}_t)$ is the vectorization of the matrix $\boldsymbol{A}_t$, representing an m^2p dimensional column vector.

$$vec(\mathbf{A}_t) = vec(\boldsymbol{A}_{t-1}) + \xi_t,\ \ \xi_t|\Omega_{t-1} \sim N(0, \boldsymbol{\Xi}_t) \tag{2}$$

Unlike traditional TVP-VAR models that utilize Markov Chain Monte Carlo (MCMC) for estimation, this model employs a Kalman filter integrated with a forgetting factor during the estimation phase to ensure numerical stability. By utilizing the estimated time-varying parameters in conjunction with the Wold representation theorem, the TVP-VAR model is converted into a Vector Moving Average (TVP-VMA) model. Following this conversion, coefficients are extracted from the TVP-VMA model for the purpose of computing Generalized Impulse Response Functions (GIRFs). GIRFs illustrate the response of variable i to shocks in all variables j, calculated as demonstrated in Eq. (3).

$$\begin{cases} \mathrm{GIRF}_t\,(H, \delta_{j,t}, \Omega_{t-1}) = E(y_{t+H}|e_j = \delta_{j,t}, \Omega_{t-1}) - E\Big(y_{t+J}\Big|\Omega_{t-1}\Big) \\ \Psi_{j,t}(H) = \dfrac{B_{H,t}\Sigma_t e_j}{\sqrt{\Sigma_{jj,t}}}\,\dfrac{\delta_{j,t}}{\sqrt{\Sigma_{jj,t}}}\ \ \delta_{j,t} = \sqrt{\Sigma_{jj,t}} \end{cases} \tag{3}$$

The Generalized Forecast Error Variance Decomposition (GFEVD) represents the contribution share of variable j to the forecast error variance of variable i. Normalizing these variance shares ensures that the sum of each row equals one, where $\sum_{j=1}^{m} \tilde{\phi}_{ij,t}(H) = 1$, $\sum_{i,j=1}^{m} \tilde{\phi}_{ij,t}(H) = m$. The underlying calculation process is outlined in Eq. (4).

$$\tilde{\phi}_{ij,t}(H) = \frac{\sum\limits_{t=1}^{H-1} \Psi_{ij,t}^2}{\sum\limits_{j=1}^{m}\sum\limits_{t=1}^{H-1} \Psi_{ij,t}^2} \tag{4}$$

The Generalized Forecast Error Variance Decomposition (GFEVD) is employed to quantify the risk spillover indices among diverse energy companies. The total spillover index, denoted as $TOTAL_t(H)$, indicates the interconnectedness among all energy companies in the sample, as calculated in Eq. (5).

$$TOTAL_t(H) = \frac{\sum_{i,j=1, i\neq j}^{m} \tilde{\phi}_{ij,t}(H)}{\sum_{i,j=1}^{m} \tilde{\phi}_{ij,t}(H)} * 100 \tag{5}$$

The directional spillover index consists of spillover and spillover indices, where the spillover index $TO_{i\rightarrow j,t}(H)$ reflects the spillover of a certain energy enterprise i to all other energy companies, as shown in Eq. (6).

$$TO_{i\rightarrow j,t}(H) = \frac{\sum_{j=1, i\neq j}^{m} \tilde{\phi}_{ji,t}(H)}{\sum_{j=1}^{m} \tilde{\phi}_{ji,t}(H)} \times 100 \tag{6}$$

The spillover index $FROM_{i\leftarrow j,t}(H)$, indicates that an energy firm is subject to spillover from all other energy firms in the system, as shown in Eq. (7).

$$FROM_{i\leftarrow j,t}(H) = \frac{\sum_{j=1, i\neq j}^{m} \tilde{\phi}_{ij,t}(H)}{\sum_{i=1}^{m} \tilde{\phi}_{ij,t}(H)} \times 100 \tag{7}$$

The net spillover index $NET_{i,t}(H)$, denotes the net spillover from one energy firm to all other energy firm, as shown in Eq. (8). Employing $NPDC_{ij}(H)$, calculate the bidirectional connectivity of energy companies in the system to examine mutual spillover relationships, as shown in Eq. (9).

$$NET_{i,t}(H) = TO_{i\rightarrow j,t}(H) - FROM_{i\leftarrow j,t}(H) \tag{8}$$

$$NPDC_{ij}(H) = \left(\tilde{\phi}_{jit}(H) - \tilde{\phi}_{ijt}(H)\right) * 100 \tag{9}$$

This paper employs the TVP-VAR-DY model to investigate the intensity and direction of risk spillovers among Chinese energy listed companies, based on actual stock data. Furthermore, we utilize complex network analysis to construct a risk spillover network of energy listed companies and focus on the evolution of this network under various “Dual-Carbon” events. Fig. 1 clearly illustrates the primary research approach and framework of this study.

2.2. Data source

Stock prices serve as an external indicator of a company's operational status, with fluctuating peaks and troughs reflecting the inherent volatility in a company's operations. Therefore, this paper utilizes stock price data from listed companies as a proxy to measure the risk spillover effects. The data were obtained from the Wind database (www.wind.com.cn), a prominent financial data service provider in China renowned for its comprehensive and accurate data coverage. Specifically, daily closing price data were selected for listed companies operating in the coal, integrated oil and gas, and new energy sectors, based on the industry classification standards provided by Wind database. The sample period spans from January 2, 2018, to September 30, 2022, covering a significant period of market fluctuations and industry dynamics. To guarantee data reliability, companies with substantial data gaps, delisting concerns, or other potential issues that could compromise the analysis's validity were excluded. After rigorous screening, the final sample comprised 15 listed companies in the coal sector, 18 in the new energy sector, and 7 in the oil and gas sector.

Since the initiation of China's “Dual-Carbon” goals, relevant policy information has been frequently discussed in major national conferences and news reports, garnering attention and discussion from various sectors of society. Investors in the energy industry have recognized the potential impact of these events on the profits, costs, and risks of energy companies. To focus specifically on the impact of these events on the risk spillover of Chinese energy companies, the selection of events considered several factors. On one hand, priority was given to significant conference events or policy documents related to the transformation requirements of the energy industry. On the other hand, the timing distribution of events needed to be rational, avoiding mutual interference between events. Finally, events were selected from different perspectives, covering major domestic and international conferences, relevant policy documents, and more. The paper ultimately selected 10 important events from 2020 to 2022, as shown in Table 1.

3. Research results

3.1. Analysis of risk spillover effects among energy listed companies

The results of spillover indices among coal-listed companies, estimated based on the entire sample, are presented in Table 2. Due to space constraints, only a portion of the static spillover results for selected companies is displayed in the table. Each row represents the spillover intensity a single company receives from another, while each column represents the spillover degree a single company imposes on another. The “From” column indicates the overall spillover intensity a single listed company receives from all other companies. The “TO” row represents the total spillover intensity a single company generates for all other companies. The “NET” row signifies the net spillover intensity of a single company. A positive value in this row indicates that the company is a net risk contributor, while a negative value implies that the company is a net risk receiver. Static effect analysis reveals the mutual influence relationships among companies during the entire sample period, further assessing the degree of spillover effects between each pair.

From an overall perspective, coal-listed companies exhibit a comparatively high overall risk spillover rate, indicating a pronounced spillover correlation among them. At a macro level, supply-side structural reforms are a crucial factor shaping the supply-demand landscape in the coal industry. The uncertainty factor of coal imports adds complexity to the supply and demand dynamics, with policy changes potentially causing imbalances in the coal industry. Particularly influenced by policies such as the “Dual-Carbon” initiative, the willingness of coal companies to expand production diminishes, leading to resource continuity challenges for some coal mines. The supply curve for coal becomes steeper, contributing significantly to the overall increase in spillover risk among coal-listed companies. Notably, LHKC exhibits the most prominent risk spillover effect on other coal energy companies, with a spillover index reaching 95.9%. Following closely is SHNY, with a risk spillover index of 89.5%. In terms of net spillover indices, JMNY plays the role of the largest net risk receiver in the system, with a net spillover index of −12.7%. LHKC, with the highest net spillover index, emerges as the primary net risk contributor in the system. It displays strong connections with other coal-based companies, excelling in information dissemination and absorption. While having a significant influence on the entire system, LHKC also bears substantial risk.

The spillover index results among comprehensive oil and gas-

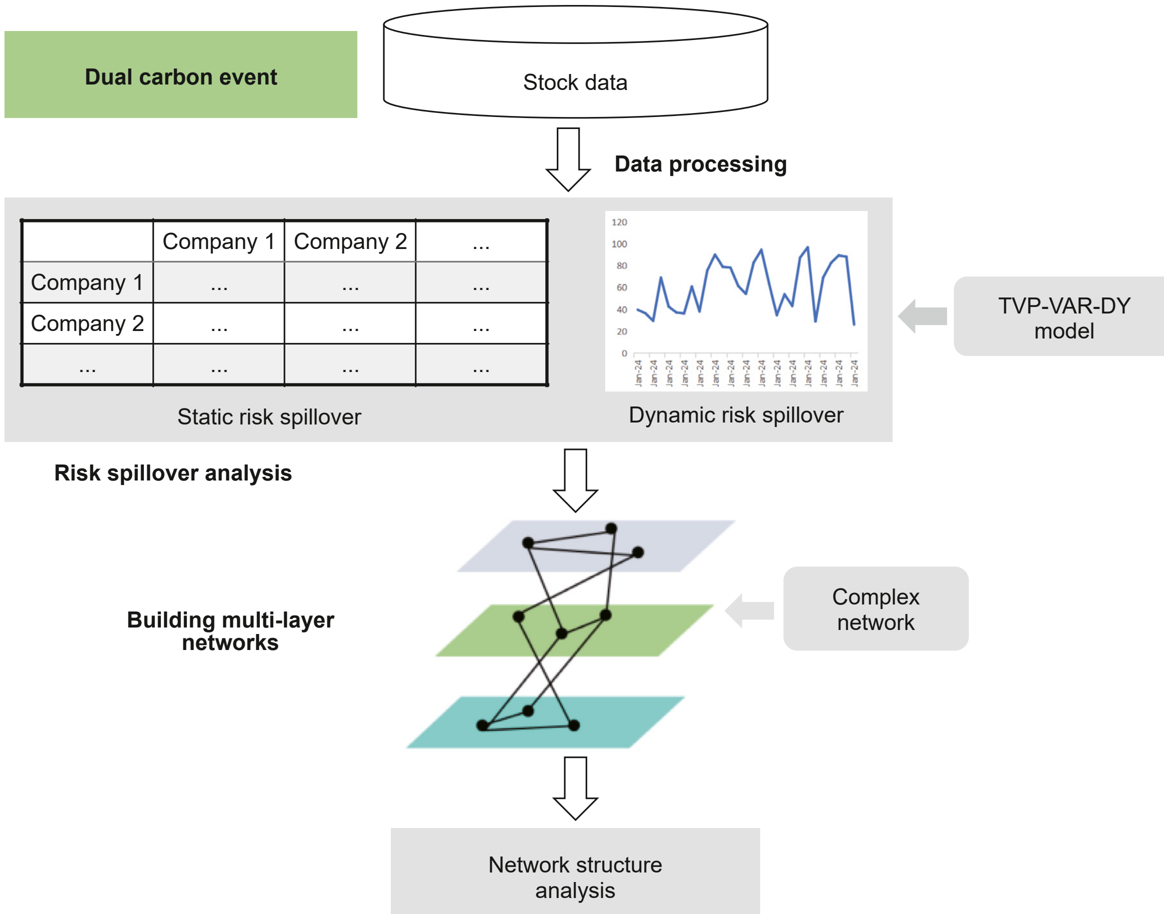

Fig. 1. Framework for assessing risk spillovers among energy listed companies.

Table 1
Key events related to “Dual-Carbon” initiative.

Event	Date	Content
1	September 22, 2020	75th United Nations General Assembly
2	December 12, 2020	Climate Ambition Summit
3	February 19, 2021	United States Rejoins the Paris Agreement
4	March 15, 2021	9th Meeting of the Central Finance and Economic Affairs Commission
5	June 28, 2021	European Council Adopts the European Climate Law
6	July 16, 2021	Official Launch of China's Carbon Emission Trading Market
7	October 26, 2021	State Council Issues the “Action Plan for Peak Carbon by 2030″
8	February 10, 2022	National Development and Reform Commission, National Energy Administration Issue “Opinions on Improving System Mechanisms and Policy Measures for Green and Low-Carbon Energy Transformation"
9	March 22, 2022	National Development and Reform Commission, National Energy Administration Issue the “14th Five-Year Plan for Modern Energy System"
10	June 1, 2022	National Development and Reform Commission and Eight Other Departments Issue “14th Five-Year Plan for Renewable Energy Development"

listed companies, estimated based on the entire sample, are provided in the appendix. From an overall perspective, the overall linkage level among comprehensive oil and gas companies is relatively high. Simultaneously, the risk spillover indices between ZSY and ZSH are substantial, reaching 33.7% and 33.9%, respectively. This is primarily due to the large scale of these two companies, occupying a significant market position. From the perspective of individual companies, SHRQ is a net risk receiver in the system, with ZSY having the largest net spillover index, positioning it as the net risk contributor in the system.

The results of static spillover indices among new energy companies, estimated based on the entire sample, are provided in the appendix. Overall, new energy companies exhibit a high level of overall linkage. LYB, ZGHN, and GDLS demonstrate strong risk spillover effects, reaching 54.6%, 50.8%, and 50.6%, respectively. In terms of risk-bearing, LYB and GDLS experience substantial risk impacts, reaching up to 47.9%. ZGKJ, on the other hand, bears a smaller risk impact, at only 13.7%.

To better reflect the dynamic risk characteristics of energy companies over different periods, this study reveals the dynamic spillover direction and intensity of information transmission among energy listed companies over time, as illustrated in Fig. 2.

Table 2
Static risk spillover indices of coal-listed companies.

	LHKC	SHNY	ZSH	JNKJ	ZGQF	YKNY	YDZ	YTMT	LLFZ	FROM
LHKC	25.6	15.2	10.4	8.2	0.9	7	1.7	3	0.8	74.4
SHNY	15.7	27.4	9.9	7.4	0.6	6.7	1.4	3.5	0.7	72.6
ZSH	11.7	10.9	29.2	4.9	0.7	10	1.6	3.6	0.7	70.8
JNKJ	12.1	10.5	6.6	39.7	0.5	5	1.8	2	0.5	60.3
ZGQF	2.4	1.6	1.6	1.1	75.6	1.5	1.3	2.2	0.9	24.4
YKNY	8.1	7.6	10.2	3.9	0.8	30.2	2.1	4.9	0.9	69.8
YDZ	3.5	2.7	3.2	2.5	1.2	4.2	61.8	2.6	2	38.2
YTMT	5	5.3	4.8	2.2	1.6	7.1	2.4	51.1	1.1	48.9
LLFZ	2	1.7	2	0.8	1.3	2.5	1.8	1.7	75.3	24.7
TO	95.9	89.5	79.4	51	16.2	82	26	40.8	14.5	
NET	21.5	17	8.5	−9.2	−8.2	12.1	−12.2	−8.1	−10.2	

Throughout the entire sample period, coal energy companies exhibit a high dynamic total spillover index, fluctuating in the range of approximately 40%–62%. This indicates a relatively close information transmission among various coal-listed companies. Over time, coal companies' total spillover index shows varying degrees of fluctuation. Notably, from the beginning of 2018 to the end of 2019, the total spillover index exhibited a declining trend. During 2020 to 2021, impacted by significant unforeseen events such as the COVID-19 pandemic, the overall energy market faced severe shocks, resulting in a significant fluctuation in the total spillover index. From the end of 2021 to the beginning of 2022, the total spillover index showed an upward trend, coinciding with China's formal proposal of carbon neutrality. This indicates the impact of the "Dual-Carbon" initiative, as investors expressed doubts about the prospects of traditional coal, leading to an upward trend in the total spillover index. From January to March 2022, the total spillover index showed an initial increase followed by a decline.

In comparison to the results for coal-listed companies, the overall spillover index level for comprehensive oil and gas-listed companies is relatively weak, generally below the 30% threshold. This suggests that the interconnectivity of comprehensive oil and gas companies is weaker than that of coal-listed companies. This difference could be attributed to the substantial variation in the scale of comprehensive oil and gas companies, and the lower degree of business overlap among sample companies, resulting in an overall lower level of risk spillover indices. For instance, JSNY engages in petroleum and natural gas development in the United States and silver sales in China. ZGSY, ZGSH, and SHRQ demonstrate strong risk spillover output and receptivity capabilities. On the other hand, JSNY and BNGJ generally exhibit weaker risk spillover and receptivity capabilities over the sample period. In terms of the temporal characteristics of net spillover indices, ZGSY and ZGSH are net risk contributors, while SHRQ acts as a net risk receiver. Being global leading companies, ZGSY and ZGSH transmit information and risks at a significantly faster pace than smaller energy companies, potentially causing more extensive risk propagation when global energy companies face risks.

Similarly, relative to the results for coal-listed companies, the overall spillover index level for new energy-listed companies is relatively weak, generally below 50%, but higher than that of comprehensive oil and gas-listed companies. The interconnectivity among new energy companies falls between the aforementioned two categories. New energy companies such as LYDL, LYB, and HNFZ exhibit strong risk spillover and receptivity capabilities, playing the role of information transmitters in the entire system. Conversely, energy companies like FSKG and TJXNY demonstrate relatively weaker risk spillover and receptivity capabilities. In contrast to the aforementioned energy companies, certain new energy companies exhibit alternating positive and negative net spillover effects, indicating a distinct time-varying characteristic in their risk spillovers. When confronted with significant unexpected events or other external shocks, these energy companies' roles undergo corresponding changes.

3.2. Multilayer risk spillover network of energy listed companies

This study predominantly illustrates the magnitude and direction of risk spillovers among energy listed companies during different periods of "Dual-Carbon" events in the form of a multilayer network. The results of risk spillover indices, computed using the TVP-VAR-DY model, are used to construct a multilayer risk spillover network for energy listed companies during ten "Dual-Carbon" events.

Taking the 75th United Nations General Assembly event as an example, given its high significance and widespread global attention, we focus on analyzing the characteristics of the multilayer risk spillover network among energy listed companies during this event, as depicted in Fig. 3. Each layer in the figure represents a different risk spillover network for energy-listed companies, arranged from top to bottom as new energy, comprehensive oil and gas, and coal categories. The size of nodes in the figure represents the degree of nodes, reflecting the status of each company in the entire network—larger nodes indicating a more crucial position in the network. The thickness of the lines between nodes indicates the level of risk spillover between them, with thicker lines representing higher spillover indices. In this risk spillover network, a few energy-listed companies play a more critical role in diffusing overall financial risks. Once these companies are impacted by external risks, they can rapidly propagate financial risks into the market, potentially causing widespread financial risk contagion in the energy market.

According to the results, during the 75th United Nations General Assembly, there is a notable risk spillover between a minority of coal-listed companies and new energy-listed companies, while the risk spillover between comprehensive oil and gas-listed companies and new energy-listed companies is relatively weaker.

Under the influence of the "Dual-Carbon" policy, traditional energy companies face the challenge of transformation. In the coal-listed companies, the willingness to invest in coal main business capital has weakened. To ensure future market positions and competitive advantages, energy transformation has become a consensus among coal-listed companies. For example, the coal-listed energy enterprise HYGF has started laying out the entire industry chain of sodium-ion batteries and providing integrated energy solutions for photovoltaics and flywheel energy storage. YKNY is also actively planning new energy, new materials, and high-end equipment businesses. Therefore, under the "Dual-Carbon" goal, regulators and investors should focus on the risk spillover effects between coal-listed energy companies and new energy-listed energy companies. Although the research results show that large energy companies have higher importance in multilayer risk spillover networks, the interconnectedness of small and medium-

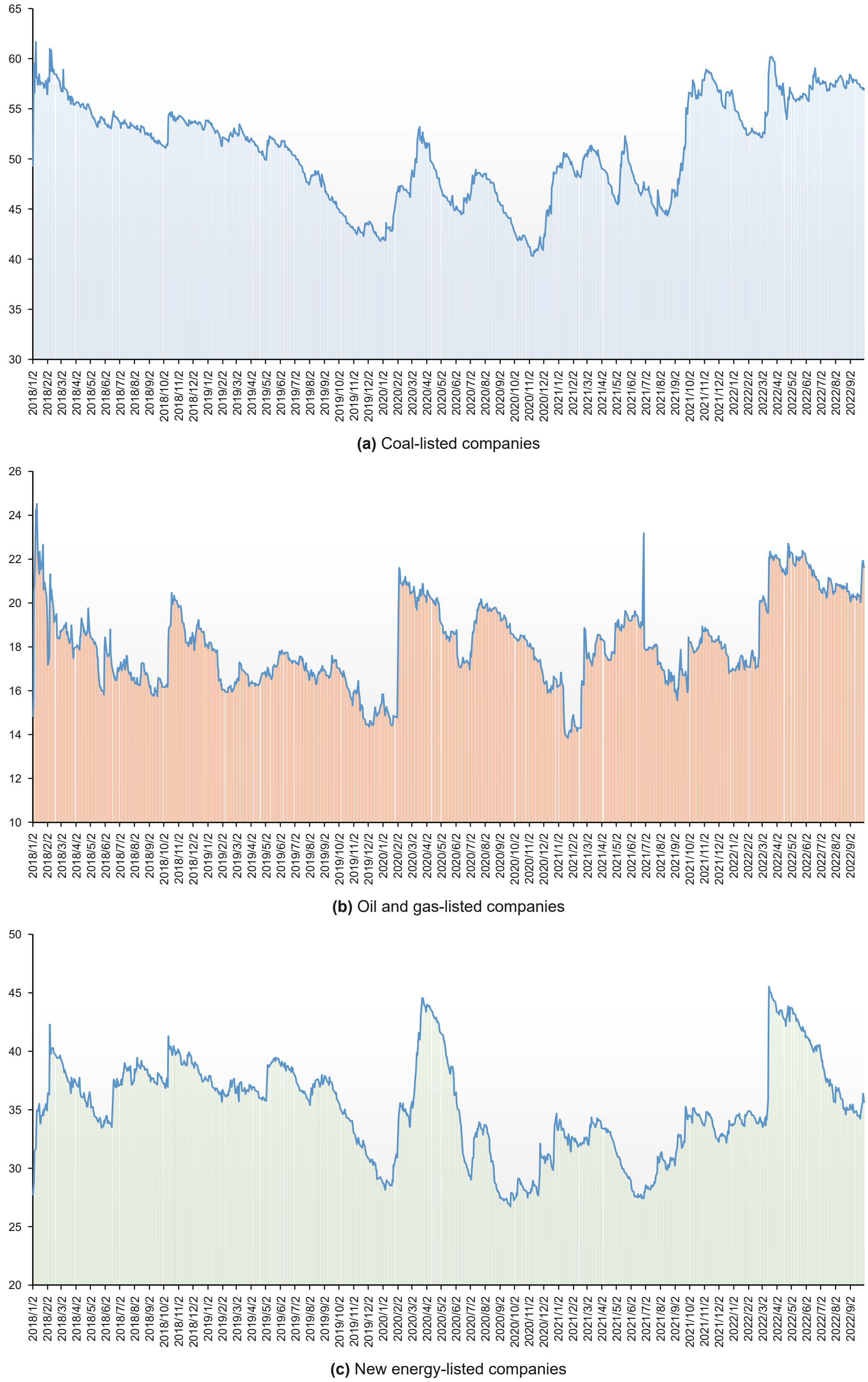

Fig. 2. Dynamic total spillover index of energy listed companies.

sized energy companies should also be highly regarded, especially considering the higher frequency of risk events in these companies in recent years.

3.3. Evolution of multilayer risk spillover networks in energy companies

The average degree of the network indicates that the networks during events one and four exhibit higher compactness, whereas those during events two and seven show relatively weaker connectivity. Overall, the multilayer risk spillover networks of Chinese energy companies have a large density, suggesting strong connections among companies over different event periods. Notably, during event five, the network density is particularly high, reaching 0.222, signifying enhanced interconnectedness among Chinese energy companies. In contrast, during events two and seven, the networks are relatively dispersed, indicating weaker connections among nodes (see Table 3).

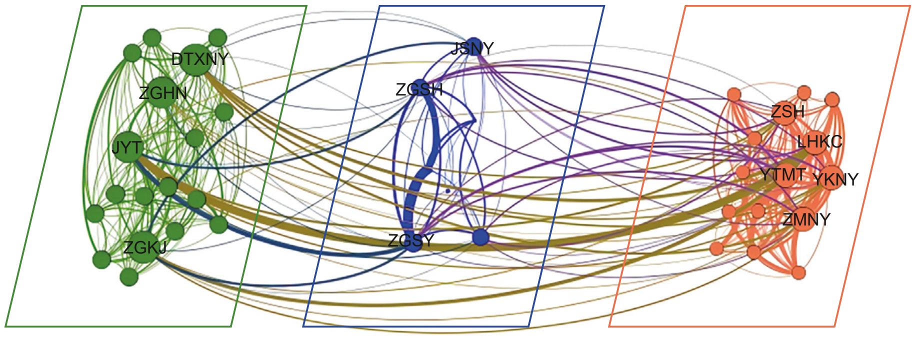

Fig. 3. Multilayer risk spillover network of energy listed companies (Event 1).

The clustering coefficient of the network reflects its density. Generally, the multilayer risk spillover networks of Chinese energy companies have a high clustering coefficient, indicating extensive connections among companies. Specifically, during event one, the clustering coefficient is significant, reaching 0.462, indicating the highest degree of node aggregation. In event seven, the clustering coefficient is 0.446, suggesting relatively reduced connections among companies during this period.

Examining the average path length of the network, it is observed that the multilayer risk spillover network of Chinese energy companies maintains an average path length between 1.8 and 2.9, suggesting that traversing from one node to another typically requires approximately two intermediaries. However, variations in the average path length are evident across different event periods. Notably, during event eight, the average path length is only 1.848, indicating relatively rapid information transmission within this network.

The network diameter, representing the longest distance between two nodes in the network, is generally maintained between 5 and 8 for the multilayer risk spillover networks of Chinese energy companies. Events four, seven, and eight exhibit the smallest network diameters, indicating higher turnover efficiency and better connectivity during these periods.

To compare the evolution of centrality among important nodes under different events and emphasize the positions and roles of different types of energy companies in the network, this study analyzes the changes in centrality rankings of various energy companies. The companies selected for analysis maintained their centrality rankings within the top five across different networks, and their evolving significance is reviewed.

The centrality ranking changes of Chinese energy companies in risk spillover networks under different "Dual-Carbon" events are illustrated in Fig. 4. Blue nodes represent coal companies, red nodes represent integrated oil and gas companies, and green nodes represent new energy companies. Examining the centrality ranking changes throughout the ten events reveals that coal companies consistently maintain higher rankings, with minimal variations in importance across different events. This indicates that coal companies represented by LHKC and ZSH have stronger connections with other companies, exhibiting greater interconnectedness and significance in the network.

Analyzing the betweenness centrality rankings of nodes in the risk spillover network from event one to event ten reveals that coal and new energy companies serve as pivotal hubs in the risk spillover network. Represented by companies such as YTMT, ZMNY, and YKNY for coal, and DTXNY, JYTZGHN, etc., for new energy, these companies play a crucial role in facilitating risk spillover, while integrated oil and gas companies, represented solely by JSNY, act as pivotal positions. This underscores that during "Dual-Carbon" events, risk propagation is primarily channeled through these companies, highlighting their substantial intermediary roles. Moreover, the roles undertaken by various types of energy companies within the network differ significantly, and the importance of each node is not immutable.

In contrast to closeness and betweenness centrality rankings, eigenvector centrality results show that new energy companies occupy the top five positions. Eigenvector centrality measures a company's role and status based on the importance of its neighboring nodes in the risk spillover network. This suggests that, throughout the study period, new energy companies collaborate closely with other nodes. Under the "Dual-Carbon" objectives, the pace of energy transition accelerates significantly, and cooperation between traditional and new energy becomes a growing trend. Thus, the high eigenvector centrality rankings of new energy companies reaffirm their pivotal role from another perspective.

4. Conclusion and policy implications

Since the "Dual-Carbon" targets were announced, the energy market has undergone significant transformation, with the

Table 3
Structural characteristics of multi-layer risk spillover networks of energy companies.

Event	Average degree	Network diameter	Network density	Average clustering coefficient	Average path length
1	8.525	6	0.219	0.462	2.512
2	8.375	6	0.215	0.446	2.404
3	8.450	7	0.217	0.454	2.385
4	8.525	5	0.219	0.461	2.394
5	8.476	6	0.222	0.456	2.357
6	8.475	7	0.217	0.455	2.388
7	8.375	5	0.215	0.446	2.388
8	8.425	5	0.216	0.450	1.848
9	8.500	8	0.218	0.458	2.848
10	8.475	7	0.217	0.456	2.667

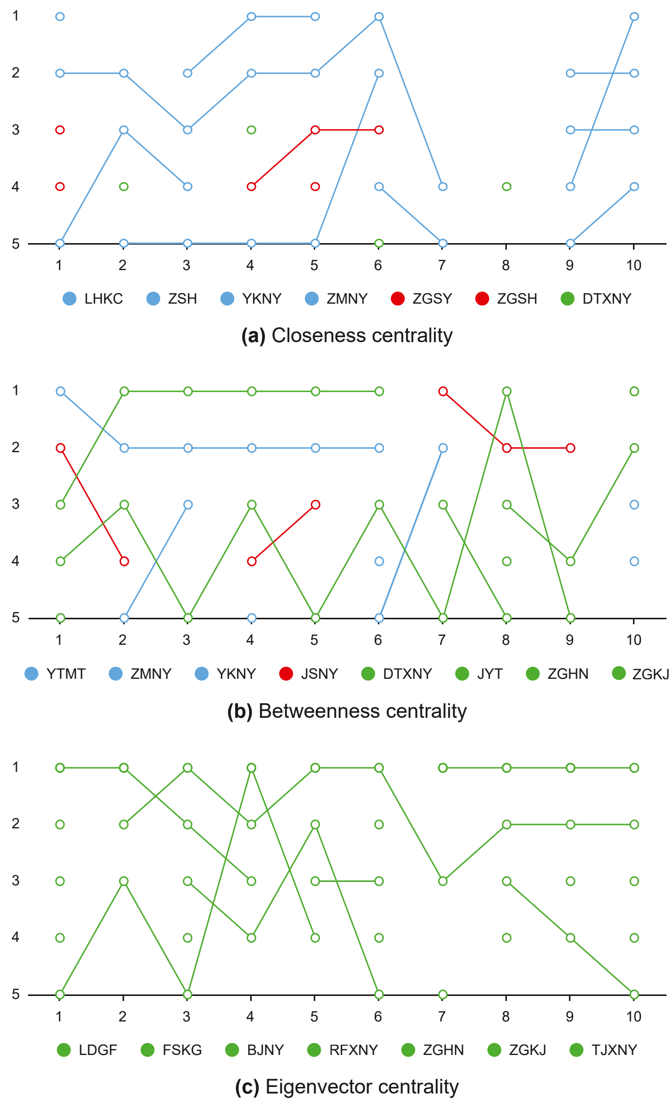

Fig. 4. Energy companies risk spillover network node centrality ranking.

financial sector feeling the ripple effects. Energy companies, as key players in the stock market, face increased complexity in risk spillovers due to the “Dual-Carbon” initiative. Despite this, the risk contagion among these companies in the pursuit of carbon neutrality has not yet drawn broad attention. This study applies the TVP-VAR-DY model to thoroughly examine the mechanisms of risk spillover among different energy companies, considering both static and dynamic aspects. By employing a multi-layer complex network model, we've built a three-tier risk spillover network for energy companies, providing a comprehensive analysis of the sector's interconnected risks.

The study has three main findings. First, there exist differences in the risk spillover effects amidst different types of energy companies, and the risk spillover indices of the three categories of energy companies exhibit distinctive time-varying characteristics. Specifically, coal-based energy companies exhibit the most prominent spillover effect, followed by renewable energy and integrated oil and gas companies. The prominent time-varying characteristics of the dynamic spillover index of renewable energy companies are particularly evident. A small number of energy companies play a role as net exporters of risk spillovers, thereby playing a crucial role in the risk spillover of similar energy companies.

Second, from the perspective of the impact of carbon neutrality policies, coal-based energy companies are more prone to the influence of “Dual-Carbon” related policies. Furthermore, there are notable differences in the network topological characteristics pertaining to different types of “Dual-Carbon” events.

Third, energy companies assume diverse roles in the multi-layer risk spillover network. Coal-based energy companies demonstrate stronger connectivity with other energy companies in the network. A few energy companies consistently occupy pivotal core node positions in the network. Renewable energy companies collaborate more closely with other types of energy companies, especially with coal-based energy companies, indicating that cooperation between traditional and renewable energy companies has become a prevailing trend.

4.1. Policy implications

This study has significant policy implications for the overall layout of China's energy system and the regulation of energy market dynamics. Based on the results, the following implications are obtained:

At the level of government regulation, when developing energy-saving and emission reduction policies for the energy industry, the government should carefully consider their actual and potential impact. It is important to continuously enhance and optimize the regulatory framework and incentive system associated with these policies. In the context of carbon neutrality, detailed guidance or plans should be provided when issuing relevant policies to enhance investor confidence, and energy companies should be encouraged to announce emission reduction targets and actions for carbon emissions and fossil fuel consumption on schedule. Regulatory authorities in various countries should fully understand the direction and scale of risk spillovers between different types of energy companies, and use policy tools to strengthen targeted policy coordination.

Regulators should develop and refine rules to prevent financial risks in the energy sector as part of “Dual-Carbon” goals. They must monitor energy companies' risks comprehensively and regulate their investment and financing. During critical events, targeted actions should be taken to slow and reduce the spread of risks based on how energy companies are connected. Focusing on risk management and early warnings, authorities should use real-time monitoring to detect new risks and tailor oversight to each company's role in the financial network, to limit the spread of financial risks.

From the perspective of energy enterprise management, coal-based energy companies need to intensify their cooperation with new energy companies, while actively exploring new energy businesses. These coal companies should prioritize their focus on green electricity operations, such as photovoltaic and wind power, as well as hydrogen energy and new energy storage. Furthermore, it is imperative to expedite the development of low-carbon technologies and reduce the costs associated with technological research and development. For integrated oil and gas energy companies, they should prioritize establishing partnerships with similar or other types of energy companies for joint research and development. For new energy companies, they should not only enhance their competitiveness and actively explore domestic and international markets, but also strengthen their sense of cooperation and actively share technology and resources with large traditional energy companies.

From the perspective of investors, the time-varying characteristics of spillover levels among energy companies can be leveraged to optimize trading decisions. For instance, investors can modify their portfolios, investment strategies, and trading decisions in response to negative events. From the viewpoint of energy enterprise management, in the context of "Dual-Carbon" targets, managers should not only be cognizant of the impacts arising from their own transition risks, but they must also consider the comprehensive influence of various factors, including the risk profile of partner companies.

4.2. Future research and limitations

There are a few limitations in this study that could be addressed in future research. Firstly, due to limitations in data accessibility and availability, this paper categorizes energy-listed companies into three types only, and future research may potentially expand the scope of selection for such companies. Secondly, as this study primarily focuses on the context of carbon neutrality, it is advisable to consider further developing regression models to analyze the driving factors behind the risk spillover effects among energy-listed companies. Finally, given the current limitations in data collection for various energy-listed companies, future endeavors in constructing multilayered complex networks may incorporate additional attribute information of nodes for further supplementation.

CRediT authorship contribution statement

Wen-Wen Zhou: Conceptualization. **Rui-Lin Feng:** Writing – review & editing, Writing – original draft, Visualization. **Xiao-bo Song:** Resources. **Yu Shi:** Formal analysis, Data curation.

Declaration of competing interest

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

Appendix A. The abbreviation list of energy companies mentioned in the text

Abbreviations	Full Term
LHKC	Shanxi Huayang Group New Energy Co., Ltd.
HYGF	Shanghai Datun Energy Co., Ltd.
SHNY	China Shenhua Energy Company Limited
ZSH	Jinneng Science and Technology Co., Ltd.
JNKJ	Mongolia Energy Corporation Limited
MGNY	Shougang Fushan Resources Group Limited
SGZY	China Qinfa Group Co., Ltd.
ZGQF	Yankuang Energy Group Co., Ltd.
YKNY	Hengding Industrial International Development Company Limited
HDSY	Yonghui Coking Coal Co., Ltd.
YDZ	China National Coal Development Corporation Limited
ZMNY	Inner Mongolia Yitai Coal Co., Ltd.
YTMT	Henan Jinma Energy Co., Ltd.
JMNY	Power Development Group Holdings Limited
LLFZ	Shouhua Gas Technology Co., Ltd.
SHRQ	China Petroleum & Chemical Corporation (Sinopec)
ZGSH	PetroChina Company Limited
ZGSY	Champion Technology Group Holdings Limited
GJKJ	New Era Energy Limited
XSDNY	Jinshan Energy Group Holdings Limited
JSNY	Power Energy International Holdings Limited
BNGJ	Beijing Jingyuntong Technology Co., Ltd.
JYT	Guangdong Changqing (Group) Co., Ltd.
CQJT	Hunan Development Group Co., Ltd.
HNFZ	Lingda Group Co., Ltd.
LDGF	Zhongke Photoelectric Holdings Limited
ZGKJ	Tianjin Zhonglv Dian Investment Co., Ltd.
GYFZ	Beijing Enterprises Clean Energy Group Limited
SGXNY	Tongjing New Energy Group Holdings Limited
TJXNY	Ruifeng Galaxy New Energy Holdings Limited
RFXNY	Shanghai Lingyun Industrial Development Co., Ltd.
LYB	Fullshare Holdings Limited
FSKG	Panda Green Energy Group Limited
BJNY	Shanghai Camtec Solar Technology Co., Ltd.
KMDK	Shanxi Huayang Group New Energy Co., Ltd.

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